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Connecting Past to Present: Institutionalized Racism in Housing Markets and Neighborhood Health Inequities

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Connecting Past to Present: Institutionalized Racism in Housing Markets and Neighborhood Health Inequities

By

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ABSTRACT

Connecting Past to Present: Institutionalized Racism in Housing Markets

and Neighborhood Health Inequities

by

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Government endorsed redlining practices carried out by the Home Owners' Loan Corporation (HOLC) beginning in the mid-1930s have garnered attention in the population health literature over the last few years, with increased recognition of structural racism and *de jure* residential segregation as fundamental causes of racial/ethnic health disparities. HOLC's appraisal process was carried out in cities with at least 40,000 residents and entailed the assignment of color-coded "risk grades" to residential properties in urban neighborhoods based on perceived risk for foreclosure. Neighborhoods with concentrations of Black and/or immigrant residents were systematically graded in the highest risk category and experienced subsequent declines in property values, private investment, and lending opportunities associated with the "hazardous" designation. Digitization of HOLC's infamous "residential security maps" by the University of Richmond's Mapping Inequality Project has enabled researchers to link historical redlining patterns to a range of contemporary social, economic and health outcomes, from birth outcomes to chronic disease. The connection between historical redlining practices and contemporary health outcomes may highlight an important pathway by which structural racism produces and reproduces racialized and place-based health inequities across generations.

Despite the recent profusion of evidence associating historical redlining and contemporary health outcomes, few studies have probed these relationships for heterogeneity across population groups or

geographic areas, and few have examined the mechanisms by which historical redlining practices may impact contemporary neighborhood conditions and health. This dissertation links data from the Centers for Disease Control and Prevention (CDC) PLACES Project (2020 release), Historic Redlining Scores Project, American Community Survey 5-year estimates (2013-2017), and the Home Mortgage Disclosure Act database (2013-2017) to examine historical and contemporary forms of institutionalized racism in housing markets as drivers of neighborhood health inequities. In the first empirical chapter (Chapter 2), I examine whether and how associations between historical redlining patterns and neighborhood health – specifically, prevalence of poor mental health and diagnosed diabetes – are moderated by contemporary neighborhood racial/ethnic composition. The findings of this study may point to differential impacts of historical to contemporary structural racism across racial/ethnic groups. In the second empirical chapter (Chapter 3), I examine whether and to what extent features of contemporary housing markets explain the documented association between historical redlining patterns and neighborhood prevalence of poor mental health. As inequities within local housing markets have particularly affected Black communities, I also examine whether the effects of historical redlining patterns through features of contemporary housing markets are dependent on the relative size of the Black population within a neighborhood. The findings of this study suggest neighborhood property values, homeownership rates, and loan denial rates for home purchase explain a large share of the association between redlining patterns and poor mental health. Finally, in the third empirical chapter (Chapter 4), I examine whether and how associations between historical redlining patterns and neighborhood diabetes prevalence vary across metropolitan areas. Specifically, I examine a novel composite measure of institutionalized anti-Black racism in housing markets as a possible metropolitan/micropolitan area-level modifier of the relationship between historical redlining and neighborhood diabetes prevalence. This study suggests contemporary institutionalized racism in local housing markets may be perpetuating legacies of historical redlining practices and other exclusionary policies. Overall, these studies contribute to a burgeoning body of literature examining the roles of historical to contemporary forms of institutionalized racism in housing markets in the (re)production of racial/ethnic and place-based health inequities. This work is particularly timely as policymakers have garnered stronger interest in pursuing reparations for historical injustices imposed on Black communities, including use of the HOLC maps to prioritize neighborhoods for place-based investments.

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Chapter 1 | INTRODUCTION

Between March 2020 and April 2023, Black Americans were more than twice as likely to be hospitalized with COVID-19 than their non-Hispanic white counterparts and more than 50 percent more likely to die (*COVID-19 Cases, Data, and Surveillance: Hospitalization and Death by Race/Ethnicity*, 2023). At the same time, the United States saw national outrage and an outcry of support for the Black Lives Matter movement following the murders of George Floyd, Ahmaud Arbery, and Breonna Taylor – among so many other Black Americans – at the hands of law enforcement officers in the spring of 2020. These stark disparities and overt acts of anti-Black racism and violence – though by no means new phenomena – increased public awareness of structural racism and demand for large-scale social change (Nguyen et al., 2021). In April 2021, the Centers for Disease Control and Prevention (CDC) formally recognized racism as a serious public health threat, and many state and local agencies declared it a public health crisis. Racial disparities in health have been an important topic in public health for decades; however, only more recently has the discussion shifted away from a focus on "race" as a risk factor for adverse outcomes to recognition of racism as a fundamental driver of racial health inequities (Gee & Ford, 2011; Williams et al., 2019). In support, public health scholars have called for increased attention, measurement, and explicit naming of structural and institutional racism in the study of racial health inequities (Hardeman et al., 2018).

Over the last 30 years, views of what racism is and how it affects health have evolved (Bailey et al., 2017; Bonilla-Silva, 1997; Dean & Thorpe, 2022; Gee & Ford, 2011; C. P. Jones, 2000; Williams et al., 2019; Williams & Sternthal, 2010). For example, Camara Jones' (2000) framework for understanding racism delineates three levels at which racism acts to influence health – internalized racism, interpersonal racism, and institutionalized racism – where institutionalized racism is defined as "differential access to the goods, services, and opportunities of society by race." Jones further explains that "institutionalized racism is normative, sometimes legalized, and often manifests as inherited disadvantage. It is structural, having been codified in our institutions of custom, practice, and law, so there need not be an identifiable perpetrator. Indeed, institutionalized racism is often evident as inaction in the face of need" (C. P. Jones, 2000). Similarly, Williams et al. (2019) define racism as "an organized social system in which the dominant racial group, based on an ideology of inferiority, categorizes and ranks people into social groups called "races" and uses its power to devalue, disempower, and differentially allocate valued societal resources and opportunities to groups defined as inferior." They also note that "a characteristic of racism is that its structure and ideology can persist in governmental and institutional policies in the absence of individual actors who are explicitly racially prejudiced" (Williams et al., 2019). Finally, Bailey et al. (2017) define structural racism as the "totality of ways in which societies foster [racial] discrimination, via mutually reinforcing [inequitable] systems… (e.g., in housing, education, employment, earnings, benefits, credit, media, health care, criminal justice, etc.) that in turn reinforce discriminatory beliefs, values, and distribution of resources" (Bailey et al., 2017). Although there is no single agreed upon definition or framework, all arguments suggest that racism does not simply manifest through private prejudices and discrimination. Rather, racism acts on multiple levels and is embedded within the foundations of social, economic, and political systems through laws, policies, practices, and social and cultural norms (Bailey et al., 2021). Further, as stated by Jones (2000) and Williams et al. (2019), racism persists within systems even in the absence of identifiable perpetrators or racially prejudiced actors – ultimately, structural and institutional racism have been baked into societal norms and structures in ways that will self-perpetuate unless intentionally interrupted.

As racism acts on multiple levels, there are many different mechanisms by which racism influences downstream health outcomes. As suggested by the definitions offered above, one such mechanism is the differential distribution of resources, opportunities, and exposures across racialized population groups. Historically, racial segregation within residential, educational, service, and occupational spaces was a means to intentionally and efficiently funnel resources to privileged white communities to the detriment of communities of color (Rothstein, 2017; Williams et al., 2019; Williams & Collins, 2001). Racial residential segregation remains particularly relevant today because, despite the passing of the Fair Housing Act in 1968, the patterns established by 20th century segregationist housing policies and practices have broadly persisted across American cities, and neighborhood inequalities remain inextricably associated with neighborhood racial composition. Williams and Collins (2001) have called racial residential segregation a "fundamental cause of racial disparities in health" because it shapes social and economic opportunities and structures conditions within physical and social environments differentially across groups in ways that are either beneficial or harmful to health. Within the population health literature, researchers have begun to trace these structural drivers of racialized health inequities back to their historical roots. Broadly, this dissertation contributes to a burgeoning body of literature examining the roles of historical to contemporary forms of institutionalized racism – as they relate to local housing markets – in the (re)production of racial/ethnic and place-based health inequities. Specifically, this work probes the documented association between historical redlining practices and contemporary neighborhood health outcomes. Below, I provide additional background and historical context, followed by an overview of the three empirical chapters and overarching methodological considerations.

Background

Historical redlining, 1930s

The structure of our contemporary housing market was built on a foundation of racial exclusion that in many ways was endorsed or even directed by the federal government (Rothstein, 2017). Following the foreclosure crisis of the Great Depression, the New Deal era established the modern-day framework for housing, including the promotion of homeownership as an important vehicle to build wealth and achieve the "American Dream." However, federal initiatives to increase access to homeownership placed severe restrictions on benefits for African Americans and in some cases excluded Black families altogether (Rothstein, 2017). One such mechanism was in the assessment of urban neighborhoods for foreclosure risk carried out by the Home Owners' Loan Corporation (HOLC) in the mid- to late-1930s. This process widely known as "redlining" was carried out in cities with at least 40,000 residents beginning in 1933 and entailed the assignment of one of four color-coded "risk grades" to neighborhoods based on perceived risk for foreclosure: "A" (green) represented "best" and lowest perceived investment risk; "B" (blue) indicated "still desirable;" "C" (yellow) meant "definitely declining;" and "D" (red) represented "hazardous" and highest perceived investment risk (Greer, 2013; K. T. Jackson, 1985; Mitchell & Franco, 2018). These grades were represented on a series of "residential security maps" that were subsequently used to inform decisions around loans for home purchase, refinance, or improvement. On the surface, these practices were intended to "protect homeownership" by making home loans more affordable and preventing future foreclosures (K. T. Jackson, 1985). HOLC's activities, however, along with a slew of New Deal initiatives to expand homeownership opportunities, imposed severe limitations on residents who were non-white or not of Western European descent. For example, HOLC's neighborhood appraisal process was explicitly racist in that neighborhoods with concentrations of Black and/or immigrant residents, particularly those of East Asian or "Latin" descent, were systematically assigned a "D" risk grade, or in other words, redlined. Conversely, neighborhoods that were assigned an "A" or "B" grade were predominantly white and, particularly in "A" graded areas, had additional measures in place, such as racially restrictive covenants, to prevent an influx of non-white residents. Overall, "C" was the most common grade and often corresponded to relatively diverse neighborhoods perceived as being on the decline in terms of neighborhood conditions and property values, often based solely on the presence of Black and/or immigrant families.

The common narrative in much of the literature is that historically redlined neighborhoods were predominantly Black and remain so today (Brandt, 2020; C. Jackson, 2021). Indeed, the Black population was the largest group to be targeted by redlining and other forms of spatial racism; however, these activities affected a wide range of minoritized immigrant, cultural, and religious groups. For example, a recent analysis of the area description sheets that accompany the HOLC maps found that neighborhoods containing any number of East Asian or Pacific Islander (Asian/PI) residents were redlined more than 75 percent of the time and were never assigned an "A" or "B" grade (Markley, 2022). Neighborhoods which were mentioned as having any number of Black residents were redlined just under 75 percent of the time, and a very small number of neighborhoods containing Black residents were assigned a "B" grade but were never assigned an "A" grade. Neighborhoods mentioned as containing any number of residents of "Latin" descent were redlined about 60 percent of the time and in very few cases assigned an "A" or "B" grade. Conversely, neighborhoods mentioned as containing "American" residents or neighborhoods without any mention of the area's racial or ethnic composition, likely indicating the presence of only white residents, were assigned an "A" or "B" grade about half of the time and very rarely assigned a "D" grade (Markley, 2022).

Racial residential segregation, 1970-present

Over the last 90 years since the HOLC maps were created, the racial and ethnic composition of historically redlined neighborhoods has evolved; however, patterns of racial residential segregation have broadly persisted in large metropolitan areas. Some scholars have argued segregation persists because of economic differences between racial groups; some argue personal preferences and discrimination are primary factors; others argue segregation has become a self-perpetuating process (Krysan & Crowder, 2017). Despite the supposed end of *de jure* segregation in 1968 with the passage of the Fair Housing Act, which prohibited discrimination in the sale and rental of housing (or most housing) on the basis of race or national origin, the 1970 census marked the peak of Black-white residential segregation in many U.S cities (Massey & Tannen, 2018). Thus, 1970 is somewhat of an inflection point in the demographic transition of the U.S., and, given the presumed absence of government intervention to maintain segregation, the beginning of "natural" movement of people across space, where neighborhood demographic shifts are largely a result of changes in the housing market, real estate practices, and individual residential decision-making processes (Krysan & Crowder, 2017). Since then, we have seen only minor declines in segregation among non-Hispanic white and Black populations and overall, a trend toward greater diversity in metropolitan areas where large populations of Asian and Hispanic immigrants have settled over the last several decades.

Since 1970, Black-white segregation has declined moderately while Hispanic-white and Asian-white segregation have remained stable (Massey & Tannen, 2018; Rugh & Massey, 2014). One of the most commonly used measures of racial residential segregation is the dissimilarity index, which compares the extent to which two population groups are evenly distributed across an area (e.g., a city or metropolitan area). The measure ranges from zero to one and indicates the proportion of residents from a particular group which would need to move to achieve an even distribution of the two groups (*Appendix B. Measures of Residential Segregation*, 2021). Across all metropolitan areas in the U.S., the Black-white dissimilarity index dropped from 0.73 in 1980 to 0.55 in 2020. By this most recent estimate, 55 percent of the Black or white population would need to move to a different neighborhood in order to achieve an even distribution. Despite the decline in Black-white segregation, the Black population has remained the most segregated group from the non-Hispanic white population (Logan & Stultz, 2022). By comparison, the Hispanic/Latino-white dissimilarity index was 0.50 in 1980 and 0.45 in 2020, and the Asian/PI-white dissimilarity index consistently ranged between 0.40-0.41 from 1980-2020. Metropolitan areas with relatively large Black and/or Hispanic populations have tended to show the highest degrees of segregation among these groups. For example, Newark, Milwaukee, Detroit, New York, Chicago, Miami, and Philadelphia had Black-white dissimilarity index values above 0.70 even in 2020. Likewise, Salinas (CA), Newark, Los Angeles, and Philadelphia had Hispanic-white dissimilarity index values at or above 0.60 in 2020. Despite the relatively high degree of segregation from the non-Hispanic white population in these metros, most have seen notable declines since 1980. Interestingly, segregation between Asian/PI and white populations has increased substantially in certain metros with the largest Asian/PI populations. For example, the Asian/PI-white dissimilarity index in the New Brunswick-Lakewood, NJ metro area increased from 0.39 in 1980 to 0.57 in 2020 (Logan & Stultz, 2022).

Neighborhood change, 1980-present

These large-scale demographic transitions across U.S. metropolitan areas are, of course, more nuanced at the neighborhood level. Delmelle (2017) identified 33 pathways of neighborhood change for the 1980-2010 period, 15 of which suggest a “descending trajectory” and 9 of which suggest an “ascending trajectory;” the remaining pathways suggest relative stability across 9 unique clusters of neighborhood types (Delmelle, 2017). For example, neighborhoods which are characterized by a “wealthy, white, educated” population have largely remained stable or in some places have transitioned to “white/Asian multifamily, college educated” neighborhoods or to neighborhoods characterized by “newer white, single-family homes.” Conversely, neighborhoods characterized by “Black, high poverty, vacant homes” have largely remained stable or transitioned to “Hispanic and Black, higher poverty, aging homes” (Delmelle, 2017).

In general, many of the trajectories Delmelle describes are consistent with prior theories of neighborhood change. For example, the combination of declining conditions in urban centers and increasing suburbanization between 1950-1980 stimulated a white flight process that diminished the white population in many cities, particularly in the Northeast and Midwest. The Great Migration continued until 1970 as millions of African Americans left the rural South seeking employment and better conditions in urban areas of the Northeast, Midwest, and West. At the same time, growing numbers of Hispanic and Asian immigrants repopulated cities and established multiethnic neighborhoods as well as concentrated ethnic enclaves in areas that had previously been predominantly white or mixed (W. Zhang & Logan, 2016). In the last two decades, gentrification processes have become more prominent as white Americans have returned in large numbers to urban areas. Studies have found gentrification is most likely to occur in neighborhoods with an Asian presence or which are ethnically diverse and least likely in predominantly Black or Hispanic neighborhoods (Delmelle, 2016; Hwang & Sampson, 2014). Finally, the most common form of neighborhood change is no change at all – a process of relative stability is most relevant to the highly affluent and highly impoverished neighborhoods. In the context of this dissertation, this pattern of relative stability among the most advantaged and disadvantaged neighborhoods is likely characteristic of historically “A” and “D” graded neighborhoods, respectively. Particularly in older cities, legacies of discrimination in housing and enduring patterns of racial residential segregation have impeded change in high-poverty Black and Hispanic neighborhoods and have simultaneously stabilized the reputations and conditions of affluent, predominantly white neighborhoods (Solari, 2012; Wilson, 2008).

Neighborhoods and health

Public health as a discipline has long recognized that population-level health outcomes and disparities are products of more than individual-level decisions and behaviors. Health is in large part shaped by the social determinants of health, defined by the World Health Organization as "the conditions in which people are born, grow, live, work and age" (*Social Determinants of Health*, 2023) and more broadly by the structural factors driving inequality across those conditions (Braveman & Gottlieb, 2014). Ultimately the individual characteristics, behaviors, and exposures which influence health occur within household and community environments, as well as their interactions with broader social, economic, and political contexts. Residential contexts are uniquely important in shaping health over the life course, as neighborhoods often structure residents' access to high-quality housing, transportation systems, educational institutions, health care services, sources of healthy foods, and spaces for exercise and recreation, as well as residents' exposures to crime, violence, pollution, and other potential hazards to health and safety (Diez Roux & Mair, 2010). Features of neighborhood physical environments and land use patterns have been linked to adverse health behaviors, including poor diet (Larson et al., 2009) and lack of physical activity (Kaczynski & Henderson, 2008; Saelens & Handy, 2008), as well as a range of adverse outcomes, including chronic diseases (Auchincloss, 2009; Auchincloss et al., 2008; Morland et al., 2006; Mujahid et al., 2008) and poor mental health (Dupéré & Perkins, 2007; Galea, 2005; Latkin & Curry, 2003). Relatedly, aspects of neighborhood social environments, including social cohesion, social capital, safety/violence, and residential stability have been linked to depression and other mental health outcomes (Aneshensel et al., 2007; Fitzpatrick et al., 2005; Gary et al., 2007; Mair et al., 2009; Yen et al., 2006), health behaviors (Bennett et al., 2007), and in some cases, chronic disease (Chaix et al., 2008; Sundquist et al., 2006). Studies have also shown differences in neighborhood conditions and opportunities explain a large portion of variation in life expectancy across U.S. neighborhoods (Arias et al., 2018; Shanahan et al., 2022).

Under mounting evidence of neighborhood effects on health – and increasing recognition that neighborhood inequalities contribute to widening health inequities – the idea that "your ZIP code matters more than your genetic code" has become widely accepted (Iton & Ross, 2017; Orminski, 2021; Warhover, 2014). Neighborhood inequalities are a defining feature of the American urban landscape – as sociologist Robert Sampson comments in *Great American City: Chicago and the Enduring Neighborhood Effect*, "what is truly American is not so much the individual but neighborhood inequality" (Sampson, 2012). The reproduction of neighborhood inequalities over time has been particularly harmful to Black communities (Sampson, 2009). Racial residential segregation and chronic disinvestment in historically Black neighborhoods have created conditions that contribute to racialized and place-based health inequities across urban neighborhoods. After decades of disinvestment and exclusion, segregated Black neighborhoods today experience, on average, greater and more prolonged exposures to concentrated disadvantage relative to neighborhoods which are predominantly white, Hispanic, or Asian/other, including higher rates of poverty, unemployment, and violent crime, greater industrial pollution, lower rates of college education and homeownership, and lower property values (Krysan & Crowder, 2017). Researchers have linked these inequitable conditions and environmental exposures to racial disparities in health across a range of outcomes, including life expectancy, cognitive development, mental health, and chronic disease (Clarke et al., 2010; Freedman et al., 2011; Mehdipanah et al., 2017; Schulz et al., 2000; Sharkey & Elwert, 2011; Sharkey & Faber, 2014). Sharkey and Faber (2014) astutely argue that the question is no longer whether or not residential contexts matter for health, but rather how neighborhoods differentially influence health across spatial, temporal, and population strata.

Historical redlining and contemporary health

Digitization of HOLC's infamous "residential security maps" by the University of Richmond's Mapping Inequality Project (Nelson et al., 2021) has enabled researchers to link historical redlining patterns to a range of contemporary social, economic and health outcomes, from birth outcomes to chronic disease (Diaz et al., 2021; Krieger et al., 2020; Lee et al., 2021; Lynch et al., 2021; Mujahid et al., 2021; Nardone, Casey, et al., 2020; Nardone, Chiang, et al., 2020). A recent systematic review of health outcomes in redlined versus non-redlined neighborhoods found that areas graded by HOLC in the 1930s as being high risk for lending and investment experience significantly worse health today, including greater odds of premature birth, higher prevalence of poor self-rated health and chronic diseases such as asthma, diabetes, and hypertension, as well as higher rates of other adverse outcomes including stroke, heat-related illnesses, and firearm injuries (Lee et al., 2021). Associations between historical redlining patterns and contemporary health outcomes have been documented in virtually every region of the United States (Nardone, Chiang, et al., 2020). This connection between historical redlining practices and contemporary health outcomes may highlight an important pathway by which structural racism produces and reproduces racialized and place-based health inequities across generations.

Research overview

Despite this recent profusion of evidence rooting contemporary inequities within these historical contexts, several gaps remain. This dissertation aims to address three of these gaps related to historical and contemporary forms of institutionalized racism in housing markets as drivers of neighborhood health inequities. Broadly, the following three empirical chapters examine: (1) the heterogeneity in associations between historical redlining patterns and neighborhood health outcomes based on contemporary neighborhood racial/ethnic composition; (2) the mechanisms by which historical redlining may contribute to contemporary neighborhood health inequities; and (3) the ways in which broader contexts of contemporary institutionalized racism in local housing markets may reinforce associations between historical redlining patterns and contemporary neighborhood health.

Conceptual framework

Based on the historical narrative around the development and use of the HOLC maps, as well as evidence from existing literature, the hypothesized pathways by which historical redlining practices and other forms of spatial racism continue to affect the health of historically redlined neighborhoods include: (1) systematic neighborhood disinvestment and concentration of social and economic disadvantage (Aaronson et al., 2020; Aaronson, Faber, et al., 2021; Faber, 2021); (2) conflation of neighborhood racial composition with property values and chronic devaluation of Black property (Graetz & Esposito, 2021; Howell & Korver-Glenn, 2021; Perry et al., 2018); (3) institutionalization of mortgage lending discrimination and relatedly, inequitable opportunities for homeownership and accumulation of capital (Woods, 2012); (4) declining infrastructure and housing conditions; and finally, (5) established patterns of racial and economic residential segregation (Rothstein, 2017).

Over the last three decades, numerous studies have linked various forms of residential segregation to poor health, particularly among Black communities (Kramer & Hogue, 2009). Depressed neighborhood socioeconomic conditions in tandem with patterns of racial residential segregation have contributed to the concentration of disadvantage, creating a stark differential in neighborhood opportunity and resources (e.g., access to high quality education, high-paying jobs, sources of healthy food, transportation, and healthcare services) as well as disproportionate exposures to environmental hazards and crime, (Krysan & Crowder, 2017; Massey & Denton, 1993; Rothstein, 2017) factors which in turn have direct implications for health.

Studies have also tied contemporary mortgage lending discrimination and inequitable homeownership rates to poor health outcomes (Lindblad & Quercia, 2015; Lynch et al., 2021; Matoba et al., 2019; Mendez et al., 2011; Ortiz & Zimmerman, 2013). Although overt discrimination in housing has been outlawed since the passing of the Fair Housing Act in 1968, Black Americans continue to face inequities in homeownership, mortgage lending, and property values. In 2020, roughly 45 percent of African Americans owned their homes compared to 75 percent of white Americans (*Quarterly Residential Vacancies and Homeownership, Second Quarter 2021*, 2021). These disparities in homeownership rates stem from historical structures that excluded Black families from housing markets, and their persistence offers evidence of continued institutionalized racism within housing systems. In support, only about half of the gap in Black-white homeownership can be explained by differences in income, educational attainment, marital status, credit scores, and age distribution (Choi et al., 2019). Nationwide, Black applicants in 2020 were three times as likely to be denied a loan for home purchase and twice as likely to be denied for refinance relative to non-Hispanic white applicants (Liu et al., 2021). Black applicants are also disproportionately targeted for high-cost loans and other predatory lending practices (Barwick, 2010). Homes in majority Black neighborhoods are undervalued by over 20 percent relative to homes in neighborhoods with fewer than one percent Black residents, even after adjusting for structural features and neighborhood amenities (Perry et al., 2018). Neighborhood racial composition is a bigger predictor of property values today than it was in 1980 (Howell & Korver-Glenn, 2021). The devaluation of Black property impedes the accumulation of wealth among Black households and has important implications for inequities in other systems (e.g., school funding). Relatedly, the racial wealth gap has seen little improvement since 1980; on average, Black families today have one-sixth of the wealth held by their white counterparts (Derenoncourt et al., n.d.). Without adequate reparative action, researchers estimate it will take more than 200 years for Black families to achieve the level of wealth currently held by white families (Asante-Muhammad et al., 2016).

These patterns of mortgage lending discrimination, inequitable homeownership opportunities, and reduced property values have together made it more difficult for Black families to accumulate capital and build wealth across generations (Krivo & Kaufman, 2004). Limited family assets, including both socioeconomic status and intergenerational wealth, have important implications for health, acting directly through reduced ability to access needed resources and indirectly through increased instability, decreased sense of control, and increased stress (Cutler et al., 2008). Likewise, poor housing quality has both direct and indirect consequences for health (Swope & Hernández, 2019). Poor housing conditions have been linked to a range of adverse outcomes including asthma, chronic disease, and poor physical and mental health (Boch et al., 2020). Further, many of these pathways stemming from historical structural racism act through their contribution to chronic stress (S. C. T. Jones et al., 2020) and health behaviors, both of which have well-documented links to poor physical and mental health outcomes (Schneiderman et al., 2005).

This conceptual framework is shown in Figure 1-1 below and offers a broad overview of the complex mechanisms by which historical structural racism in housing may contribute to contemporary health inequities. Many other factors are at play in the production of health inequities across racial/ethnic groups, including racism in other sectors (e.g., education, employment, healthcare, etc.) and at different levels (e.g., inter-personal discrimination). This research intends to capture only the ways in which historical and contemporary racism in housing markets may contribute to neighborhood health inequities within different contexts and through a subset of hypothesized mechanisms.

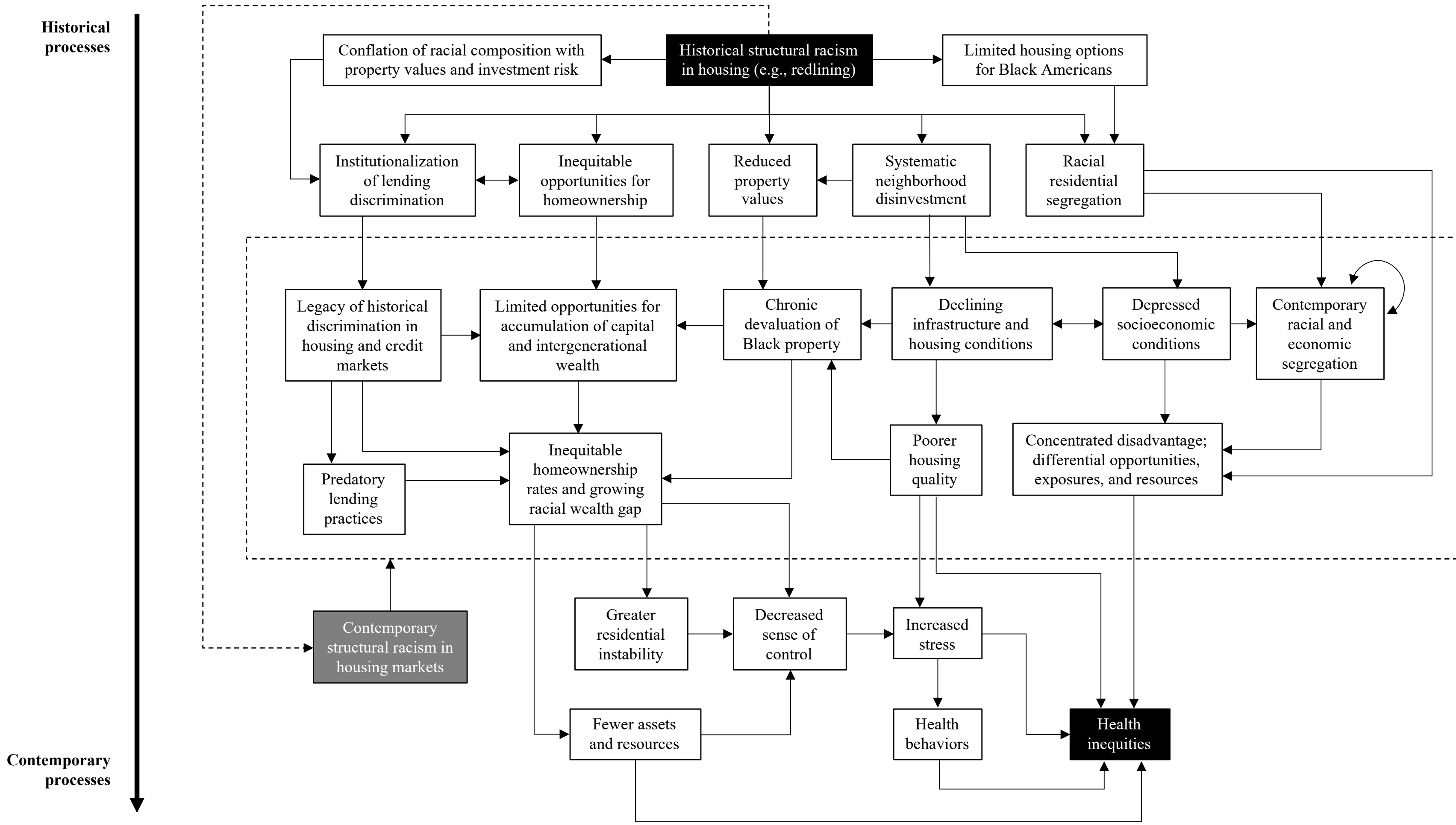

Figure 1-1. Conceptual framework for how historical redlining patterns relate to contemporary neighborhood health inequities

Data sources

Chapters 2-4 draw on many of the same data sources. First, we obtained data on neighborhood-level health outcomes from the 2020 release of the Centers for Disease Control and Prevention (CDC) PLACES Project. Observed differences in health across even the most granular geographic units in the U.S. motivated the development of the 500 Cities Project in 2015 by the CDC, Robert Wood Johnson Foundation, and CDC Foundation. The project utilized data from the Behavioral Risk Factor Surveillance System (BRFSS) and applied small area estimation methods to create census tract-level measures of health outcomes, risk factors, and utilization of preventive health care services for the 500 largest American cities. The project was later expanded to include all U.S. census tracts in what is now called PLACES: Local Data for Better Health (*PLACES Project*, 2020). The 2020 release utilizes data from the 2017-2018 BRFSS. The first empirical chapter (Chapter 2) examines two outcomes – neighborhood prevalence of poor mental health and neighborhood prevalence of diagnosed diabetes. The subsequent empirical chapters focus on a single outcome, where Chapter 3 examines neighborhood prevalence of poor mental health, and Chapter 4 examines neighborhood prevalence of diagnosed diabetes. In all studies, we used census tracts as proxies for neighborhoods, a common practice in the neighborhood effects literature.

In all studies, our primary exposure of interest was historical redlining score. We utilized the "historic redlining scores" developed by researchers at the University of Michigan (Meier & Mitchell, 2021). These scores were created by overlaying digitized versions of the historical HOLC "residential security maps" onto the 2010 census tract boundaries. A numerical score, 1-4, was assigned to each historical risk grade, A-D. The final historic redlining scores represent the average score for each census tract, weighted by the proportion of land area covered by each historical risk grade. Scores were created for all tracts which had at least 20 percent overlap with areas graded by HOLC. We utilized these continuous scores in all regression analyses. For descriptive purposes, we used an interval measure which categorized scores into four even intervals such that the top 25 percent of scores were categorized into interval 4, representing the most "redlined" areas, and the bottom 25 percent of scores were categorized into interval 1, representing the most “greenlined” areas. The historical HOLC maps were created for cities which had at least 40,000 residents in the 1930s. Thus, the maps were not created for all areas of the country, nor do they include areas where populations may have expanded after the fact. The original sample of census tracts with a corresponding historical redlining score included 12,864 tracts across 143 core-based statistical areas (CBSAs) (i.e., metropolitan/micropolitan areas).

Next, we utilized data from the American Community Survey (ACS) 5-year estimates for 2013-2017 to construct measures of neighborhood racial/ethnic composition, socioeconomic conditions, and housing characteristics at census tract and CBSA levels. We also used these data to construct measures of racial residential segregation at the CBSA level. Finally, Chapters 3-4 additionally utilize data from the Home Mortgage Disclosure Act (HMDA) database to characterize mortgage lending patterns at tract and CBSA levels. The HMDA database contains application-level information on loans for home purchase, refinance, and home improvement, including applicant characteristics such as race and ethnicity.

The three empirical chapters are each structured as standalone scholarly journal articles. Thus, each chapter has its own abstract, introduction, methods section, results, discussion, and conclusions. At a later time, each of these chapters will be formatted for a specific scholarly journal in public health and submitted for publication. A brief summary of each empirical chapter is provided below.

Chapter 2 summary

Historical redlining practices carried out by the Home Owners Loan Corporation (HOLC) beginning in the 1930s have been linked to a range of contemporary health outcomes and inequities, where neighborhoods graded as high risk for lending and investment today experience a greater burden of disease compared to those graded more favorably. However, previous studies have yet to examine whether and how relationships between redlining patterns and health may vary based on contemporary neighborhood racial/ethnic composition. Contemporary racial/ethnic composition is an important consideration as recent studies have shown historical redlining practices affected many different population groups (Markley, 2022), and further, racial/ethnic groups have experienced very different histories of structural racism in the United States over the last century, which we know have important implications for health and health inequities (Bailey, 2017; LaVeist, 2005).

In the first empirical chapter (Chapter 2), I examine whether and how associations between historical redlining patterns and neighborhood prevalence of poor mental health and diagnosed diabetes are moderated by contemporary neighborhood racial/ethnic composition. Chapter 2 begins with an overview of current understandings of the association between historical redlining patterns and contemporary health outcomes. It then provides historical context for the major population groups in the United States and discusses why we might expect the relationship between redlining and neighborhood health outcomes to differ based on neighborhood racial/ethnic composition. We linked historical redlining scores corresponding to the 2010 census tract boundaries to demographic characteristics from the ACS 5-year estimates (2013-2017) and neighborhood-level prevalence of poor mental health and diagnosed diabetes. In spatial regression analyses, we found contemporary neighborhood racial/ethnic composition moderates the relationships between historical redlining patterns and contemporary health outcomes. Specifically, we found the magnitude of these relationships was greater among majority non-Hispanic Black neighborhoods, relative to majority non-Hispanic white neighborhoods; conversely, the magnitude of the relationship between redlining score and poor mental health was smaller among majority Hispanic neighborhoods.

The findings of this study may point to differential impacts of historical to contemporary structural racism across racial/ethnic groups. Given their connection to contemporary social, economic, and health outcomes, the HOLC maps have been proposed as guides for future programming and investment. Our findings suggest reparations for long histories of racism and exclusion in housing and other sectors should be contextualized to the particular communities targeted and the unique challenges they face. Further research is needed to continue to better understand the present conditions in neighborhoods and communities marginalized through historical redlining practices and other exclusionary policies.

Chapter 3 summary

Next, although prior studies suggest historical redlining patterns are associated with the distribution of social determinants of health across urban neighborhoods (Mehdipanah et al., 2023; Swope et al., 2022), few studies have formally examined the contemporary factors which may help to explain the enduring legacy of historical redlining practices and their possible contributions to racial/ethnic and place-based health inequities (Graetz & Esposito, 2021; Laurent, 2021; Lynch et al., 2021). In recognition, researchers have called for greater attention to the factors which might mediate relationships between indicators of structural racism (e.g., residential segregation; historical redlining) and health (Krieger et al., 2020; Landrine et al., 2017). Contemporary features of local housing markets are of particular interest considering historical redlining practices were directly related to and likely had continued influence on mortgage lending patterns, property values, and homeownership opportunities (Aaronson, Hartley, et al., 2021; Greer, 2013).

In the second empirical chapter (Chapter 3), I examine whether and to what extent features of contemporary housing markets explain the documented association between historical redlining patterns and neighborhood prevalence of poor mental health. As inequities within local housing markets have particularly affected Black communities, I also examine whether the effects of historical redlining patterns through features of contemporary housing markets are dependent on the relative size of the Black population within a neighborhood. Chapter 3 utilizes data from the CDC PLACES Project (2020 release), ACS 5-year estimates (2013-2017), HMDA database (2013-2017), and Historic Redlining Scores Project. We used an ecological design at the census tract level to conduct mediation and first-stage conditional process analyses (moderated mediation) of our conceptual model. We found the relationship between historical redlining and contemporary prevalence of poor mental health can be explained in large part by features of contemporary housing markets, including neighborhood property values, homeownership rates, and loan denial rates for home purchase. We also found the indirect effect of redlining via relative median property value was conditional on the relative size of the Black population. Properties in historically “A” graded neighborhoods are valued more than those in neighborhoods graded less favorably – and this apparent benefit to property values is greater in neighborhoods where Black residents are underrepresented.

Our findings build on current understandings of the mechanisms by which historical redlining patterns may have lasting impacts on community health and wellbeing. Despite fair housing legislation enacted more than 50 years ago, racial inequities within contemporary housing markets persist, making it more difficult for Black families to build wealth and achieve optimal health. Racist ideologies conflating race and value must be dismantled to address the devaluation of assets in Black communities and its consequences for neighborhood health and well-being.

Chapter 4 summary

Relationships between historical redlining and health outcomes have been established in prior work; however, structural racism and its impacts on neighborhood health do not occur in a vacuum but are rather shaped by contemporary forces working at broader city and regional levels. Most studies of historical redlining and health outcomes have focused on a single city or metropolitan area; as such, few have examined the role of broader contextual features in shaping these relationships. Features of contemporary housing markets are of particular interest considering historical redlining practices may have had lasting influence on neighborhood property values, lending practices, and homeownership. Contextualizing neighborhoods with histories of redlining within contemporary housing markets may suggest conditions or processes which maintain the legacy of historical redlining practices.

In the third empirical chapter (Chapter 4), we examined whether and how associations between historical redlining patterns and neighborhood diabetes prevalence vary across metropolitan areas, and we explored whether conditions within contemporary housing markets might explain this variation. Specifically, we developed a novel composite measure of institutionalized anti-Black racism in housing markets, which we called the "IRH index," as a possible CBSA-level modifier of the relationship between historical redlining and neighborhood diabetes prevalence. We hypothesized CBSAs with higher degrees of contemporary institutionalized anti-Black racism in local housing markets would demonstrate stronger relationships between historical redlining patterns and neighborhood diabetes prevalence. We used confirmatory factor analysis to create the IRH index, which incorporated measures of racial residential segregation, discrimination in mortgage lending practices, and relative property values of neighborhoods with over- and under-representations of Black residents. In multilevel regression analyses, we found CBSAs with a higher degree of institutionalized racism in contemporary housing markets exhibit a stronger relationship between historical redlining patterns and neighborhood diabetes prevalence.

This study contributes to two related bodies of literature. First, the construction of a novel index of institutionalized anti-Black racism in housing markets aligns with calls to explicitly name and measure structural racism in health inequities research. Second, examination of historical redlining and neighborhood health within contemporary housing markets contributes to our understanding of the relevance of local context in maintaining the harmful legacy of historical redlining practices and other forms of spatial racism. Our findings suggest there remains unexplained variation in the relationship between historical redlining patterns and contemporary area-based health outcomes across CBSAs; research is needed to better understand the factors and processes by which impacts of historical structural racism are maintained or diminished.

Conclusion

The final chapter provides a brief summary of the overarching findings of the three empirical chapters described above and expands upon the implications of these findings for public health policy, practice, and research. Overall, this dissertation contributes to the burgeoning body of literature examining the consequences of structural racism for population health and health inequities. These studies offer new insights to the ways in which historical redlining practices and related forms of spatial racism may have lasting impacts on neighborhood conditions and community health and wellbeing.

Methodological considerations

These studies have several cross-cutting conceptual and methodological considerations and limitations. First, there is some debate in the literature around the relative importance of the HOLC "residential security maps" in shaping subsequent patterns of racial residential segregation, economic distress in communities of color, and access to credit and homeownership among Black Americans. Several scholars have identified significant effects of redlining on contemporary labor market outcomes, family structure, incarceration, credit scores, mortgage lending patterns, firearm violence, and health (Aaronson, Faber, et al., 2021; Faber, 2021; Lee et al., 2021; Mujahid et al., 2021; Poulson et al., 2021). However, others argue the HOLC maps had little to do with historical or contemporary lending patterns or economic decline in neighborhoods deemed high-risk for investment (Fishback et al., 2020; Hillier, 2003). Still others suggest the HOLC maps were important in shaping our current urban landscape, but not it the ways typically conveyed in the literature connecting historical redlining with contemporary neighborhood conditions. For example, Graetz and Esposito (2021) suggest the HOLC maps had a broader impact beyond the "spatial marking" of neighborhoods as high-risk for investment. They argue that the process of developing the HOLC maps, rather than the maps themselves, validated and institutionalized the conflation of neighborhood racial composition with investment risk and property values and that these government-backed segregationist policies in housing set the stage for segregation in other sectors (e.g., education) (Graetz & Esposito, 2021).

Further, redlining practices were only one mechanism of exclusion of communities of color from homeownership and movement into higher resourced areas. For example, racial zoning and racially restrictive covenants were used as early as the late-1800s to prohibit Black families or often any non-white families from purchasing or renting properties in certain neighborhoods. The Federal Housing Authority (FHA), established in 1934 under the National Housing Act, often required restrictive covenants to be in place as a condition of their insurance of new developments (Hernandez, 2008; Rothstein, 2017). Further, some scholars have argued the FHA was the most significant agency driving the segregation and ghettoization of African American communities in urban centers (Kimble, 2007).

FHA ensured historically redlined neighborhoods would have less access to credit compared to neighborhoods graded more favorably. At the time, cities were experiencing a significant demographic shift as many African Americans fled the Southern states to escape Jim Crow and pursue educational and employment opportunities in other areas of the country. As African American communities expanded, the FHA intensified its efforts to prevent the integration of so-called "inharmonious racial groups" and exclude Black residents from housing and economic opportunities (Kimble, 2007). Importantly, the multiple mechanisms by which Black Americans were segregated and excluded from housing markets often overlapped; for example, neighborhoods which were assigned an "A" grade by HOLC were often those which already had racially exclusionary covenants in place. Given the varying conceptualizations of redlining, as well as mixed evidence around the effects of redlining practices themselves versus other segregationist policies, this dissertation utilizes the HOLC maps as a reflection of existing patterns and practices in the 1930s and a broad indication of the spatial patterning of historical structural racism in housing.

In addition to varying conceptualizations of historical redlining practices, population health scholars have taken several approaches to linking the HOLC maps to contemporary administrative boundaries. For example, some have assigned risk grades to present-day census tracts based on intersection of the tract centroid with the historical grade assigned by HOLC (Nardone, Casey, et al., 2020). Others have assigned grades based on the historical risk grade that occupies a majority of the area of a census tract (Graetz & Esposito, 2021; Krieger et al., 2020). These approaches ultimately consider only the presence of a single risk grade and disregard others which might have been present within contemporary tract boundaries. Others have developed continuous scores based on the relative area of a census tract which is occupied by each historical risk grade, thereby accounting for the presence of multiple risk grades (Lynch et al., 2021). Each of these approaches has inherent limitations and risk of misclassification bias that should be considered in interpreting past and future studies linking the historical HOLC risk grades to contemporary administrative boundaries. For example, the assignment of continuous scores based on the relative area covered by each HOLC grade may allow a neighborhood historically classified as “C” by HOLC and one classified as partially “A” or “B” and partially “D” to be given the same score and ultimately lumped into the same category. We chose to use the continuous scores to best represent the variation in risk grades, or combinations of risk grades, present within contemporary administrative boundaries. However, this approach is limited in that it assumes a uniform effect across risk grades.

Limitations

Chapters 2-4 each contain a limitations section specific to the corresponding study. However, several important limitations apply to all three empirical chapters. First, all studies carried out in this dissertation utilize an ecological design at the census tract level, introducing vulnerability to ecological fallacy and precluding causal inference. For example, in the first empirical chapter, I examine whether and how associations between historical redlining and neighborhood prevalence of poor mental health and diagnosed diabetes are moderated by neighborhood racial composition. My findings suggest historical redlining has a greater impact on neighborhoods in which a majority of residents are non-Hispanic Black relative to neighborhoods in which a majority of residents are non-Hispanic white. Although this finding might suggest Black residents of historically redlined neighborhoods are impacted more so than residents of other racial/ethnic groups, due to limitations of the data and study design I cannot be sure that the cases of poor mental health or diabetes actually belong to Black residents. My use of census tracts as proxies for neighborhoods is also vulnerable to the modifiable areal unit problem (MAUP), meaning my results may be biased based on the way tract boundaries are defined (Buzzelli, 2020). Relatedly, these studies are vulnerable to the uncertain geographic context problem (UGCoP), which suggests the areal units used in ecological designs may not reflect neighborhood residents’ true geographic contexts (Kwan, 2012).

Next, selection bias is of concern given my use of observational data to examine associations between neighborhood conditions and area-based health outcomes among existing residents. We were not able to randomize people to neighborhoods, nor were we able to account for the amount of time residents have lived in a neighborhood. In an ideal world, we could randomize people to neighborhoods with different HOLC risk grades and observe their development of disease over time. However, these types of studies are rare in the neighborhood effects literature. A notable example is the Moving to Opportunity (MTO) study, which randomized families living in high-poverty neighborhoods to one of three experimental conditions – (1) Section 8 housing voucher and requirement to live in a neighborhood with less than 10 percent poverty; (2) Section 8 housing voucher with no restrictions on neighborhood of residence; and (3) no housing voucher. Although findings are somewhat mixed across outcomes, studies consistently found movement to higher resourced neighborhoods was associated with improved mental health among adults (Leventhal & Brooks-Gunn, 2003; Turney et al., 2013). Further, at least one study found movement to a low-poverty neighborhood was associated with a reduced risk of diabetes (Ludwig et al., 2011). In the context of this dissertation, these findings are important as they provide experimental evidence of neighborhood effects on physical and mental health outcomes.

Finally, all outcome data are based on self-report from the 2017-2018 Behavioral Risk Factor Surveillance System; thus, these data are vulnerable to measurement error (e.g., social desirability bias, recall bias) and may be less reliable than more objective measures of health status. As these data were subsequently modeled to create small area estimates at the census tract level, these measures are additionally vulnerable to the limitations of the modeling approach; however, the methodology used to create these estimates has been validated in several previous studies (Wang et al., 2017; X. Zhang et al., 2014, 2015).

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Chapter 2 | ASSOCIATIONS BETWEEN HISTORICAL REDLINING PATTERNS AND AREA-BASED HEALTH OUTCOMES IN THE CONTEXT OF CONTEMPORARY NEIGHBORHOOD RACIAL/ETHNIC COMPOSITION

Abstract

Historical redlining practices carried out by the Home Owners Loan Corporation (HOLC) beginning in the 1930s have been linked to a range of contemporary health outcomes and inequities, where neighborhoods graded as high risk for lending and investment today experience a greater burden of disease compared to those graded more favorably. Although historical redlining practices targeted multiple racial and ethnic subpopulations, previous studies have yet to examine whether and how relationships between redlining patterns and neighborhood health may vary accordingly. In this study, we examined whether and how associations between historical redlining patterns and contemporary area-based health outcomes differ depending on the contemporary racial and ethnic composition of a neighborhood. We linked historical redlining scores corresponding to the 2010 census tract boundaries to demographic characteristics from the American Community Survey 5-year estimates (2013-2017) and neighborhood-level prevalence of poor mental health and diabetes from the 2020 release of the Centers for Disease Control and Prevention PLACES Project. In spatial regression analyses, we found the prevalence of adverse health outcomes increased with historical redlining score, and we found these relationships were moderated by contemporary neighborhood racial and ethnic composition. The magnitude of these relationships was greater among majority non-Hispanic Black neighborhoods, relative to majority non-Hispanic white neighborhoods; conversely, the magnitude of the relationship between historical redlining score and prevalence of poor mental health was smaller among majority Hispanic neighborhoods. Given their connection to contemporary social, economic, and health outcomes, the HOLC maps have been proposed as guides for future programming and investment. However, reparations for long histories of racism and exclusion in housing and other sectors should be contextualized to the

particular communities targeted and the unique challenges they face. Further research is needed to continue to better understand the present conditions in neighborhoods and communities marginalized through historical redlining practices and other exclusionary policies.

Introduction

Government endorsed redlining practices carried out by the Home Owners Loan Corporation (HOLC) in the mid- to late-1930s have garnered attention in the population health literature over the last few years, with increased recognition of structural racism and *de jure* residential segregation as fundamental causes of racial/ethnic health disparities (Bailey et al., 2017; Williams & Collins, 2001). Digitization of HOLC's infamous "residential security maps" has enabled researchers to link historical redlining patterns to a range of contemporary social, economic, and health outcomes (Nelson et al., 2021). A recent systematic review found areas graded as "high risk" for lending and investment by HOLC in the 1930s experience significantly worse health today, including greater odds of premature birth, higher prevalence of poor self-rated health and chronic diseases such as asthma, diabetes, and hypertension, as well as higher rates of stroke, heat-related illnesses, and firearm injuries (Lee et al., 2021). Associations between historical redlining patterns and contemporary health outcomes have been documented in virtually every region of the United States (Nardone, Chiang, et al., 2020). This connection between historical redlining practices and contemporary health outcomes may highlight an important pathway by which structural racism produces and – through enduring discriminatory housing practices and widening wealth disparities – reproduces place-based and racial/ethnic health inequities across generations.

Despite increased focus on historical redlining practices and other forms of spatial racism in the population health literature, researchers have yet to examine how associations between historical redlining patterns and contemporary health outcomes may differ depending on the racial or ethnic composition of a neighborhood. Contemporary racial/ethnic composition is an important consideration as recent studies have shown historical redlining practices affected many different population groups

(Markley, 2022), the racial/ethnic composition of historically redlined neighborhoods may have shifted over time with gentrification, immigration, and other processes of change, and further, different racial/ethnic populations have experienced very different histories of structural racism in the United States over the last century, which we know have important implications for health and health disparities (Bailey, 2017; LaVeist, 2005). In this study, we examine whether and how associations between historical redlining patterns and neighborhood prevalence of poor mental health and diagnosed diabetes depend on contemporary neighborhood racial/ethnic composition. Our findings may point to differential impacts of historical to contemporary structural racism across racial/ethnic subpopulations. This work is particularly timely considering recent formal recognition at the federal level of structural racism as a public health threat as well as ongoing efforts to develop reparations proposals for African Americans.

Historical context

HOLC's appraisal process was carried out in cities with at least 40,000 residents beginning in 1933 and entailed the assignment of color-coded "risk grades" to neighborhoods based on perceived risk for foreclosure: "A" (green) as "best" and lowest perceived investment risk; "B" (blue) as "still desirable;" "C" (yellow) as "definitely declining;" and "D" (red) as "hazardous" and highest perceived investment risk (Greer, 2013; K. T. Jackson, 1985; B. Mitchell & Franco, 2018). HOLC used these grades to produce a series of "residential security maps" that were intended to inform lending decisions for home purchase, refinance, or improvement. On the surface, these practices were proposed to "protect homeownership" by making home loans more affordable and preventing future foreclosures (K. T. Jackson, 1985). HOLC's activities, however, along with a slew of New Deal initiatives to expand homeownership opportunities, imposed severe limitations on residents who were non-white or not of Western European descent.

The common narrative in much of the literature is that historically redlined neighborhoods were predominantly Black and remain so today (Brandt, 2020; C. Jackson, 2021). Indeed, the Black population was the largest group to be targeted by redlining and other forms of spatial racism; however, these activities also targeted a wide range of minoritized immigrant, cultural, and religious groups (Markley, 2022). For example, HOLC's neighborhood appraisal process systematically assigned a "D" grade to neighborhoods with concentrations of Black and/or immigrant residents, particularly those of East Asian or "Latin" descent. Conversely, HOLC most frequently assigned an "A" or "B" grade to neighborhoods that were predominantly white. These neighborhoods, particularly "A" graded areas, often had additional measures in place such as racially restrictive covenants to prevent the settlement of non-white residents. Overall, HOLC assigned a "C" grade most often; these neighborhoods were relatively racially diverse and perceived as being on the decline in terms of neighborhood conditions and property values, a judgement often based solely on the presence of Black and/or immigrant families.

The racial and ethnic composition of neighborhoods across the spectrum of historical risk grades has evolved over time. A combination of declining conditions in urban centers and increasing suburbanization between 1950-1980 spurred a white flight process that diminished the white population in many cities, particularly in older Northern and Midwestern cities (Delmelle, 2017). The Great Migration began in the 1910s and continued until 1970 as millions of African Americans left the rural South to escape the legal and extralegal terrorism and violence of Jim Crow, seeking employment and better conditions in urban areas of the Northeast, Midwest, and West (Tolnay, 2003). Post-1970, Black families increasingly moved into suburban areas (Schneider & Phelan, 1993). At the same time, growing numbers of Hispanic and Asian immigrants repopulated cities and established multiethnic neighborhoods as well as concentrated ethnic enclaves in areas that had previously been predominantly white or mixed (Zhang & Logan, 2016). Hispanic immigration and urbanization played an important role in the maintenance and growth of urban populations, particularly in the last 50 years (Tienda & Sánchez, 2013). Between 1940-1970, the U.S. saw a three-fold increase in residents of Latin American heritage, many of whom came to the U.S. seeking greater economic opportunities.

While Hispanic immigration to the U.S. was fairly steady during the 20th century, Asian immigration occurred in relatively distinct phases related to U.S. policy priorities. Many early Asian immigrants clustered in urban centers, establishing the beginnings of Chinatowns in major U.S. cities

(Takaki, 1998); these areas, particularly in the West, offered respite during the end of the 19th century and beginning of the 20th century, with increasing anti-Asian hostility and violence (Tchen & Yeats, 2014). The 1965 Immigration Act introduced the largest influx of Asian immigrants in U.S. history. This phase of immigration policy favored family reunification and those with higher levels of education. During this time, Southeast Asian immigrants, including those from Laos, Vietnam, and Cambodia, were largely refugees fleeing conflict and dictatorships which had been enabled, in part, by U.S. economic policy. Refugees often settled in urban centers with established Asian American communities, whereas more recent Asian immigrants tend to be wealthier, more highly educated, and more likely to reside in suburban areas. This period of expansive growth in the Asian American population in the U.S., along with a combination of preestablished Asian communities, continued anti-immigrant sentiment and discrimination, and economic differences, has contributed to the growth of Asian ethnic enclaves in central cities and increasingly in suburban areas. Under an ever-changing landscape of xenophobia and immigration law in the U.S., Hispanic and Asian American communities have faced discrimination in housing, employment, and healthcare based on ethnicity or country of origin, language, and immigration or legal status (Tchen & Yeats, 2014; Tienda & Sánchez, 2013). As such, the formation of ethnic enclaves in urban areas is likely a result of government-sponsored segregationist practices such as redlining, as well as the selection of individuals into neighborhoods where they share social, cultural, and linguistic ties with existing residents.

In the last two decades, gentrification processes have become more prominent as white Americans have returned in large numbers to urban areas. Studies have found gentrification is most likely to occur in neighborhoods with an Asian presence or which are ethnically diverse and least likely in predominantly Black or Hispanic neighborhoods (Delmelle, 2016; Hwang & Sampson, 2014). The most common form of neighborhood change since 1970, however, is no change at all. Particularly in older cities, legacies of discrimination in housing and enduring patterns of racial residential segregation have impeded change in high-poverty Black and Hispanic neighborhoods and have simultaneously stabilized the reputations and conditions of affluent, predominantly white neighborhoods (Solari, 2012; Wilson, 2008). In the context of the present study, this pattern of relative stability among the most advantaged and disadvantaged neighborhoods is likely characteristic of historically "A" and "D" graded neighborhoods, respectively.

Given this context, studies linking historical redlining patterns to contemporary health outcomes have yet to adequately contextualize these relationships in terms of contemporary neighborhood racial and ethnic composition. In recognition, recent studies have called for examination of potential effect modification by race/ethnicity in the relationship between historical redlining and contemporary health outcomes (Needham et al., 2022). In this study, we begin to fill this gap by examining whether and how relationships between historical redlining patterns and contemporary area-based health outcomes – specifically, prevalence of poor mental health and diagnosed diabetes – are moderated by contemporary neighborhood racial/ethnic composition. This works aims to draw attention to the differential consequences of historical structural racism in our housing system.

Hypotheses

Hypothesis 1. Neighborhoods will exhibit positive associations between historical redlining patterns and contemporary prevalence of poor mental health and diabetes regardless of majority racial or ethnic group.

Previous studies have found historically redlined neighborhoods are today more likely to be denied loans, receive subprime loans, and have fewer economic opportunities (Aaronson et al., 2021; Faber, 2021; Lynch et al., 2021). The impact of depressed housing and socioeconomic conditions on health is well-established and perhaps best explained by Link and Phelan's theory of fundamental causes, which suggests the relationship between socioeconomic status (SES) and health persists despite changes in risk factors because SES encompasses a range of resources that protect health regardless of broader contextual changes (Link & Phelan, 1995; Phelan et al., 2010). The relationship between neighborhood socioeconomic conditions and health has been documented across major racial and ethnic population groups and endures even after accounting for individual-level SES (Winkleby & Cubbin, 2003). As such, we anticipate a positive relationship between historical redlining and contemporary prevalence of poor mental health and diabetes will hold across all racial/ethnic groups, likely due to a mediating role of neighborhood socioeconomic and housing conditions.

Hypothesis 2. Neighborhoods which are predominantly non-Hispanic Black, Hispanic, or non-Hispanic Asian or other race will consistently exhibit higher predicted prevalence of poor mental health and diabetes across all historical risk grades relative to neighborhoods which are predominantly non-Hispanic white.

A large body of research has documented health inequities across a wide range of outcomes among historically minoritized communities in the U.S., including Black or African American, Hispanic, and Asian American populations (LaVeist, 2005). Our hypothesis aligns with recent work that puts these inequities into historical context and specifically names structural racism in creating the conditions that produce and reproduce racial/ethnic disparities in health over generations (Bailey et al., 2017; Gee & Ford, 2011; Hardeman et al., 2018; Williams et al., 2019). We further hypothesize that predicted prevalence of poor mental health and diabetes will be highest among predominantly non-Hispanic Black neighborhoods compared to other neighborhoods across all historical risk grades. African American, Hispanic, and Asian American communities have all faced structural exclusion in the history of the U.S.; however, the Black population has experienced perhaps the most extreme and enduring forms of structural racism, exclusion, and violence over the course of more than 250 years of slavery and 100 years of Reconstruction and Jim Crow (Painter, 2006). The starting point for social and economic mobility among Black Americans was ultimately set leagues behind the relatively new concentrations of Hispanic and Asian immigrants settling in the urban U.S. during the 20th century. In recognition, scholars have suggested structural racism "often manifests as inherited disadvantage" (Jones, 2000). Even in the post-Civil Rights era and after the passing of the Fair Housing Act in 1968, African Americans have remained the most segregated group (Iceland et al., 2002), spatial separation which has been coupled with a range of social, economic, and environmental consequences that contribute to contemporary health inequities (Krysan & Crowder, 2017). We suspect predominantly non-Hispanic Black neighborhoods will exhibit a greater burden of poor health across historical risk grades due to a combination of intergenerational effects of structural racism on Black communities as well as its lasting impacts on the spaces in which they reside.

Hypothesis 3. The relationship between historical redlining patterns and contemporary prevalence of poor mental health and diabetes will differ in magnitude based on neighborhood racial/ethnic composition.

As discussed previously, multiple population groups were targeted by redlining practices and other forms of spatial racism, particularly Black or African American, East Asian/Pacific Islander, and Hispanic/Latinx communities (Markley, 2022). However, the extent to which these injustices manifest in contemporary health inequities may vary across groups, as different populations have had very different migration patterns and experiences of structural racism in the U.S. over the last century. While several racial/ethnic subpopulations were affected, the marginalization of Black communities through redlining was perhaps most perceptible given the relative size of the group as well as the enduring legacy of slavery and structural violence against African Americans. As such, we suspect the systematic disinvestment in historically redlined neighborhoods to have been most severe in areas with sustained concentrations of Black residents; however, to our knowledge studies have yet to specifically examine this assertion. In alignment with the "minority-poverty" or "concentration effects" hypotheses (Wilson, 1987), we anticipate the discrepancy in outcomes between predominantly Black and white neighborhoods to be greatest in historically redlined areas due to compounding effects of race/class disadvantage that have accumulated over the last century. In other words, we anticipate the slopes of the relationships between historical redlining and neighborhood prevalence of poor mental health and diagnosed diabetes will be steeper among predominantly Black neighborhoods relative to predominantly white neighborhoods.

Conversely, we anticipate a potentially protective ethnic enclave effect among predominantly Hispanic and Asian/other neighborhoods will temper the relationship (i.e., slope) between historical redlining and contemporary prevalence of poor mental health and diabetes. Although the literature is somewhat mixed, studies suggest living in an ethnic enclave may be protective for health, particularly among immigrants, because they may offer culturally and linguistically appropriate services, institutions, and social connections to navigate the new setting (Durazo et al., 2016; Lim et al., 2017; Osypuk et al., 2009). Black communities likewise draw together in enclaves for similar reasons, but the lasting effects of anti-Black racism, from forced segregation and neighborhood disinvestment to law enforcement practices, may partly explain why Black neighborhood concentration is associated with poorer health for Black residents but better health, in some cases, among other racial/ethnic groups (M. R. Kramer & Hogue, 2009; Yang et al., 2017). Our hypothesis for predominantly Hispanic and Asian/other neighborhoods generally aligns with the "diminishing returns" hypothesis, which suggests gains in SES have less benefit to minority populations than to white populations in the context of structural barriers to upward mobility (Willie, 1989). Given the historical context discussed above, however, we anticipate differences in the distribution of Asian subgroups across the historical HOLC risk grades may influence our results.

Data and methods

We utilized an ecological design, using census tracts as proxies for neighborhoods. We drew the sample of tracts with at least 20% overlap with areas appraised by HOLC in the 1930s and 1940s, consistent with methodology developed by Meier and Mitchell (2021). Our analytic sample included 12,864 census tracts, spanning 143 core-based statistical areas (CBSAs) across the U.S.

Data sources

This study linked three publicly available data sources. The first is the Historic Redlining Scores Project developed by the University of Michigan Institute for Social Research (Meier & Mitchell, 2021). We linked these data to health outcome measures from the 2020 release of the Centers for Disease Control and Prevention (CDC) PLACES Project, which provides model-based small area estimates for health behaviors, risk factors, and outcomes for U.S. census tracts based on the 2017-2018 Behavioral Risk Factor Surveillance System (BRFSS) (Centers for Disease Control and Prevention, 2020). Finally, we obtained contemporaneous neighborhood demographic information from the American Community Survey 5-year estimates for 2013-2017.

Outcome measures

We examined two outcomes: census tract prevalence of self-reported poor mental health (last 30 days) and diagnosed diabetes (lifetime) (Centers for Disease Control and Prevention, 2022), as measured by BRFSS survey items; (Centers for Disease Control and Prevention, 2019). The aim in selecting multiple measures was to examine how relationships with historical redlining patterns may differ depending on the outcome of interest. Poor mental health prevalence offers a point-in-time measure of community well-being, whereas diabetes prevalence reflects long-term impact on physical health, disproportionately affects Black, Hispanic/Latinx, and Asian American groups, and is partly contingent upon access to healthcare services (Dias et al., 2020).

Exposure classification

In this study, we used the continuous "historic redlining scores" constructed by Meier and Mitchell (2021) as the primary predictor of interest. The authors created these scores by overlaying digitized versions of the HOLC maps onto the 2010 census tract boundaries, calculating the relative physical area of each tract that had been assigned a particular grade (A-D), and generating a continuous score (1-4) weighted by the corresponding proportion of land area covered. Meier and Mitchell further categorized scores into intervals 1-4 with rough equivalence to historical risk grades, where interval 1 is essentially equivalent to the "A" grade and the interval 4 corresponds to the "D" grade. We utilized these "historical risk intervals" (or "intervals") for descriptive analyses, and we used the continuous "redlining scores" in subsequent regression analyses, in alignment with Linde et al. (2022).

Neighborhood racial/ethnic composition

We categorized neighborhood racial/ethnic composition into one of five mutually exclusive racial/ethnic typologies based on the majority group within a tract: non-Hispanic Black majority (Black-majority); non-Hispanic white majority (white-majority); non-Hispanic Asian or other race majority (Asian/other-majority); Hispanic-majority; or no-majority. In sensitivity analyses we tested higher thresholds (>60 percent; >70 percent) for defining neighborhood racial/ethnic composition.

Covariates

In all models we included census tract population density, proportion of residents under the age of 18, proportion of residents over the age of 65, and proportion of foreign-born residents. We selected these covariates to account for differences in age distribution which may impact health outcomes. We included population density, which has been associated with mental health outcomes in previous literature (Cramer et al., 2004; Fassio et al., 2013). We controlled for proportion of residents who are foreign-born to account for differences in nativity across the population groups of interest in this study, as mental health and diabetes outcomes differ by immigrant generation (Afable-Munsuz et al., 2014; Close et al., 2016; Engelman & Ye, 2019). We also included fixed effects for U.S. census region (reference = Northeast), as the major regions have historically experienced different migration patterns among population groups examined in this study.

Statistical analysis

First, we produced descriptive statistics and choropleth maps for select cities to characterize the contemporary racial and ethnic composition of neighborhoods by historical risk interval. We also calculated the population-weighted mean prevalence of poor mental health and diabetes across intervals and majority groups and conducted pairwise comparisons using the Games-Howell Test (Toothaker, 1993). Next, we estimated relationships between redlining scores and health outcomes using ordinary least squares and Beta regression models, which are generally appropriate for proportion outcomes (when observations are not close to 0 or 1, in the case of OLS). We included all observations with complete data for the regression variables (n = 12,851). To examine differential effects across neighborhood racial/ethnic typologies, we included an interaction term between historical redlining score and an indicator of the majority racial/ethnic group within a census tract (reference = white-majority). We confirmed the presence of spatial autocorrelation using Moran's *I* and subsequently built spatial error regression models using queen contiguity to account for the presence of spatial dependence in the residuals, a violation of the OLS assumption of independence. These spatial error models were the best fit for both outcomes of interest based on the Akaike Information Criterion (AIC) and Lagrange Multiplier Test (Anselin, 2010), and are thus presented in our results section below. Finally, we estimated predicted mean prevalence of poor mental health and diabetes, holding covariates at their group-specific means.

Results

Descriptive results

Neighborhoods historically appraised by HOLC today vary widely in their contemporary demographic composition. Although neighborhoods have changed substantially since the creation of the HOLC maps in the 1930s and 1940s, the general patterns of racial/ethnic composition are what might be expected given the assignment of risk grades was largely based on residents' race or ethnicity. Table 2-1 below shows the distribution of census tracts based on majority racial or ethnic group across the historical risk intervals (1-4) as of 2017.

As of 2017, 81.9 percent of neighborhoods within historical risk interval 1 were majority non-Hispanic white, while 44.9 percent of all neighborhoods (i.e., across all intervals) were majority white. Conversely, neighborhoods with any other majority group (or no-majority) were underrepresented in interval 1. For example, 9.7 percent of interval 1 neighborhoods were majority Black, compared to 22.7 percent of all neighborhoods. Even more stark, only 2.4 percent of interval 1 neighborhoods were majority Hispanic, compared to 15.8 percent of all neighborhoods. Conversely, among historically redlined neighborhoods (i.e., interval 4), nearly one-third were majority Black and one-fifth majority Hispanic. Asian/other-majority neighborhoods comprised a relatively small share of tracts across the risk grades; however, Asian/other-majority neighborhoods were overrepresented within interval 3 and underrepresented within interval 1. Diverse no-majority neighborhoods, where no group makes up 50 percent or more of the total population, were distributed across the historical risk intervals fairly evenly, except for interval 1, where no-majority neighborhoods accounted for only 5.2 percent of tracts.

Table 2-1. Contemporary neighborhood racial/ethnic composition (majority group) by historical risk interval

	Historical risk interval									
	1		**2**		**3**		**4**			**prop. all**
Majority group	n	prop.	n	prop.	n	prop.	n	prop.	**Total**	**tracts**
Black	87	0.0968	438	0.1786	1059	0.1978	1336	0.3212	2920	0.2270
Hispanic	22	0.0245	228	0.0930	959	0.1792	827	0.1988	2036	0.1583
Asian/other	7	0.0078	40	0.0163	168	0.0314	65	0.0156	280	0.0218
White	736	0.8187	1477	0.6024	2267	0.4235	1292	0.3106	5772	0.4487
No-majority	47	0.0523	269	0.1097	900	0.1681	640	0.1538	1856	0.1443
Total	899	1.0000	2452	1.0000	5353	1.0000	4160	1.0000	12864	1.0000

Figure 2-1 below shows the spatial arrangement of neighborhoods by historical risk interval and majority racial/ethnic group in four major U.S. cities, one in each of the four Census regions: (1) Oakland, California (West); (2) Milwaukee, Wisconsin (Midwest); (3) Philadelphia, Pennsylvania (Northeast); and (4) Atlanta, Georgia (South). For each city, each panel shows neighborhoods representing one of the four historical risk intervals, shaded by majority racial/ethnic group. For example, in Oakland, CA, all neighborhoods in historical risk interval 1, concentrated in the affluent "Oakland Hills," were majority white as of 2017, whereas neighborhoods in historical risk interval 4 were a mix by majority group as well as a relatively large number of diverse no-majority neighborhoods. Milwaukee and Philadelphia show somewhat more variation within historical risk interval 1. The few interval 1 neighborhoods in Milwaukee were largely white-majority, with a small number of Black-majority. On the other end, interval 4 showed large clusters of Black-majority and Hispanic-majority neighborhoods, divided by the

Kinnickinnic River. Philadelphia showed perhaps the most variation across the intervals. Interval 1 neighborhoods included white-majority, Black-majority, and diverse no-majority neighborhoods. Intervals 2-4 contained a mix of white-, Black-, Hispanic-, and no-majority neighborhoods, although there were clear patterns of clustering by city area. For example, looking across intervals 2-4, Hispanic-majority neighborhoods clustered around the Feltonville and Hunting Park neighborhoods, north of the city center. Within interval 4, Black-majority neighborhoods largely clustered west and northwest of the city center, whereas white-majority neighborhoods clustered south and northeast of the city center. Finally, of the four cities shown in Figure 2-1, Atlanta showed the least variation in racial/ethnic composition across intervals. Like Oakland, all neighborhoods in interval 1 were majority white as of 2017. Within interval 4, most neighborhoods were majority Black. Even with simple majority group indicators, together these maps begin to demonstrate the variation in the demographic composition of neighborhoods historically appraised by HOLC. Although a large proportion of neighborhoods in historical risk interval 1, essentially equivalent to the historically "A" graded neighborhoods, were majority white as of 2017, we see substantial variation across intervals 2-4. This variation underscores the need to examine relationships between historical redlining patterns and contemporary health outcomes in the context of contemporary neighborhood racial and ethnic composition.

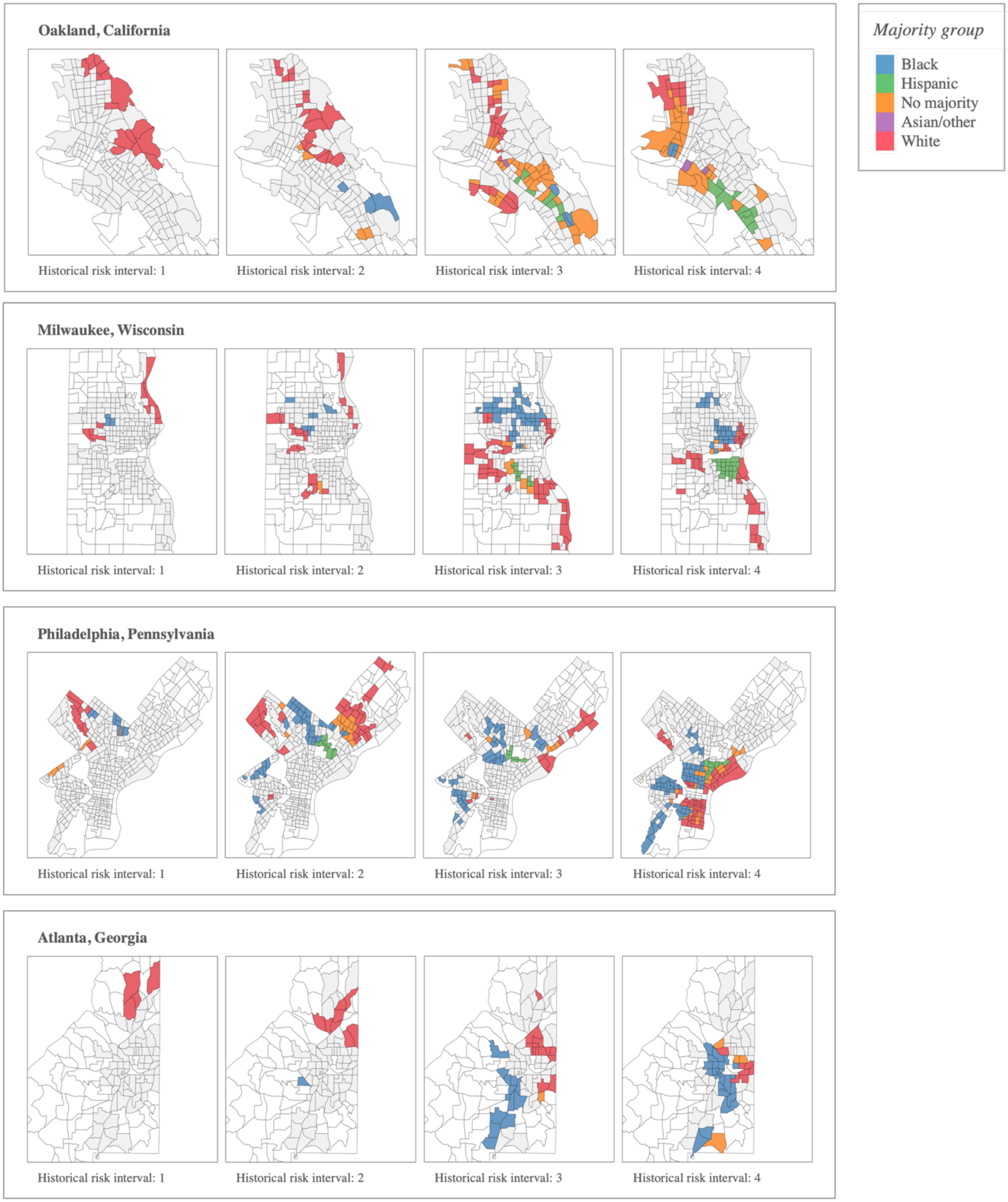

Figure 2-1. Maps of neighborhood majority group by historical risk interval in four U.S. cities

Figure 2-2 and Figure 2-3 below show the population-weighted means and standard deviations of tract-level poor mental health prevalence and diabetes prevalence, respectively, by historical risk interval and majority racial or ethnic group. We found a graded relationship between historical redlining and contemporary neighborhood health outcomes, where neighborhoods graded by HOLC as higher risk for lending and investment showed worse outcomes compared to neighborhoods graded more favorably. For example, the overall average prevalence of poor mental health was 11.4 percent among interval 1 neighborhoods, versus 16.2 percent for interval 4, and this pattern held when neighborhoods were stratified by majority racial or ethnic group. However, Black-majority neighborhoods, on average, showed the highest prevalence of poor mental health in every interval relative to neighborhoods with any other majority group. Further, Black-majority neighborhoods within interval 1 had higher prevalence of poor mental health than Asian/other-, white-, and no-majority neighborhoods within interval 4. Asian/other-majority neighborhoods had the lowest mean prevalence of poor mental health compared to neighborhoods with any other majority group.

In general, these trends were similar for diabetes prevalence; however, inequities across the majority racial/ethnic groups are even more apparent. For example, Black-majority neighborhoods experienced roughly double the burden of diabetes relative to white-majority neighborhoods in every risk interval. White-majority and diverse no-majority neighborhoods showed relatively consistent average prevalence of diabetes across risk intervals, though the distribution of diabetes prevalence widened at higher risk intervals; this pattern was largely consistent across racial/ethnic typologies. Across all historical risk intervals, Black-, Hispanic-, and Asian/other-majority neighborhoods had higher prevalence of diabetes, on average, than white-majority neighborhoods.

Pairwise comparisons using the Games-Howell Test identified significant differences in mean prevalence of poor mental health and diabetes across historical risk intervals and majority racial/ethnic groups, with few exceptions. For example, differences in mean prevalence of poor mental health were not statistically significant in comparing interval 1 and interval 2 among Black-majority neighborhoods; or in comparing white-majority and Hispanic-majority neighborhoods within interval 1. All pairwise comparisons were significant across majority groups within intervals 2-4. Similarly, diabetes prevalence differed across groups within each historical risk interval with few exceptions. Within-group comparisons across intervals were mixed. For example, differences in diabetes prevalence between intervals 1 and 2 were not statistically significant for any majority group. Complete results are provided in the Appendix (Table 2-4 to Table 2-7).

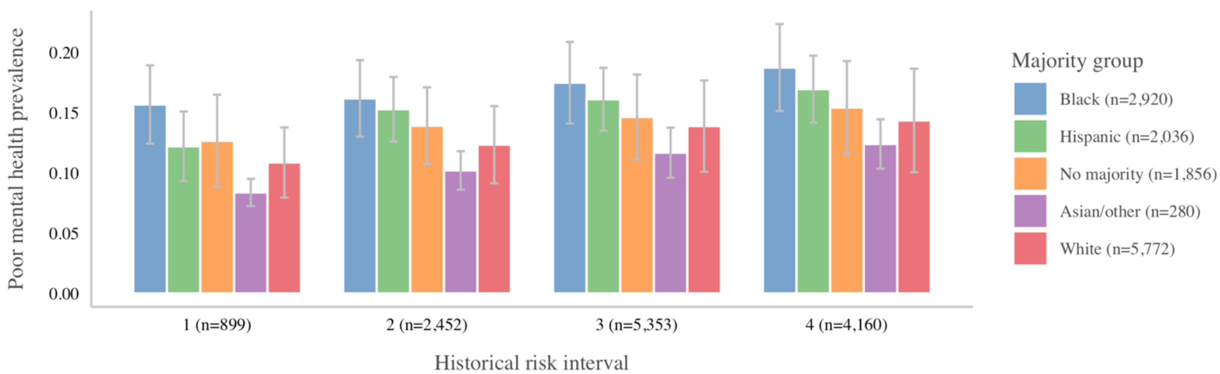

Figure 2-2. Prevalence of poor mental health by historical risk interval and majority racial/ethnic group
Note: population-weighted means and standard deviations

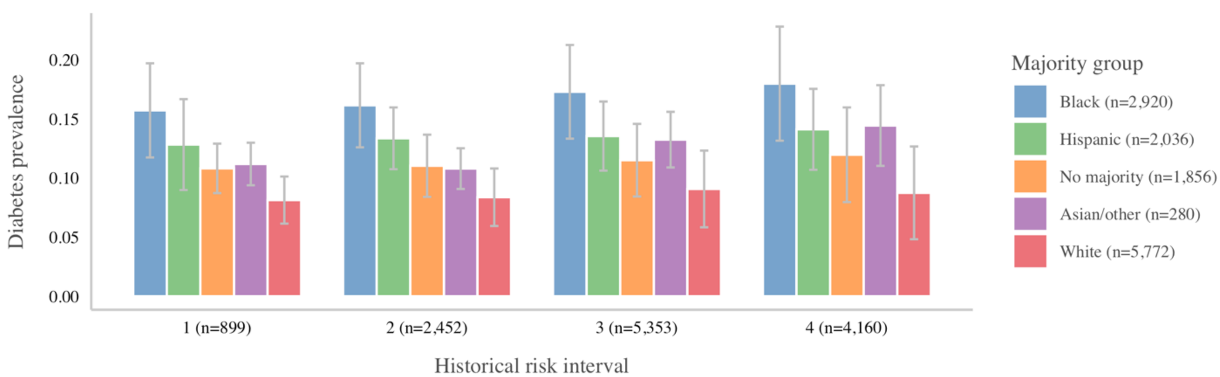

Figure 2-3. Prevalence of diabetes by historical risk grade and majority racial/ethnic group
Note: population-weighted means and standard deviations

Regression results

Table 2-2 and Table 2-3 below present the spatial error regression results for poor mental health prevalence and diabetes prevalence, respectively, on historical redlining score, neighborhood majority racial/ethnic group, and selected covariates. In each table, Model 1 includes main effects for redlining score and majority racial/ethnic group, whereas Model 2 adds interaction effects between historical redlining score and majority racial/ethnic group. In both models and for both health outcomes of interest, historical redlining score was a significant predictor, where higher redlining scores corresponded to higher prevalence of poor mental health and diabetes. Among white-majority neighborhoods (the reference group), a one-point increase in historical redlining score corresponded to approximately 1.0-1.1 percentage point increases in prevalence of poor mental health and diabetes, all else held constant. In Model 1 (Table 2-2) consistent with our descriptive results, Black-, Hispanic-, and no-majority neighborhoods were associated with higher prevalence of poor mental health relative to white-majority neighborhoods. Counter to our descriptive results, which showed Asian/other-majority neighborhoods had lower prevalence of poor mental health compared to white-majority neighborhoods at all historical risk intervals, after we adjusted for covariates, Asian/other-majority neighborhood was associated with a higher prevalence of poor mental health relative to white-majority. In alignment with our descriptive results for diabetes prevalence, Model 1 (Table 2-3) found Black-, Hispanic-, Asian/other-, and no-majority neighborhoods were associated with higher prevalence of diagnosed diabetes relative to white-majority neighborhoods.

In Model 2, the interaction results suggested the relationship between historical redlining score and each of the outcomes of interest differed depending on the racial/ethnic composition of a neighborhood. For both poor mental health prevalence and diabetes prevalence, Black-majority neighborhoods had a statistically significant positive interaction. Each one-point increase in historical redlining score was associated with a 1.3 percentage point increase in poor mental health among Black-majority neighborhoods (main effect + interaction effect) and a 1.4 percentage point increase in diabetes prevalence, all else held constant. Conversely, although Hispanic-majority neighborhoods had higher prevalence of poor mental health relative to white-majority neighborhoods across all redlining scores, these neighborhoods demonstrated a negative interaction for poor mental health prevalence, such that a one-point increase in historical redlining score corresponded to approximately 0.8 percentage point increases in prevalence of poor mental health and diabetes. For poor mental health prevalence, the interactions were not statistically significant for Asian/other-majority or no-majority neighborhoods, suggesting discrepancies in prevalence of poor mental health relative to white-majority neighborhoods were similar between historically "A" and "D" graded neighborhoods. Similarly, for diabetes prevalence, the interactions were not statistically significant at $p<0.05$ for Hispanic, Asian/other, and no-majority neighborhoods; however, the interaction was approaching significance ($p < 0.10$) for Hispanic and Asian/other-majority neighborhoods.

The results of our sensitivity analyses, which defined neighborhood racial/ethnic composition using higher thresholds (>60 percent, >70 percent) are available in the Appendix (Table 2-8 and Table 2-9). These results were broadly consistent with our main findings reported here. For example, in models of diabetes prevalence, the interactions remained positive for predominantly Black neighborhoods, although the interaction term no longer reached statistical significance at concentrations above 70 percent. The interactions corresponding to predominantly Black neighborhoods were not statistically significant for poor mental health prevalence. However, for both poor mental health prevalence and diabetes prevalence, predominantly Hispanic neighborhoods exhibited negative interaction terms, suggesting a weaker relationship between historical redlining and the outcomes of interest among Hispanic communities relative to predominantly non-Hispanic white communities.

Figure 2-4 below shows the predicted mean prevalence of poor mental health (left panel) and diabetes (right panel) by historical redlining score and neighborhood racial/ethnic majority group, based on Model 2, holding all covariates at their group-specific means and setting region to the Northeast. Among Black-majority neighborhoods, those with a historical redlining score of 1 had a predicted mean prevalence of poor mental health of 13.5 percent [95% CI: 13.2-13.7], versus 17.4 percent [95% CI: 17.3-17.5] for those with a score of 4. Hispanic-majority neighborhoods with a score of 1 had a predicted mean prevalence of poor mental health of 14.2 percent [95% CI: 14.0-14.5], versus 16.6 percent [95% CI: 16.5-16.7] for those with a score of 4.

The results for diabetes prevalence showed some similar trends; however, discrepancies in predicted mean prevalence of diabetes among Black-, Hispanic-, Asian/other-, and no-majority neighborhoods relative to white-majority neighborhoods were more pronounced. Among Black-majority neighborhoods, those with a historical redlining score of 1 had a predicted mean prevalence of diabetes of approximately 12.5 percent [95% CI: 12.2-12.8], versus 16.7 percent [95% CI: 16.6-16.8] for those with a score of 4. In comparison, the predicted mean prevalence of diabetes in white-majority neighborhoods was 7.1 percent [95% CI: 7.0-7.2] and 10.1 percent [95% CI: 10.06-10.2] for neighborhoods with scores 1 and 4, respectively. Hispanic-majority, Asian/other-majority, and no-majority neighborhoods also had higher predicted mean prevalence of diabetes relative to white-majority neighborhoods at all levels of historical redlining score.

Table 2-2. Spatial error regression results for poor mental health prevalence on historical redlining score and majority racial/ethnic group

	Model 1			Model 2		
Variables	Estimate	Std. error	p-value	Estimate	Std. error	p-value
(Intercept)	0.1010	0.0021	< 0.0001	0.1006	0.0022	< 0.0001
Historical redlining score	0.0113	0.0004	< 0.0001	0.0114	0.0005	< 0.0001
Majority racial/ethnic group (ref = white-majority)						
Black-majority	0.0258	0.0008	< 0.0001	0.0202	0.0026	< 0.0001
Hispanic-majority	0.0165	0.0010	< 0.0001	0.0276	0.0034	< 0.0001
Asian/other-majority	0.0055	0.0019	0.0034	0.0104	0.0071	0.1450
No-majority	0.0111	0.0007	< 0.0001	0.0143	0.0025	< 0.0001
Interactions (ref = white-majority)						
Historical redlining score*Black-majority				0.0017	0.0008	0.0348
Historical redlining score*Hispanic-majority				-0.0035	0.0010	0.0007
Historical redlining score*Asian/other-majority				-0.0016	0.0023	0.4736
Historical redlining score*No-majority				-0.0010	0.0008	0.1903
Covariates						
Proportion foreign-born	-0.0063	0.0027	0.0190	-0.0060	0.0027	0.0265
Population density	0.0000	0.0000	< 0.0001	0.0000	0.0000	< 0.0001
Proportion population under 18	0.0651	0.0031	< 0.0001	0.0649	0.0032	< 0.0001
Proportion population over 65	-0.1235	0.0036	< 0.0001	-0.1233	0.0036	< 0.0001
Fixed effects (ref = Northeast)						
Midwest	0.0124	0.0019	< 0.0001	0.0125	0.0019	< 0.0001
South	0.0187	0.0023	< 0.0001	0.0185	0.0023	< 0.0001
West	-0.0060	0.0022	0.0074	-0.0060	0.0023	0.0083
Number of observations	12,851			12,851		
Lambda	0.7857	0.0054	< 0.0001	0.7864	0.0054	< 0.0001
AIC (error model)	-63,268			-63,281		
AIC (OLS model)	-54,017			-54,070		

Table 2-3. Spatial error regression results for diabetes prevalence on historical redlining score and majority racial/ethnic group

	Model 1			Model 2		
Variables	Estimate	Std. error	p-value	Estimate	Std. error	p-value
(Intercept)	-0.0006	0.0020	0.7576	0.0020	0.0022	0.3679
Historical redlining score	0.0108	0.0004	< 0.0001	0.0100	0.0005	< 0.0001
Majority racial/ethnic group (ref = white-majority)						
Black-majority	0.0555	0.0008	< 0.0001	0.0431	0.0027	< 0.0001
Hispanic-majority	0.0308	0.0011	< 0.0001	0.0375	0.0036	< 0.0001
Asian/other-majority	0.0313	0.0020	< 0.0001	0.0192	0.0076	0.0115
No-majority	0.0219	0.0007	< 0.0001	0.0180	0.0027	< 0.0001
Interactions (ref = white-majority)						
Historical redlining score*Black-majority				0.0040	0.0008	< 0.0001
Historical redlining score*Hispanic-majority				-0.0019	0.0011	0.0748
Historical redlining score*Asian/other-majority				0.0040	0.0009	0.0986
Historical redlining score*No-majority				0.0013	0.0024	0.1180
Covariates						
Proportion foreign-born	-0.0016	0.0028	0.5730	-0.0012	0.0028	0.6749
Population density	0.0000	0.0000	0.0065	0.0000	0.0000	0.0054
Proportion population under 18	0.1419	0.0033	< 0.0001	0.1400	0.0034	< 0.0001
Proportion population over 65	0.2342	0.0039	< 0.0001	0.2331	0.0039	< 0.0001
Fixed effects (ref = Northeast)						
Midwest	0.0116	0.0016	< 0.0001	0.0118	0.0017	< 0.0001
South	0.0247	0.0020	< 0.0001	0.0244	0.0020	< 0.0001
West	-0.0034	0.0019	0.0810	-0.0033	0.0019	0.0852
Number of observations	12,851			12,851		
Lambda	0.7274	0.0064	< 0.0001	0.7296	0.0064	< 0.0001
AIC (error model)	-61,882			-61,906		
AIC (OLS model)	-55,515			-55,560		

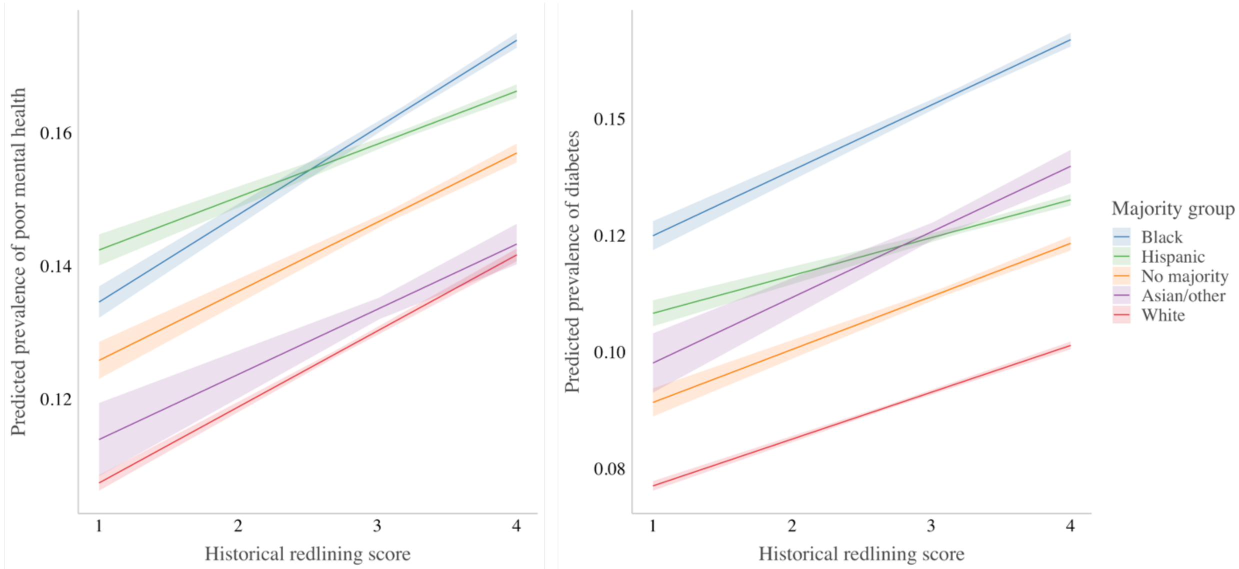

Figure 2-4. Predicted mean prevalence and 95% confidence intervals for poor mental health (left) and diabetes (right) by historical redlining score and neighborhood majority racial/ethnic group

Note: Covariates were set to their group-specific means; region was set to the reference group (Northeast)

Discussion

We found neighborhoods historically appraised by the Home Owners Loan Corporation (HOLC) in the 1930-1940s vary widely in their contemporary racial and ethnic composition. As expected, given the racialized nature of HOLC's appraisal process, most neighborhoods which were assigned an "A" grade were majority non-Hispanic white as of 2017, whereas those assigned a "C" or "D" grade consisted of a wider range of racial/ethnic typologies. Consistent with prior literature, we found a positive association between historical redlining score and contemporary health outcomes, where neighborhoods graded by HOLC as higher risk for lending and investment today experience a greater burden of poor health compared to neighborhoods graded more favorably (Krieger et al., 2020; Lynch et al., 2021; Nardone, Casey, et al., 2020; Nardone, Chiang, et al., 2020). In alignment with Hypothesis 1, this relationship held across neighborhoods regardless of majority racial/ethnic group, likely reflective of an enduring impact of neighborhood socioeconomic conditions on health regardless of race/ethnicity or individual SES (Winkleby & Cubbin, 2003).

In alignment with Hypothesis 2, we found discrepancies in outcomes between Black-, Hispanic-, or Asian/other-majority neighborhoods and white-majority neighborhoods across historical redlining scores. Further, in alignment with Hypothesis 3, we found relationships between historical redlining patterns and contemporary health outcomes were moderated by contemporary racial/ethnic composition. Our findings suggest Black-, Hispanic-, and no-majority neighborhoods had higher predicted prevalence of poor mental health relative to white-majority neighborhoods across all historical redlining scores. Among historically redlined neighborhoods, those in which a majority of residents identify as Black had the highest predicted prevalence of poor mental health, consistent with our descriptive analysis. This finding largely aligns with 2018 national estimates, where 15.3 percent of Black adults reported feeling sad at least some of the time, compared to 10.9 percent of white adults (National Center for Health Statistics, 2018). In alignment with the minority-poverty hypothesis, discrepancies in outcomes between Black-majority and white-majority neighborhoods were most pronounced in historically redlined areas, suggesting synergistic effects of race/class disadvantage (Wilson, 1987). Increased mental distress particularly among African Americans has been linked in previous studies to experiences of discrimination and racism within societal institutions and structures (R. Williams & Williams-Morris, 2000). For example, a recent study found highly public incidents of anti-Black violence are associated with increased poor mental health days among Black Americans, on average, but not among white Americans (Curtis et al., 2021). Thus, our findings may be reflective of the enduring impacts of historical structural racism, ongoing anti-Black racism and violence, and their compounding effects with socioeconomic stressors within historically redlined neighborhoods. In support, between 2000-2020, fatal encounters with police were 66 percent more likely to occur within historically redlined neighborhoods and most likely to affect young Black men even after accounting for neighborhood racial composition, suggesting redlining practices may have contributed to the contemporary conditions which perpetuate anti-Black structural violence (J. Mitchell & Chihaya, 2022) and consequences for mental health.

Conversely, although our findings showed Hispanic-majority neighborhoods experience a greater burden of poor mental health and diabetes than white-majority neighborhoods, discrepancies in outcomes were generally least pronounced in historically redlined areas. This finding lends support to the potentially beneficial effects of residence in an ethnic enclave on both mental and physical health outcomes (Durazo et al., 2016). Although Hispanic communities face structural barriers to social and economic mobility in the U.S., as well as stress related to anti-immigrant sentiment, discrimination, and acculturation, studies have shown social connectedness and “familism” values act as buffers against these drivers of poor mental health (Hong et al., 2014; Katiria Perez & Cruess, 2014; Mulvaney-Day et al., 2007).

Our findings suggest Asian/other-majority neighborhoods were similar to white-majority neighborhoods in predicted prevalence of poor mental health; however, our descriptive analysis showed Asian/other-majority neighborhoods had lower unadjusted mean prevalence of poor mental health relative to white-majority neighborhoods within each historical risk interval. This discrepancy likely relates to differences in the distribution of covariates between Asian/other-majority neighborhoods and neighborhoods with other majority groups. Asian/other-majority neighborhoods in our sample were older, on average, than neighborhoods with any other majority group, having smaller populations under age 18 and larger populations over age 65 across all historical risk intervals. These differences may be relevant to our findings as older Asian Americans tend to report lower prevalence of mental health problems than older adults from other racial/ethnic groups (Kim et al., 2020). Further, studies have documented differences in mental health status and outcomes by immigration generation. For example, first generation migrants tend to report worse mental health compared to second and third generation migrants (Afable-Munsuz et al., 2014). In our sample, Asian/other-majority neighborhoods had substantially larger foreign-born populations than neighborhoods with other majority groups; as such, these differences in age distribution and foreign-born population likely explain the discrepancy between our descriptive and analytic results. National estimates suggest Asian American adults experience similar rates of mild to moderate mental distress to white Americans but less frequently report serious psychological distress (National Center for Health Statistics, 2017; U.S. Department of Health and Human Services Office of Minority Health, 2018). To our knowledge, however, the BRFSS survey is not conducted in any Asian languages – only English and Spanish – which may severely limit its reach within Asian American communities. Furthermore, because mental health issues are often stigmatized within Asian communities, measurement may present challenges in our analysis and in other studies (E. J. Kramer et al., 2002).

Finally, our findings suggest Black-majority, Hispanic-majority, Asian/other-majority, and no-majority neighborhoods had higher predicted prevalence of diabetes relative to white-majority neighborhoods. This finding was consistent across our hypothesis testing for pairwise differences and regression analyses. Consistent with our hypotheses, Black-majority neighborhoods had the highest predicted prevalence of diabetes across all historical risk intervals, and, as with poor mental health, the discrepancy in diabetes prevalence between Black-majority and white-majority neighborhoods was most pronounced in historically redlined areas. Conversely, the discrepancy in diabetes prevalence between Hispanic-majority and white-majority neighborhoods was least pronounced in historically redlined areas, likely reflective of a beneficial ethnic enclave effect. Counter to our anticipated outcomes, we found the discrepancy in diabetes prevalence between Asian/other-majority and white-majority neighborhoods was most pronounced in historically redlined neighborhoods, although the interaction term was not statistically significant under our majority-rule definition of neighborhood racial/ethnic composition. In our sensitivity analyses, however, the interaction term was positive and statistically significant when the concentration of Asian/other residents reached 60 percent. As discussed previously, this finding might relate to differences in the distribution of Asian subgroups across the historical HOLC risk grades. For example, given their unique immigration histories and differential human and economic capital on arrival, we might expect larger concentrations of lower-income Chinese, Vietnamese, Cambodian, and Laotian Americans to reside in historically redlined areas, while larger concentrations of higher-income Chinese, Japanese, and Filipino Americans might reside in areas graded more favorably. Although not specifically examined in this study, the distribution of Asian subgroups across historical risk grades is relevant to our findings as Asian subgroups have varying prevalence of diabetes and associated risk factors (Karter et al., 2013). For example, Filipino and South Asian populations in the U.S. experience substantially higher prevalence of diabetes compared to non-Hispanic white and African American populations. The aggregation of Asian subgroups makes it difficult to identify specific relationships and may bias our estimates toward the null.

To our knowledge, only two previous studies have explicitly examined differences in the relationship between historical redlining patterns and contemporary health outcomes by race/ethnicity (Mujahid et al., 2021; Wing et al., 2022). In examining the relationship between HOLC grade and ideal cardiovascular health (CVH) among a diverse cohort, Mujahid and colleagues (2021) found the relationship between HOLC grade and ideal CVH held only for Black participants. This finding aligns with our study in that Black-majority neighborhoods which were historically redlined experience worse outcomes compared to neighborhoods comprised of other racial/ethnic groups. However, our findings suggest the relationship between redlining and health holds across groups. We suspect this difference in findings may reflect differences in the specific outcomes examined. For example, the mean composite measure of ideal CVH varied relatively little across groups or across HOLC grades, and when disaggregated, only select characteristics of CVH were associated with historical redlining. Wing et al. (2022) used a similar design and analytic approach as the present study and found the association between historical redlining and stroke prevalence in Columbus, OH, while positive and statistically significant, was not moderated by neighborhood racial composition. However, the study used a dichotomous indicator of neighborhood racial composition – greater than or less than 50 percent racial/ethnic minority. Our findings suggest differential impacts of historical redlining patterns across racial/ethnic groups; thus, aggregating all minoritized racial/ethnic populations may have obscured an interactive effect in this prior study. In this context of previous literature, our findings underscore the need for additional individual- and multi-level analyses that specifically examine effect modification by race/ethnicity as well as cross-level interactions between individual race/ethnicity and neighborhood conditions.

Limitations

This study has several important limitations. First, our use of majority group is a simple characterization of neighborhood racial/ethnic composition and does not capture multi-group dynamics or within-group differences, or consider the intersectional identities of residents. Further, this measure ignores groups which make up less than 50 percent of a tract but which may still account for a large portion of the population. For example, only approximately 10 percent of Asian Americans live in Asian-majority neighborhoods (Pew Research Center, 2013), whereas approximately 90 percent of non-Hispanic white Americans live in white-majority neighborhoods. Despite these limitations, this measure is an improvement over others which aggregate multiple minoritized racial/ethnic groups into a single population. Our findings suggest it is important to examine the differential impacts across subpopulations of historical redlining practices and other forms of spatial racism on health – and this study offers a useful starting point. City- or regionally-specific analyses that incorporate local context may allow for a better understanding of the nuances of neighborhood demographics, conditions, and change in relation to contemporary health outcomes.

Next, our use of a continuous indicator of historical redlining may be vulnerable to misclassification bias. However, these historic redlining scores and associated risk intervals have been effectively validated through comparison to the original grades assigned by HOLC. Another limitation relates to the substantial time lag between the development of the HOLC maps and neighborhood health outcomes of interest. As have several previous studies, our study aims to describe and probe the relationship between historical redlining patterns and contemporary outcomes as evidence of lasting impacts of historical structural racism. Our intent was not to establish a causal relationship; rather, we utilized the HOLC residential security maps as a representation of existing patterns and practices at the time they were produced. Our findings ultimately provide additional evidence of the need for more critical investigation of the mechanisms by which historical redlining and other racist practices are perpetuated over time.

Finally, our use of an ecological design is vulnerable to ecological fallacy and further precludes causal inference. Although our findings are suggestive of group differences in the relationship between historical redlining and contemporary health outcomes, we cannot be sure cases of poor mental or diabetes belong to members of the majority group. Rather, our study suggests there may be important neighborhood contextual differences at play that differentially impact the health of individuals.

Conclusion

In this study, we found historical redlining patterns are associated with a greater burden of poor mental health and diagnosed diabetes. However, there are important differences in these relationships based on contemporary neighborhood racial and ethnic composition. This work is particularly timely as policymakers have garnered stronger interest in pursuing reparations for historical injustices imposed on Black communities, such as use of the HOLC maps to prioritize neighborhoods for subsidized down payments. Our findings suggest reparations for long histories of structural racism, exclusion, and violence must be contextualized to the particular communities targeted and the unique challenges they face. Further research is needed to better understand the present conditions within neighborhoods and communities marginalized through historical redlining practices, including specific attention to differential experiences and consequences across racial and ethnic strata.

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Appendix A

Pairwise comparisons in mean prevalence of poor mental health and diabetes

We used to Games-Howell test to examine pairwise comparisons in mean prevalence of poor mental health and diabetes across historical risk intervals (Table 2-4 and Table 2-6, respectively) and across neighborhood majority racial/ethnic group (Table 2-5 and Table 2-7, respectively). The Games-Howell test is nonparametric and is appropriate for group comparisons when variances are unequal, as is the case in our sample.

Table 2-4. Games-Howell test for pairwise difference in mean prevalence of poor mental health across historical risk intervals (within group)

Majority group	Historical risk intervals compared		estimate (difference)	conf.low	conf.high	p.adj
White	1	2	0.0154	0.0119	0.0189	< 0.0001
	1	3	0.0309	0.0275	0.0344	< 0.0001
	1	4	0.0370	0.0329	0.0412	< 0.0001
	2	3	0.0155	0.0126	0.0185	< 0.0001
	2	4	0.0216	0.0179	0.0254	< 0.0001
	3	4	0.0061	0.0024	0.0098	0.0001
Black	1	2	0.0067	-0.0031	0.0166	0.2900
	1	3	0.0208	0.0113	0.0303	< 0.0001
	1	4	0.0332	0.0238	0.0427	< 0.0001
	2	3	0.0141	0.0093	0.0188	< 0.0001
	2	4	0.0265	0.0218	0.0311	< 0.0001
	3	4	0.0124	0.0087	0.0161	< 0.0001
Hispanic	1	2	0.0317	0.0140	0.0494	0.0002
	1	3	0.0391	0.0218	0.0563	< 0.0001
	1	4	0.0484	0.0311	0.0657	< 0.0001
	2	3	0.0074	0.0023	0.0124	0.0010
	2	4	0.0167	0.0115	0.0219	< 0.0001
	3	4	0.0094	0.0061	0.0127	< 0.0001
No majority	1	2	0.0075	-0.0081	0.0231	0.5870
	1	3	0.0150	-0.0002	0.0301	0.0540
	1	4	0.0252	0.0098	0.0405	0.0004
	2	3	0.0075	0.0016	0.0133	0.0060
	2	4	0.0177	0.0113	0.0240	< 0.0001
	3	4	0.0102	0.0052	0.0151	< 0.0001
Asian/other	1	2	0.0198	0.0048	0.0347	0.0100
	1	3	0.0333	0.0186	0.0480	0.0004
	1	4	0.0381	0.0231	0.0531	0.0001
	2	3	0.0136	0.0057	0.0214	0.0001
	2	4	0.0184	0.0090	0.0277	< 0.0001
	3	4	0.0048	-0.0030	0.0126	0.3830

Table 2-5. Games-Howell test for pairwise difference in mean prevalence of poor mental health across majority racial/ethnic groups (within historical risk interval)

Historical risk interval	**Majority groups compared**		**estimate**	**conf.low**	**conf.high**	**p.adj**
1	White	Black	0.0470	0.0369	0.0571	< 0.0001
	White	Hispanic	0.0127	-0.0058	0.0313	0.2840
	White	No majority	0.0234	0.0073	0.0395	0.0010
	White	Asian/other	-0.0247	-0.0406	-0.0088	0.0060
	Black	Hispanic	-0.0343	-0.0546	-0.0140	0.0002
	Black	No majority	-0.0236	-0.0420	-0.0053	0.0050
	Black	Asian/other	-0.0717	-0.0886	-0.0548	< 0.0001
	Hispanic	No majority	0.0107	-0.0128	0.0342	0.7010
	Hispanic	Asian/other	-0.0374	-0.0594	-0.0154	0.0003
	No majority	Asian/other	-0.0481	-0.0684	-0.0278	< 0.0001
2	White	Black	0.0384	0.0336	0.0431	< 0.0001
	White	Hispanic	0.0290	0.0237	0.0344	< 0.0001
	White	No majority	0.0155	0.0097	0.0213	< 0.0001
	White	Asian/other	-0.0203	-0.0278	-0.0128	< 0.0001
	Black	Hispanic	-0.0094	-0.0158	-0.0030	0.0007
	Black	No majority	-0.0229	-0.0296	-0.0161	< 0.0001
	Black	Asian/other	-0.0587	-0.0669	-0.0504	< 0.0001
	Hispanic	No majority	-0.0135	-0.0207	-0.0063	< 0.0001
	Hispanic	Asian/other	-0.0493	-0.0579	-0.0407	< 0.0001
	No majority	Asian/other	-0.0358	-0.0447	-0.0270	< 0.0001
3	White	Black	0.0369	0.0333	0.0405	< 0.0001
	White	Hispanic	0.0209	0.0177	0.0240	< 0.0001
	White	No majority	0.0075	0.0036	0.0113	< 0.0001
	White	Asian/other	-0.0223	-0.0272	-0.0173	< 0.0001
	Black	Hispanic	-0.0161	-0.0197	-0.0124	< 0.0001
	Black	No majority	-0.0295	-0.0337	-0.0252	< 0.0001
	Black	Asian/other	-0.0592	-0.0644	-0.0539	< 0.0001
	Hispanic	No majority	-0.0134	-0.0173	-0.0094	< 0.0001
	Hispanic	Asian/other	-0.0431	-0.0481	-0.0381	< 0.0001
	No majority	Asian/other	-0.0297	-0.0352	-0.0243	< 0.0001
4	White	Black	0.0432	0.0390	0.0475	< 0.0001
	White	Hispanic	0.0241	0.0199	0.0283	< 0.0001
	White	No majority	0.0115	0.0062	0.0168	< 0.0001
	White	Asian/other	-0.0236	-0.0314	-0.0158	< 0.0001
	Black	Hispanic	-0.0191	-0.0229	-0.0153	< 0.0001
	Black	No majority	-0.0317	-0.0366	-0.0267	< 0.0001
	Black	Asian/other	-0.0668	-0.0744	-0.0592	< 0.0001
	Hispanic	No majority	-0.0126	-0.0175	-0.0076	< 0.0001
	Hispanic	Asian/other	-0.0477	-0.0553	-0.0401	< 0.0001
	No majority	Asian/other	-0.0351	-0.0433	-0.0269	< 0.0001

Table 2-6. Games-Howell test for pairwise difference in mean prevalence of diabetes across historical risk intervals (within group)

Majority group	**Historical risk intervals compared**		**estimate (difference)**	**conf.low**	**conf.high**	**p.adj**
White	1	2	0.0024	-0.0001	0.0048	0.0720
	1	3	0.0094	0.0068	0.0120	< 0.0001
	1	4	0.0085	0.0051	0.0119	< 0.0001
	2	3	0.0070	0.0046	0.0094	< 0.0001
	2	4	0.0062	0.0029	0.0094	< 0.0001
	3	4	-0.0009	-0.0042	0.0025	0.9100
Black	1	2	0.0015	-0.0105	0.0135	0.9880
	1	3	0.0150	0.0034	0.0266	0.0060
	1	4	0.0250	0.0134	0.0367	< 0.0001
	2	3	0.0135	0.0081	0.0189	< 0.0001
	2	4	0.0235	0.0180	0.0291	< 0.0001
	3	4	0.0101	0.0054	0.0147	< 0.0001
Hispanic	1	2	0.0045	-0.0186	0.0277	0.9480
	1	3	0.0056	-0.0173	0.0286	0.9020
	1	4	0.0118	-0.0112	0.0348	0.5000
	2	3	0.0011	-0.0040	0.0062	0.9440
	2	4	0.0072	0.0018	0.0126	0.0030
	3	4	0.0061	0.0022	0.0100	0.0003
No majority	1	2	0.0025	-0.0066	0.0115	0.8890
	1	3	0.0069	-0.0016	0.0153	0.1550
	1	4	0.0141	0.0051	0.0231	0.0006
	2	3	0.0044	-0.0005	0.0093	0.0990
	2	4	0.0116	0.0058	0.0174	< 0.0001
	3	4	0.0072	0.0024	0.0121	0.0007
Asian/other	1	2	-0.0012	-0.0247	0.0222	0.9980
	1	3	0.0197	-0.0037	0.0432	0.0980
	1	4	0.0305	0.0065	0.0545	0.0130
	2	3	0.0210	0.0124	0.0296	< 0.0001
	2	4	0.0318	0.0186	0.0449	< 0.0001
	3	4	0.0108	-0.0013	0.0228	0.0960

Table 2-7. Games-Howell test for pairwise difference in mean prevalence of diabetes across majority racial/ethnic groups (within historical risk interval)

Historical risk interval	Majority groups compared		estimate (difference)	conf.low	conf.high	p.adj
1	White	Black	0.0792	0.0671	0.0912	< 0.0001
	White	Hispanic	0.0472	0.0228	0.0717	0.0001
	White	No majority	0.0267	0.0179	0.0356	< 0.0001
	White	Asian/other	0.0295	0.0040	0.0550	0.0270
	Black	Hispanic	-0.0319	-0.0585	-0.0053	0.0120
	Black	No majority	-0.0524	-0.0669	-0.0380	< 0.0001
	Black	Asian/other	-0.0497	-0.0755	-0.0239	0.0004
	Hispanic	No majority	-0.0205	-0.0460	0.0050	0.1610
	Hispanic	Asian/other	-0.0178	-0.0493	0.0138	0.4730
	No majority	Asian/other	0.0028	-0.0226	0.0281	0.9950
2	White	Black	0.0783	0.0734	0.0833	< 0.0001
	White	Hispanic	0.0494	0.0444	0.0545	< 0.0001
	White	No majority	0.0269	0.0221	0.0316	< 0.0001
	White	Asian/other	0.0259	0.0179	0.0339	< 0.0001
	Black	Hispanic	-0.0289	-0.0355	-0.0223	< 0.0001
	Black	No majority	-0.0515	-0.0578	-0.0451	< 0.0001
	Black	Asian/other	-0.0524	-0.0614	-0.0434	< 0.0001
	Hispanic	No majority	-0.0226	-0.0290	-0.0161	< 0.0001
	Hispanic	Asian/other	-0.0235	-0.0326	-0.0145	< 0.0001
	No majority	Asian/other	-0.0010	-0.0098	0.0079	0.9980
3	White	Black	0.0848	0.0810	0.0886	< 0.0001
	White	Hispanic	0.0435	0.0403	0.0467	< 0.0001
	White	No majority	0.0242	0.0208	0.0276	< 0.0001
	White	Asian/other	0.0398	0.0345	0.0452	< 0.0001
	Black	Hispanic	-0.0413	-0.0455	-0.0371	< 0.0001
	Black	No majority	-0.0606	-0.0649	-0.0562	< 0.0001
	Black	Asian/other	-0.0449	-0.0509	-0.0389	< 0.0001
	Hispanic	No majority	-0.0193	-0.0231	-0.0155	< 0.0001
	Hispanic	Asian/other	-0.0037	-0.0093	0.0020	0.3820
	No majority	Asian/other	0.0156	0.0099	0.0214	< 0.0001
4	White	Black	0.0957	0.0910	0.1004	< 0.0001
	White	Hispanic	0.0505	0.0461	0.0549	< 0.0001
	White	No majority	0.0323	0.0270	0.0376	< 0.0001
	White	Asian/other	0.0515	0.0393	0.0637	< 0.0001
	Black	Hispanic	-0.0452	-0.0500	-0.0403	< 0.0001
	Black	No majority	-0.0634	-0.0690	-0.0578	< 0.0001
	Black	Asian/other	-0.0442	-0.0566	-0.0318	< 0.0001
	Hispanic	No majority	-0.0182	-0.0236	-0.0128	< 0.0001
	Hispanic	Asian/other	0.0010	-0.0113	0.0133	0.9990
	No majority	Asian/other	0.0192	0.0066	0.0318	0.0005

Sensitivity analysis

Table 2-8. Sensitivity analysis for poor mental health prevalence on historical redlining score and predominant racial/ethnic group

	Predominant group >= 60%			Predominant group >= 70%		
Variables	Estimate	Std. error	p-value	Estimate	Std. error	p-value
(Intercept)	0.0966	0.0023	< 0.0001	0.0917	0.0023	< 0.0001
Historical redlining score	0.0122	0.0005	< 0.0001	0.0126	0.0005	< 0.0001
Predominant racial/ethnic group (ref = white)						
Black	0.0292	0.0028	< 0.0001	0.0305	0.0031	< 0.0001
Hispanic	0.0326	0.0038	< 0.0001	0.0356	0.0045	< 0.0001
Asian/other	0.0047	0.0090	0.5995	0.0138	0.0162	0.3963
None	0.0203	0.0019	< 0.0001	0.0205	0.0018	< 0.0001
Interactions (ref = white)						
Historical redlining score*Black	-0.0003	0.0009	0.7022	-0.0007	0.0010	0.4385
Historical redlining score*Hispanic	-0.0045	0.0011	0.0001	-0.0057	0.0013	< 0.0001
Historical redlining score*Asian/other	0.0010	0.0028	0.7361	-0.0024	0.0050	0.6290
Historical redlining score*None	-0.0023	0.0006	0.0002	-0.0022	0.0006	0.0003
Covariates						
Proportion foreign-born	-0.0090	0.0027	0.0007	-0.0084	0.0026	0.0013
Population density	0.0000	0.0000	< 0.0001	0.0000	0.0000	< 0.0001
Proportion population under 18	0.0688	0.0031	< 0.0001	0.0769	0.0031	< 0.0001
Proportion population over 65	-0.1216	0.0036	< 0.0001	-0.1166	0.0036	< 0.0001
Fixed effects (ref = Northeast)						
Midwest	0.0122	0.0019	< 0.0001	0.0124	0.0019	< 0.0001
South	0.0186	0.0023	< 0.0001	0.0193	0.0023	< 0.0001
West	-0.0060	0.0023	0.0073	-0.0060	0.0023	0.0077
Number of observations	12,851			12,851		
Lambda	0.7863	0.0054	< 0.0001	0.7866	0.0054	< 0.0001
AIC (error model)	-63,314			-63,219		
AIC (OLS model)	-54,115			-54,068		

Table 2-9. Sensitivity analysis for diabetes prevalence on historical redlining score and predominant racial/ethnic group

	Predominant group >= 60%			Predominant group >= 70%		
Variables	Estimate	Std. error	p-value	Estimate	Std. error	p-value
(Intercept)	-0.0018	0.0022	0.4272	-0.0079	0.0024	0.0009
Historical redlining score	0.0101	0.0005	< 0.0001	0.0102	0.0006	< 0.0001
Predominant racial/ethnic group (ref = white)						
Black	0.0541	0.0030	< 0.0001	0.0577	0.0034	< 0.0001
Hispanic	0.0419	0.0040	< 0.0001	0.0425	0.0048	< 0.0001
Asian/other	0.0130	0.0096	0.1770	0.0044	0.0178	0.8044
None	0.0204	0.0021	< 0.0001	0.0158	0.0020	< 0.0001
Interactions (ref = white majority)						
Historical redlining score*Black	0.0027	0.0009	0.0035	0.0014	0.0010	0.1648
Historical redlining score*Hispanic	-0.0030	0.0012	0.0127	-0.0042	0.0015	0.0041
Historical redlining score*Asian/other	0.0063	0.0030	0.0399	0.0095	0.0055	0.0818
Historical redlining score*None	0.0012	0.0007	0.0682	0.0026	0.0007	0.0001
Covariates						
Proportion foreign-born	-0.0010	0.0027	0.7201	0.0027	0.0028	0.3266
Population density	0.0000	0.0000	0.0023	0.0000	0.0000	0.0001
Proportion population under 18	0.1462	0.0033	< 0.0001	0.1626	0.0034	< 0.0001
Proportion population over 65	0.2335	0.0039	< 0.0001	0.2411	0.0040	< 0.0001
Fixed effects (ref = Northeast)						
Midwest	0.0117	0.0017	< 0.0001	0.0118	0.0017	< 0.0001
South	0.0248	0.0020	< 0.0001	0.0264	0.0021	< 0.0001
West	-0.0028	0.0019	0.1429	-0.0028	0.0020	0.1704
Number of observations	12,851			12,851		
Lambda	0.7298	0.0064	< 0.0001	0.7347	0.0063	< 0.0001
AIC (error model)	-62,013			-61,258		
AIC (OLS model)	-55,576			-54,766		

Chapter 3 | RELATIONSHIPS BETWEEN HISTORICAL REDLINING, CONTEMPORARY HOUSING MARKET DYNAMICS, RACIAL COMPOSITION, AND MENTAL HEALTH IN U.S. URBAN NEIGHBORHOODS: A CONDITIONAL PROCESS ANALYSIS

Abstract

Objectives. To examine features of contemporary housing markets, including neighborhood property values, homeownership rates, and loan denial rates for home purchase, as mediators of historical redlining patterns and contemporary prevalence of poor mental health and to assess the role of the relative size of the Black population as a moderator of these associations.

Methods. Data were obtained from the CDC PLACES Project (2020 release), American Community Survey 5-year estimates (2013-2017), Home Mortgage Disclosure Act database (2013-2017), and Historic Redlining Scores Project. We used an ecological design at the census tract level to conduct mediation and first-stage conditional process analyses (moderated mediation) of our conceptual model.

Results. We found significant indirect effects of historical redlining on contemporary prevalence of poor mental health via neighborhood property values, homeownership rates, and loan denial rates for home purchase. The indirect effect of redlining via relative median property value was conditional on the relative size of the Black population. Properties in historically "A" graded neighborhoods are valued more than those in neighborhoods graded less favorably – and this apparent benefit to property values is greater in neighborhoods where Black residents are underrepresented.

Conclusions. Despite fair housing legislation enacted more than 50 years ago, racial inequities within contemporary housing markets persist, making it more difficult for Black families to build wealth and achieve optimal health. Racist ideologies conflating race and value must be dismantled to address the devaluation of assets in Black communities – and its consequences for individual, family, and community health and wellbeing.

Introduction

Historical redlining practices have been linked to a wide range of contemporary social, economic, and health outcomes, including poor mental health. Among neighborhoods subjected to appraisal by the Home Owners' Loan Corporation (HOLC) in the 1930s and 1940s, those which were graded as "hazardous" for lending and investment today exhibit a greater burden of poor health compared to those graded more favorably (Lee et al., 2021). Prior studies suggest historical redlining patterns are associated with the distribution of social determinants of health across urban neighborhoods (Mehdipanah et al., 2023; Swope et al., 2022). However, few studies have formally examined the contemporary factors which may help to explain the enduring legacy of historical redlining practices and their possible contributions to racial/ethnic and place-based health inequities (Graetz & Esposito, 2021; Laurent, 2021; Lynch et al., 2021).

In recognition, researchers have called for greater attention to the factors which might mediate relationships between indicators of structural racism (e.g., residential segregation; historical redlining) and health (Krieger et al., 2020; Landrine et al., 2017). Contemporary features of local housing markets are of particular interest considering historical redlining practices were directly related to and likely had continued influence on mortgage lending patterns, property values, and homeownership opportunities (Aaronson et al., 2021; Greer, 2013). In this study, we examined whether and to what extent features of contemporary housing markets explain the documented association between historical redlining patterns and neighborhood prevalence of poor mental health. As inequities within local housing markets have particularly affected Black communities, we also examined whether the effects of historical redlining patterns through features of contemporary housing markets are dependent on the relative size of the Black population within a neighborhood. Our study contributes to a burgeoning body of literature examining the roles of historical to contemporary forms of structural and institutional racism in the (re)production of racial/ethnic and place-based health inequities. Specifically, our findings build on current understandings of the mechanisms by which historical redlining patterns may have lasting impacts on community health and well-being.

Historical context

Following the foreclosure crisis of the Great Depression, the New Deal era set in motion by the Roosevelt administration established the modern-day framework for housing, including the promotion of homeownership as an important vehicle to build wealth and achieve the "American Dream." The New Deal established the Home Owners' Loan Corporation (HOLC) to purchase and refinance mortgages at risk of default and to introduce the amortized mortgage, which allowed homebuyers to pay off their debt over two or three decades rather than the previously standard five-year home loan (Baradaran, 2017). These federal initiatives to increase access to homeownership placed severe restrictions on benefits for African Americans and in some cases excluded Black families altogether. One such mechanism was in the assessment of neighborhoods for foreclosure risk carried out by HOLC in cities with more than 40,000 residents in the mid- to late-1930s. This process widely known as "redlining" entailed the systematic grading of neighborhoods with concentrations of Black and/or immigrant families as highest risk for mortgage lending and investment. These "risk grades" assigned by HOLC appraisers were drawn onto "residential security maps," which color-coded neighborhoods by the assigned grade: "A" (green) represented "best" and lowest perceived investment risk; "B" (blue) indicated "still desirable;" "C" (yellow) meant "definitely declining; and "D" (red) represented "hazardous" and indicated the highest perceived investment risk (Mitchell & Franco, 2018).

The process of redlining became institutionalized within local housing markets and often prevented the purchase and/or insurance of homes in neighborhoods deemed high-risk. Redlined neighborhoods also experienced declines in property values associated with the "hazardous" designation, and property owners were often unable to take out loans even for home maintenance or improvements, further degrading housing quality and neighborhood reputations (Rothstein, 2017). The backlash following these racist policies and related declines in neighborhood conditions contributed to the rise of the Civil Rights Movement in the 1950s and 1960s. In 1968, the Fair Housing Act was passed by the Johnson administration to prohibit discrimination in the sale and rental of housing (or most housing) on the basis of race, color, national origin, religion, sex, familial status or disability. It wasn't until 1974, however, when discrimination in mortgage lending was addressed through the Equal Credit Opportunity Act, which prohibited discrimination by race in "any aspect of a credit transaction" (*Equal Credit Opportunity*, 1974). One year later, the Home Mortgage Disclosure Act of 1975 mandated reporting by financial institutions of demographic information for all mortgage applicants to allow for tracking of discriminatory practices in mortgage lending (*Home Mortgage Disclosure*, 1975).

Although intentional discrimination in housing has been officially outlawed, Black Americans continue to face inequities in homeownership, mortgage lending, and property values. In 2020, roughly 45% of African Americans owned their homes compared to 75% of white Americans (*Quarterly Residential Vacancies and Homeownership, Second Quarter 2021*, 2021). Nationwide, Black applicants in 2020 were three times as likely to be denied a loan for home purchase and twice as likely to be denied for refinance relative to non-Hispanic white applicants (Liu et al., 2021). Further, homes in majority Black neighborhoods are valued at roughly half that of homes in neighborhoods with less than one percent Black residents (Perry et al., 2018). In large part, these inequities stem from historically racist housing policies, including redlining practices, that began nearly a century ago. The primary purpose of HOLC's "residential security maps" was to identify neighborhoods at high risk for housing foreclosure. This racialized appraisal process ultimately restricted access to credit among neighborhoods with concentrations of African American and immigrant families – or identified neighborhoods that were already experiencing disinvestment (Hillier, 2003). The "hazardous" status was also damaging to neighborhood reputations such that redlined neighborhoods experienced declines in property values even after the practice was deemed unconstitutional. Further, property appraisal practices to this day incorporate historical data – and use racial composition in identifying "comparable" neighborhoods – suggesting property values may still be (directly or indirectly) influenced by risk grades assigned in the 1930s. In support, Aaronson et al. (2021) found the 1930s HOLC maps have had lasting causal effects on neighborhood homeownership rates, access to credit, and property values, as well as the share of Black residents (Aaronson et al., 2021). These patterns – and ultimately the institutionalization – of mortgage lending discrimination, inequitable homeownership opportunities, and property devaluation have together made it more difficult for Black families to accumulate capital and build wealth across generations (Krivo & Kaufman, 2004). Without adequate reparative action, researchers estimate it will take more than 200 years for Black families to achieve the level of wealth currently held by white families – and even then, gaps between Black and white families would be even more severe (Asante-Muhammad et al., 2016).

Relative limitations in family assets, in terms of both socioeconomic status and intergenerational wealth, have direct implications for mental health, acting directly through reduced ability to meet basic needs (e.g., housing and food security) and indirectly through decreased sense of control, increased instability, and chronic stress (Cutler et al., 2008; Schneiderman et al., 2005; Suglia et al., 2011; Swope & Hernández, 2019). In support, features of local housing markets have been linked to mental health outcomes and inequities. Home foreclosures, for example, are associated with self-reported poor mental health, acting through chronic stress associated with personal experiences of foreclosure as well as through neighborhood deterioration at the community level (Tsai, 2015). Studies have also linked contemporary mortgage lending discrimination to poor mental health, as well as adverse birth outcomes and poorer cancer survival (Beyer et al., 2021; Lynch et al., 2021; Matoba et al., 2019; Mendez et al., 2011, 2014). Relatedly, studies suggest homeownership has non-financial benefits, including for health, likely acting through residential stability and perceived control (Lindblad & Quercia, 2015; Manturuk, 2012; Mehdipanah et al., 2017). Manturuk (2012), for example, found that homeowners within low-wealth urban areas experience better mental health than respective renters, even after accounting for possible selection bias, and that the effect of homeownership on mental health was entirely mediated by perceived sense of control.

In this study, we examined whether features of contemporary housing markets mediate the relationship between historical redlining practices and neighborhood mental health outcomes. Specifically, we hypothesized that the association between historical redlining patterns and neighborhood prevalence of poor mental health could be explained by property values, homeownership rates, and loan denial rates for home purchase. As mortgage lending patterns and property appraisal practices have historically been explicitly racialized, we further anticipated the mediating role of these housing market features would be moderated by the size of the Black population within a neighborhood relative to its corresponding metropolitan/micropolitan area. Figure 3-1 below shows the conceptual model we tested in this study.

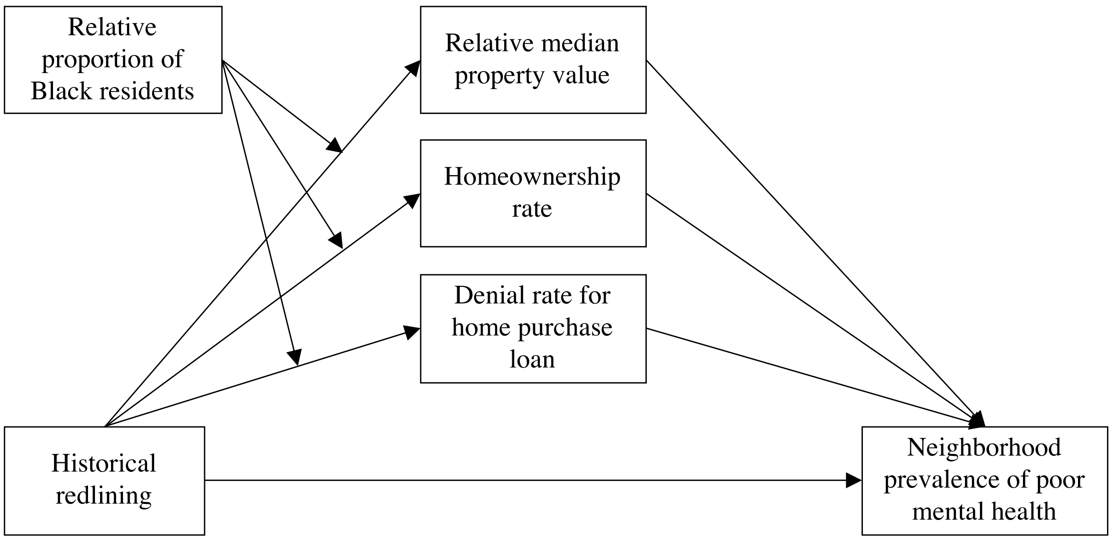

Figure 3-1. Conceptual model of indirect effects of historical redlining on neighborhood prevalence of poor mental health via features of contemporary housing markets, conditional on the relative proportion of Black residents

Data and methods

We utilized an ecological design at the census tract level. Our initial sample included census tracts with at least 20 percent overlap with areas historically appraised by the Home Owners' Loan Corporation (HOLC), in alignment with Meier and Mitchell's Historic Redlining Scores Project (2021). This sample included 12,864 tracts across 143 core-based statistical areas (CBSAs). We retained tracts with complete data for all regression variables, resulting in a final analytic sample of 12,047 tracts. Our final analytic sample did not differ substantively from the initial sample in terms of our variables of interest. We discuss issues related to missing data in more detail below.

Measures

Historical redlining score. Historical redlining score was the primary exposure of interest in our analysis. We obtained historical redlining scores normed to the 2010 census tract boundaries from Meier and Mitchell's Historic Redlining Scores Project (2021). These scores were constructed by overlaying digitized versions of HOLC's "residential security maps" on the 2010 census tract boundaries, assigning a numerical value to each historical risk grade (A = 1, B = 2, C = 3, D = 4), and calculating a tract average, weighted by the proportion of land area corresponding to each grade; as such, these continuous scores are bounded between 1-4. For descriptive purposes, historical redlining scores were categorized into one of four even intervals.

Relative median property value. We created a measure of relative median property value by dividing census tract median property value by the median property value of the corresponding CBSA. In our analyses we used a log transformation of this variable. We chose to use a relative measure to account for differences in property values across CBSAs. We obtained tract and CBSA median property values from the American Community Survey (ACS) 5-year estimates for 2013-2017.

Homeownership. We calculated tract homeownership rates by dividing the number of owner-occupied housing units within a tract by the total number of occupied housing units. We obtained these data from the ACS 5-year estimates for 2013-2017.

Denial rate. We calculated tract-level denial rates for home purchase loans using pooled data for 2013-2017 from the Home Mortgage Disclosure Act, which includes application-level information on loans for home purchase, refinance, and home improvement. For each census tract, we divided the number of applications which were denied by the total number of loan applications which had either been originated or denied. We restricted this measure to census tracts which had at least five loan applications between 2013-2017 which had either been originated or denied. We used a square root transformation to achieve approximate normality.

Poor mental health prevalence. The primary outcome of interest in our analyses was neighborhood prevalence of poor mental health. We obtained census tract prevalence of poor mental health from the Centers for Disease Control and Prevention (CDC) PLACES Project (2020 release), which utilized data from the 2017-2018 Behavioral Risk Factor Surveillance System (BRFSS) to create model-based small-area estimates for health outcomes and risk factors. Poor mental health prevalence was defined as the proportion of residents who reported their mental health was not good for at least 14 of the last 30 days, based on the survey item: “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” (CDC, 2019). As respondents were asked to report on their mental health in the last 30 days, this measure offers a point-in-time reflection of community well-being.

Relative proportion of Black residents. As a measure of relative neighborhood racial composition, we divided the proportion of Black residents within a census tract by the proportion of Black residents within the corresponding metropolitan/micropolitan area, also known as the location quotient. In alignment with Howell and Korver-Glenn (2021), we chose this approach as a relative measure is more likely than an absolute measure with some arbitrary cutoff value to capture neighborhood racial composition as it is perceived by policymakers, local residents, property appraisers, and lenders. We created this measure using tract- and CBSA-level data from the ACS 5-year estimates for 2013-2017.

Covariates. In all models we adjusted for tract age distribution, specifically, the proportion of residents under the age of 18 and the proportion of residents over the age of 65, as mental health outcomes are distributed differently across age strata (Substance Abuse and Mental Health Services Administration, 2022). As the HOLC maps were developed for cities with at least 40,000 residents in the 1930s, neighborhoods included in our analysis are generally situated in urban cores with contemporarily sizable populations; however, there remains much variation across metropolitan/micropolitan areas. As such, we also adjusted for standardized tract population density to account for differences in urbanicity. We created all covariates using data from the ACS 5-year estimates for 2013-2017.

Statistical analysis

First, we conducted a mediation analysis to investigate whether features of contemporary housing markets – specifically, relative median property value, homeownership rate, and denial rate for home purchase loans – explain the documented relationship between historical redlining patterns and neighborhood prevalence of poor mental health. We obtained the indirect effects of historical redlining score on neighborhood prevalence of poor mental health via each of our three mediating variables of interest using a structural equation modeling (SEM) approach. Next, we conducted a first-stage conditional process analysis (Hayes & Rockwood, 2020), or first-stage moderated mediation analysis, to examine whether the indirect effects of historical redlining score through our three mediating pathways of interest were conditional on the tract-to-CBSA relative proportion of Black residents. To carry out this analysis, we included in models of each mediating variable an interaction term between historical redlining score and the relative proportion of Black residents. We assessed whether moderated mediation was present using the significance of the interaction term as well as the index of moderated mediation (Hayes, 2015). In our results section, we present conditional indirect effects, with the value of the moderator set to one-half the standard deviation below and above the mean (Mean-0.5SD, Mean+0.5SD). We chose to use one-half the standard deviation so that our hypothetical values remained within realistic ranges. For both our initial mediation models and subsequent moderated mediation models, we set standard errors to be robust to clustering at the CBSA level. We completed these analyses using the *lavaan* package in R version 4.1.0.

Sensitivity analyses. Given our focus on neighborhood-level processes, our data are spatial in nature. Neighborhood characteristics and outcomes are often spatially related, as suggested by Tobler's first law of geography, which essentially states that everything is related to everything else, but near things are more related than far things (Tobler, 1970). Under this assumption, our study warranted explicit examination of spatial effects which might influence our results. We assessed the degree of spatial autocorrelation using global Moran's I and found our model residuals were spatially dependent, suggesting the standard errors obtained from our previous analyses might be underestimated. To address this issue, in sensitivity analyses we conducted our mediation and first-stage conditional process analyses by adapting the Baron and Kenny approach with spatial error regression models and CBSA fixed effects (Baron & Kenny, 1986). These spatial error regression models apply spatial weights matrices to adjust the sample size to an "effective sample size" that accounts for the influence of adjacent neighborhoods. Finally, we used the Sobel test to determine the significance of the indirect effects (Sobel, 1982). Although a bootstrap approach is recommended over the Sobel test (Shrout & Bolger, 2002), bootstrapping standard errors was not computationally feasible for our spatial analyses. We completed these analyses using the *spatialreg* package in R version 4.1.0.

As the results of our initial analyses were similar, though more conservative, than our sensitivity analyses, we present the results obtained from our more conventional SEM procedure described above. The complete regression results for our SEM mediation and conditional process analyses are available in the Appendix (Table 3-3 and Table 3-4, respectively).

Results

Table 3-1 below shows descriptive statistics for the variables included in our analysis, stratified by historical redlining interval. Expectedly, neighborhood prevalence of poor mental health and features of contemporary housing markets exhibited graded relationships with historical redlining interval, where outcomes and housing conditions were consistently less favorable at higher intervals. The relative proportion of Black residents – our potential moderator of interest – also showed a graded relationship with historical redlining; however, there was substantial variation across intervals.

Table 3-1. Summary statistics by historical redlining interval, including neighborhood prevalence of poor mental health, contemporary housing market features, relative proportion of Black residents, and covariates

	Historical redlining interval							
	[1.0, 1.75)		[1.75, 2.5)		[2.5, 3.25)		[3.25, 4.0]	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Poor mental health prevalence	0.1143	0.0319	0.1341	0.0341	0.1492	0.0360	0.1620	0.0397
Relative median property value (log)	0.3827	0.6367	-0.0295	0.5673	-0.2173	0.5381	-0.2766	0.6016
Homeownership rate	0.6732	0.1999	0.5474	0.2098	0.4583	0.2064	0.3738	0.1869
Denial rate for home purchase (sqrt)	0.3311	0.1061	0.3685	0.1178	0.4072	0.1305	0.4364	0.1420
Relative proportion of Black residents	1.0085	1.6224	1.5281	1.9237	1.7896	2.0244	2.2501	2.1177
Proportion of population under 18	0.2038	0.0629	0.2060	0.0648	0.2173	0.0732	0.2207	0.0873
Proportion of population over 65	0.1714	0.0699	0.1438	0.0554	0.1256	0.0520	0.1141	0.0520
Population density (standardized)	-0.3996	0.5836	-0.0900	0.9399	0.0043	0.8766	0.0697	1.0356

The results of our initial mediation analysis suggested the association between historical redlining score and neighborhood prevalence of poor mental health can be explained in large part by contemporary features of local housing markets. Together, relative property values, homeownership, and loan denial rates mediated approximately 83 percent of the association between historical redlining score and poor mental health prevalence. In the next stage of our analysis, we found these relationships were dependent on neighborhood racial composition. Table 3-2 below shows the results of our first-stage conditional process analysis. We found historical redlining score had a positive and statistically significant association with neighborhood prevalence of poor mental health, conditional on the relative proportion of Black residents. When the relative Black population was set to half its standard deviation below the mean (Mean-0.5SD = 0.80), the total effect of historical redlining score on poor mental health prevalence was 0.0136 (SE=0.0016, p<0.0001), meaning a one-point increase in redlining score was associated with a 1.36 percentage point increase in prevalence of poor mental health. When the relative Black population was set to half its standard deviation above the mean (Mean+0.5SD = 2.84), the total effect of historical redlining was 0.0095 (SE=0.0013, p<0.0001), meaning a one-point increase in redlining score was associated with a 0.95 percentage point increase in prevalence of poor mental health. We found the direct effect of historical redlining score on neighborhood prevalence of poor mental health remained significant after the inclusion of our mediating variables of interest (direct effect=0.0024, SE=0.0010, p=0.0220); however, the effect was substantially reduced, suggesting partial mediation.

At all levels of relative Black population (Mean-0.5SD, Mean+0.5SD), we found significant indirect effects of historical redlining score on neighborhood prevalence of poor mental health via relative median property value (Mean-0.5SD: effect=0.0066, SE=0.0013, p<0.0001; Mean+0.5SD: effect=0.0028, SE=0.0011, p=0.0078), homeownership rate (Mean-0.5SD: effect=0.0036, SE=0.0004, p<0.0001; Mean+0.5SD: effect=0.0036, SE=0.0004, p<0.0001), and denial rate for home purchase loans (Mean-0.5SD: effect=0.0010, SE=0.0003, p=0.0022; Mean+0.5SD: effect=0.0007, SE=0.0002, p=0.0018). In the case of relative median property value, for example, this result means that, when the relative proportion of Black residents is half a standard deviation below the mean (i.e., Black residents are underrepresented within a neighborhood relative to the CBSA), of the 0.0136 total effect of redlining score on neighborhood prevalence of poor mental health, 0.0066 – or roughly half the total effect – can be explained by relative median property value. Conversely, when the relative proportion of Black residents is half a standard deviation above the mean (i.e., Black residents are overrepresented within a neighborhood relative to the CBSA), of the 0.0095 total effect of redlining on poor mental health, 0.0028 – or about 30 percent – can be explained by relative median property value.

Of our three mediating variables of interest, only the indirect effect via relative median property value was conditional on the relative proportion of Black residents, as indicated by the significance of the interaction term and index of moderated mediation (IMM) for this pathway (IMM=-0.0019, SE=0.0004, p<0.0001). In other words, in neighborhoods with a relatively greater proportion of Black residents, the relationship between historical redlining score, relative median property value, and poor mental health prevalence was reduced. Likewise, the total indirect effect and total effect of historical redlining score were conditional on the relative proportion of Black residents in such a way that the total indirect effect (Mean-0.5SD: effect=0.0113, SE=0.0016, p<0.0001; Mean+0.5SD: effect=0.0071, SE=0.0013, p<0.0001) and total effect (Mean-0.5SD: effect=0.0136, SE=0.0016, p<0.0001; Mean+0.5SD: effect=0.0095, SE=0.0013, p<0.0001) decrease as the relative size of the Black population increases.

In summary, we found a substantial portion of the association between historical redlining score and neighborhood prevalence of poor mental health can be explained by contemporary features of local housing markets. When the relative proportion of Black residents is set to one-half its standard deviation below the mean, the housing market features of interest together explain approximately 82.5 percent of the association between historical redlining score and neighborhood prevalence of poor mental health (SE=0.0731, $p<0.0001$); when the relative Black population is set to one-half its standard deviation above the mean, contemporary housing conditions explain approximately 75 percent of the association (SE=0.1005, $p<0.0001$).

Table 3-2. Results of first-stage conditional process analysis of neighborhood prevalence of poor mental health on historical redlining score via features of contemporary housing markets, conditioned on relative proportion of Black residents

	Estimate	Std. Err.	z	p
Outcome: neighborhood prevalence of poor mental health				
Historical redlining score (direct effect)	0.0024	0.0010	2.2906	0.0220
Relative median property value (log)	-0.0325	0.0027	-12.2422	< 0.0001
Homeownership rate	-0.0534	0.0053	-10.1109	< 0.0001
Denial rate for home purchase loan (sqrt)	0.0304	0.0092	3.3051	0.0009
Outcome: Relative median property value (log)				
Historical redlining score	-0.2509	0.0417	-6.0128	< 0.0001
Relative proportion of Black residents	-0.2635	0.0421	-6.2524	< 0.0001
Historical redlining score * Relative proportion Black residents	0.0579	0.0125	4.6169	< 0.0001
Outcome: Homeownership rate				
Historical redlining score	-0.0671	0.0053	-12.5564	< 0.0001
Relative proportion of Black residents	-0.0216	0.0069	-3.1389	0.0017
Historical redlining score * Relative proportion Black residents	-0.0001	0.0021	-0.0644	0.9487
Outcome: Denial rate for home purchase loan (sqrt)				
Historical redlining score	0.0375	0.0074	5.0814	< 0.0001
Relative proportion of Black residents	0.0341	0.0096	3.5659	0.0004
Historical redlining score * Relative proportion Black residents	-0.0047	0.0029	-1.5925	0.1113
Conditional indirect effects via relative median property value (log)				
Relative proportion of Black residents (Mean-0.5SD)	0.0066	0.0013	4.9802	< 0.0001
Relative proportion of Black residents (Mean+0.5SD)	0.0028	0.0011	2.6623	0.0078
Conditional indirect effects via homeownership rate				
Relative proportion of Black residents (Mean-0.5SD)	0.0036	0.0004	8.6893	< 0.0001
Relative proportion of Black residents (Mean+0.5SD)	0.0036	0.0004	9.5353	< 0.0001
Conditional indirect effects via denial rate for home purchase (sqrt)				
Relative proportion of Black residents (Mean-0.5SD)	0.0010	0.0003	3.0654	0.0022
Relative proportion of Black residents (Mean+0.5SD)	0.0007	0.0002	3.1166	0.0018
Total conditional indirect effect				
Relative proportion of Black residents (Mean-0.5SD)	0.0113	0.0016	6.9183	< 0.0001
Relative proportion of Black residents (Mean+0.5SD)	0.0071	0.0013	5.4124	< 0.0001
Total conditional effect				
Relative proportion of Black residents (Mean-0.5SD)	0.0136	0.0016	8.6301	< 0.0001
Relative proportion of Black residents (Mean+0.5SD)	0.0095	0.0013	7.1978	< 0.0001
Proportion mediated				
Relative proportion of Black residents (Mean-0.5SD)	0.8254	0.0731	11.2869	< 0.0001
Relative proportion of Black residents (Mean+0.5SD)	0.7502	0.1005	7.4620	< 0.0001
Index of moderated mediation				
Relative median property value (log)	-0.0019	0.0004	-4.5335	< 0.0001
Homeownership rate	0.0000	0.0001	0.0645	0.9486
Denial rate for home purchase loan (sqrt)	-0.0001	0.0001	-1.4468	0.1480

Note: Standard errors are robust to clustering by CBSA. See complete regression results in Appendix B.

An extension from Table 3-2, Figure 3-2 shows the interactional effects of historical redlining score and relative proportion of Black residents on relative median property value (left), homeownership rate (middle), and denial rate for home purchase loans (right). As discussed above, the interaction was statistically significant for relative median property value (Estimate=0.0579, SE=0.0125, $p<0.001$), where the indirect effect of historical redlining score on poor mental health prevalence via relative median property value was reduced in neighborhoods with larger overrepresentations of Black residents. Although the interactions were not statistically significant for homeownership rate or denial rate for home purchase loans, we found significant main effects of relative proportion of Black residents, suggesting homeownership rates are lower in neighborhoods with overrepresentations of Black residents, and denial rates for home purchase loans are higher, across all levels of historical redlining score. In our sensitivity analyses, however, which applied spatial error regression modeling to the Baron and Kenny mediation approach, we found significant moderated mediation for all three pathways. The results of our sensitivity analyses suggest the indirect effects of historical redlining score on poor mental health prevalence via features of contemporary housing markets are reduced in neighborhoods with larger overrepresentations of Black residents – or conversely, the indirect effects are greater in neighborhoods with relative underrepresentations of Black residents (see Appendix B).

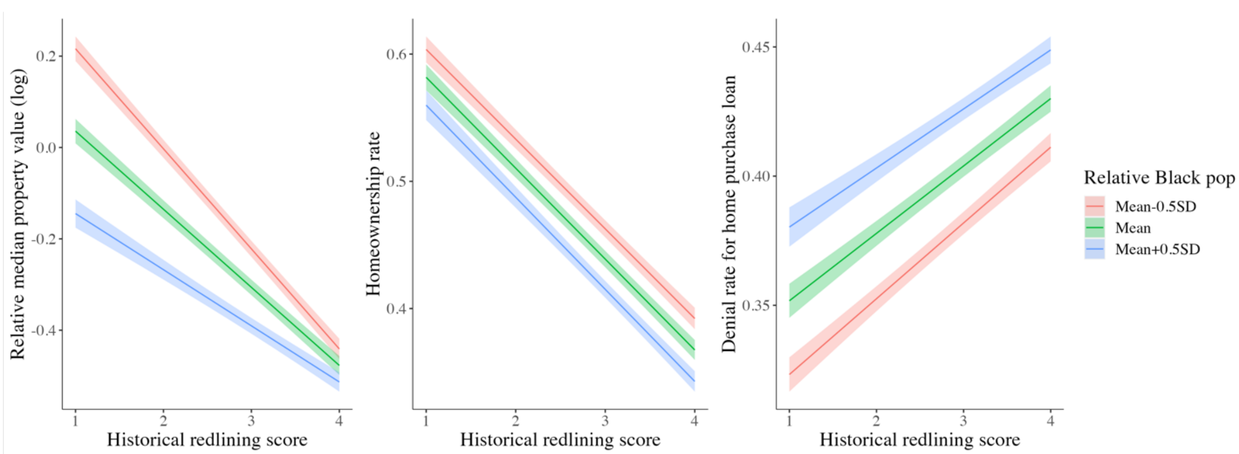

Figure 3-2. Interaction plots for features of contemporary housing markets on historical redlining score, conditioned on relative proportion of Black residents

Discussion

Structural exclusion of Black communities from local housing markets has contributed to a growing racial wealth gap, entrenched racial residential segregation, and persistence of racial health inequities across the United States (Rothstein, 2017). Despite fair housing legislation enacted more than 50 years ago, the historical risk grades ascribed to urban neighborhoods in the 1930s continue to show associations with features of contemporary housing markets, where historically redlined neighborhoods exhibit lower rates of homeownership, lower relative median property values, and higher rates of loan denial for home purchase compared to neighborhoods graded more favorably. Likewise, residents of historically redlined neighborhoods experience a greater burden of poor mental health and other adverse outcomes. To our knowledge, our study is one of the first to demonstrate that features of contemporary housing markets may be pathways in the association between historical redlining patterns and poor mental health, and that these pathways may be conditional on neighborhood racial composition.

This study adds support to a growing body of literature centering historical to contemporary structural racism as a critical public health issue. Our findings align with prior work examining the health consequences of historical redlining practices and related forms of spatial racism, with two important contributions. First, we found the association between historical redlining patterns and neighborhood prevalence of poor mental health, where a one-point increase in redlining score corresponds to a 1.36-percentage point increase in prevalence of poor mental health, can be explained in large part by features of contemporary housing markets. This finding suggests historical redlining practices may have lasting impacts on community health and well-being in part because of perpetuated inequities in local housing markets, including in mortgage lending and property appraisal practices. For example, although the explicit use of HOLC's redlining maps was outlawed in the 1970s under a combination of the Fair Housing Act (1968), Equal Credit Opportunity Act (1974), Home Mortgage Disclosure Act (1975), and Community Reinvestment Act (1977), property appraisers to this day continue to use historical data to inform appraised values. Under this commonly used "sales comparison approach" homes are valued based on sales in the same or comparable neighborhoods, suggesting appraisal processes are likely still influenced by HOLC's redlining maps in that "baseline" property values in the 1970s had been set when the maps or similar grading schemes were in use (Howell & Korver-Glenn, 2018). Further, property appraisers continue to use racial composition as a criterion in identifying "comparable" neighborhoods for sales comparison, a practice which essentially perpetuates indirect use of the HOLC maps and devaluation of assets in neighborhoods historically deemed high-risk.

Relatedly, findings from Aaronson et al. (2021) suggest a causal relationship between the historical HOLC maps and declining investment in redlined neighborhoods, as evidenced by declines in homeownership and housing values following the development of the maps. Further, studies suggest a persistent link between historical redlining patterns and discrimination in contemporary mortgage lending practices (Namin et al., 2022). As discussed, prior work has suggested homeownership and mortgage lending practices are associated with mental health outcomes. Homeowners tend to experience better mental health, likely acting through residential stability and perceived sense of control (Lindblad & Quercia, 2015; Manturuk, 2012); conversely, lower lending opportunity is associated with poorer mental health (Lynch et al., 2021). Likewise, one study shows area property values are positively associated with self-rated health (Jiao et al., 2016). Our study is one of the first to show that these features of contemporary housing markets mediate the documented association between historical redlining patterns and neighborhood prevalence of poor mental health. Our findings suggest that historical redlining patterns are associated with neighborhood prevalence of poor mental health; and this effect is largely explained by neighborhood homeownership, property values, and loan denial rates for home purchase. In short, redlining score was negatively associated with homeownership rates and relative property values and positively associated with loan denial rates; homeownership rates and property values were negatively associated, while loan denial rates were positively associated, with poor mental health prevalence. Although we focus here on mental health, our findings broadly align with one previous study which found property valuation is a significant pathway by which the historical HOLC maps may influence contemporary neighborhood life expectancies (Graetz & Esposito, 2021).

Second, and perhaps most importantly, we found the indirect effect of historical redlining on poor mental health via relative median property value was conditional on the tract-to-CBSA relative proportion of Black residents, where neighborhoods with relative overrepresentations of Black residents showed a reduced indirect effect via relative median property value, as well as a reduced total effect of historical redlining score. As shown in Figure 3-2, the reduced indirect effect is due to the reduced direct effect of historical redlining score on relative median property value among neighborhoods with larger overrepresentations of Black residents. In other words, neighborhoods with relative underrepresentations of Black residents showed a stronger relationship between historical redlining score and relative median property value. This finding suggests that – with relative consistency – properties in historically redlined neighborhoods are valued less than properties in neighborhoods that were graded more favorably, regardless of the relative share of Black residents. Conversely, properties in historically "A" graded (or "greenlined") neighborhoods are valued more than those in neighborhoods graded less favorably – and this apparent benefit to property values is greater in neighborhoods where Black residents are underrepresented.

Broadly, this finding aligns with Howell and Korver-Glenn (2021), who found neighborhood racial composition was a more important predictor of property values in 2015 than it was in 1980. Between 1980 and 2015, mean appraised home values increased to a larger degree in neighborhoods with overrepresentations of non-Hispanic white residents compared to neighborhoods with overrepresentations of Black and/or Hispanic residents (Howell & Korver-Glenn, 2021). Relatedly, studies consistently suggest homes in predominantly white neighborhoods are appraised higher – and appreciate more over time – than comparable homes in neighborhoods with concentrations of Black residents (Kim, 2000; Macpherson & Sirmans, 2001; Moye, 2014). Of course, racial and ethnic groups are not distributed evenly across historical risk grades – historically redlined neighborhoods today contain a disproportionate share of Black residents while historically "A" graded neighborhoods contain a disproportionate share of white residents. Together, these considerations might explain why we observe a larger discrepancy in relative median home values across historically "A" graded neighborhoods with relative under- and overrepresentations of Black residents. In other words, historically “greenlined” neighborhoods with contemporary overrepresentations of white residents – and underrepresentations of Black residents – have likely experienced the greatest baseline appraised values and property appreciation rates over time. In the context of our findings, we suspect these apparent benefits to property values translate to greater wealth accumulation across generations, increased ability to leverage home equity (e.g., for property improvements, education financing, etc.), and higher quality institutions and neighborhood amenities, all of which may help to explain why relative property values account for a larger share of the relationship between historical redlining patterns and poor mental health among neighborhoods with relative underrepresentations of Black residents.

An important consideration that we do not account for here is neighborhood change over time. It is possible that a historically “A” graded neighborhood was predominantly white in the 1930s but has since shifted, for example, to an integrated or predominantly Black community. Moye (2012) found that predominantly white neighborhoods in Philadelphia that experienced an influx of Black residents between 1990 and 2005 subsequently had lower levels of home value appreciation than comparable neighborhoods which remained predominantly white over this time period. Although we do not examine neighborhood change or racial turnover in this study, this further supports why we may see a stronger effect of historical redlining score on relative property values in neighborhoods with relative underrepresentations of Black residents. We suspect neighborhoods which were graded more favorably by HOLC, and which have remained predominantly white, have experienced greater appreciation in home values over time. Conversely, we suspect historically “A” graded neighborhoods which might have been predominantly white in the 1930s but subsequently saw an influx of Black residents have seen lower rates of property value appreciation. Further research is needed to better understand how neighborhood demographic shifts over time relate to property (de)valuation across historical HOLC risk grades.

In a prior study, we found the association between historical redlining score and neighborhood prevalence of poor mental health was conditional on contemporary neighborhood racial/ethnic composition (see Chapter 2). Specifically, the study found the magnitude of the relationship was greater in neighborhoods with a majority of non-Hispanic Black residents relative to neighborhoods with a majority of non-Hispanic white residents. This prior study utilized an absolute measure of neighborhood racial composition, while the present study utilizes a relative measure intended to better capture *perceived* racial composition. We find here that the total effect of historical redlining score on neighborhood prevalence of poor mental health is reduced as the relative size of the Black population increases. Importantly, neighborhoods with relative overrepresentations of Black residents could fall into any of the neighborhood racial/ethnic typologies examined in Chapter 2, making it difficult to tease apart these seemingly divergent findings. We suspect there is a complex interplay between absolute and relative racial composition, where neighborhood dynamics and conditions may be dually dependent. For example, Bécares et al. (2014) found that ethnic density among African Americans was protective against depressive symptoms – but only to a certain threshold. At concentrations above 85 percent, ethnic density was associated with poorer mental health outcomes among African Americans (Bécares et al., 2014). On one hand, neighborhoods with concentrations of Black residents may benefit from stronger social capital and cohesion, greater presence of culturally tailored institutions, and reduced exposures to interpersonal racism. On the other hand, neighborhoods with relative overrepresentation of Black residents may also experience chronic disinvestment, social and political isolation, and over-policing, factors which negatively impact mental health. Importantly, the concentration of Black residents itself does not lead to poor health – rather, broader social, economic, and political contexts shape neighborhood conditions in ways that support and/or harm health. Whether a neighborhood experiences relative benefit or harm as it relates to racial composition depends on local context. Further studies are needed to better understand whether and how people of different racial/ethnic backgrounds are differentially affected by historical structural racism in housing, and how neighborhood racial/ethnic composition, including threshold effects, may influence contemporary housing market dynamics and associations with individual and community mental health outcomes.

Finally, we found the interaction between relative proportion of Black residents and historical redlining score was not statistically significant for neighborhood homeownership rate or loan denial rate for home purchase. Importantly, however, the relative proportion of Black residents was itself a significant predictor of all three mediators of interest, where neighborhoods with overrepresentations of Black residents were associated with lower homeownership rates, lower relative property values, and higher loan denial rates across all levels of historical redlining. This finding aligns with well-established housing market inequities affecting Black Americans.

Although we found the relationship between historical redlining score and neighborhood homeownership rate was not conditional on the relative proportion of Black residents, we suspect there may be racial stratification in the relationship between homeownership and poor mental health. Studies consistently find homeownership offers differential benefit across racial and ethnic groups, where Black Americans reap less benefit for health than their non-Hispanic white counterparts (Finnigan, 2014; Ortiz & Zimmerman, 2013). This differential in benefits of homeownership may relate to differences in property values by race and neighborhood racial composition (Mehdipanah et al., 2017). Ultimately the ability of homeowners to build wealth and leverage home equity depends on home value and appreciation over time, both of which show stark discrepancies across racial/ethnic groups (Krivo & Kaufman, 2004; Markley et al., 2020). As such, racialized property appraisal processes and lending practices are likely inhibiting wealth accumulation – and related non-financial benefits of homeownership – among Black families (Howell & Korver-Glenn, 2021). Building from our first-stage conditional process analysis, future research should draw on individual-level data to pursue second-stage as well as combined first- and second-stage conditional process analyses of the relationship between historical redlining patterns and contemporary mental health outcomes. For example, a future study might examine race as a moderator of the relationship between homeownership and poor mental health, as well as home value as a potential moderator of the moderating effect of race, in other words, a moderated moderated mediation analysis (Hayes, 2018).

Limitations

Our findings should be interpreted in the context of several limitations. First, our use of neighborhood-level data introduces vulnerability to ecological fallacy and unmeasured confounding, for example, by socioeconomic factors that we have not accounted for. As such, our results are not intended to be interpreted as causal despite our use of terms which imply causality (e.g., "mediate" and "effect"). We chose not to include socioeconomic conditions as covariates in our analyses due to potential collinearity issues with our housing features of interest. We based our selection of possible mediators on our conceptual model, which we derived from the documented purpose and use of the HOLC maps as well as evidence from prior literature. However, historical redlining practices and related segregationist policies likely contributed to socioeconomic conditions; thus, the inclusion of socioeconomic conditions may have obscured a true mediating role of housing market features. Ultimately it is difficult to tease apart the effects of neighborhood socioeconomic and housing conditions when they are inextricably linked and codependent.

Next, by restricting our analytic sample to observations with complete data, we eliminated 807 census tracts from a possible 12,864 which had associated redlining scores. Over half of the missingness (n=464) was due to restrictions we imposed in calculating loan denial rates for home purchase. In an attempt to create stable estimates, we required that a tract have a minimum of five applications that had either been originated or denied between 2013-2017. This criterion might have eliminated neighborhoods which were sparsely populated – and/or excluded neighborhoods with low lending occurrence due to other barriers. Of particular concern, we found an unequal distribution of eliminated tracts across historical risk intervals, where eight percent of tracts within interval 4 were removed, compared to less than one percent of tracts within interval 1. It is possible the removal of these tracts could have biased our results toward the null, given the large majority were historically redlined neighborhoods likely to be characterized by higher degrees of discrimination in lending and property valuation. The remaining 343 observations were removed due to missing data in our original data sources.

Finally, our results presented here utilized a structural equation modeling (SEM) approach and accounted for clustering at the CBSA level; however, this analysis did not account for the spatial relationships between neighborhoods. In our sensitivity analyses, we adapted the Baron and Kenny mediation approach using spatial regression models, then manually calculated the indirect effects of historical redlining score through the three pathways of interest, conditional on the relative proportion of Black residents. Our findings were broadly similar between SEM and spatial modeling approaches. However, in our sensitivity analyses we found the interaction between historical redlining score and relative proportion of Black residents was statistically significant for all mediating pathways. The conditional indirect effects were similar in magnitude and direction between our SEM and spatial modeling approaches; however, our robust standard errors reported here were more conservative. Despite these differences, our use of multiple analytic approaches strengthens our findings that (1) features of contemporary housing markets may mediate the association between historical redlining and neighborhood prevalence of poor mental health; and (2) the indirect effect of historical redlining score via relative median property value is conditional on the relative size of the Black population. However, it is unclear from our results whether the indirect effects of redlining via homeownership rates and loan denial rates are conditional on relative Black population. This issue should be examined further in future studies.

Conclusion

In summary, we found the association between historical redlining patterns and neighborhood prevalence of poor mental health can largely be explained by contemporary features of local housing markets, including neighborhood homeownership rates, relative property values, and loan denial rates for home purchase. We also found the effect of historical redlining on poor mental health prevalence is conditional on the tract-to-CBSA relative proportion of Black residents, in part because of differential effects of redlining on property values. Our findings suggest redlining practices and related forms of spatial racism may have contributed to the concentration of wealth in historically “A” graded neighborhoods – particularly those with underrepresentations of Black residents – in ways that may provide mental health benefits to the relative detriment of Black communities. Although there is much debate in the literature about the extent to which the HOLC maps were actually used to guide lending decisions and property appraisals (Fishback et al., 2022), it is difficult to deny that, at the very least, the federal directive to assign grades to urban neighborhoods based on perceived risk for foreclosure – grades which were inextricably associated with neighborhood racial composition – codified a deeply flawed acceptance that race, place, and value are intrinsically linked (Imbroscio, 2021). As explained by Imbroscio (2021), "market values have no autonomous ontological existence… Instead, they are reflective of, and constituted by, prevailing social values and biases… In this case, anti-Black beliefs *themselves* lower property values, especially in residential property." Building from the recommendations of others (Howell & Korver-Glenn, 2021), our findings suggest property appraisal processes must be fundamentally transformed so that racial composition is not considered in appraised values or used as a criterion in identifying comparable neighborhoods. Policymakers must also be intentional in targeting investments to historically redlined areas – but in ways that provide benefit to existing residents and prevent displacement. A recent study found historically redlined neighborhoods received substantially more federal funding between 1990 and 2015 than areas graded more favorably; however, increased public investment was also associated with gentrification and – despite a general improvement in Black homeownership across risk grades – a reduced share of Black homeowners in historically "D" graded neighborhoods (Robertson et al., 2022). Place-based initiatives should continue to target historically disinvested communities but do so with explicit plans in place to address displacement pressures resulting from associated increases in property values. Lastly, and most importantly, racist ideologies conflating race and value must be dismantled to address the devaluation of assets in Black communities – and its consequences for individual, family, and community health and well-being.

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Appendix B

Table 3-3. SEM mediation analysis of historical redlining and poor mental health prevalence by features of contemporary housing markets

	Model 1A			Model 1B			Model 1C			Model 1D		
	Estimate	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**
Regression Slopes												
Poor mental health prevalence												
Historical redlining score (direct effect)	0.0065	0.0011	< 0.0001	0.0083	0.0014	< 0.0001	0.0101	0.0012	< 0.0001	0.0024	0.0010	0.022
Proportion population under 18	0.0770	0.0190	0.0001	0.2133	0.0101	< 0.0001	0.1253	0.0146	< 0.0001	0.0990	0.0173	< 0.0001
Proportion population over 65	-0.1259	0.0118	< 0.0001	-0.0487	0.0211	0.0211	-0.1634	0.0163	< 0.0001	-0.0696	0.0121	< 0.0001
Population density (standardized)	-0.0008	0.0010	0.4300	-0.0127	0.0023	< 0.0001	-0.0086	0.0016	< 0.0001	-0.0060	0.0015	0.0001
Relative median property value (log)	-0.0386	0.0030	< 0.0001							-0.0325	0.0027	< 0.0001
Homeownership rate				-0.0742	0.0078	< 0.0001				-0.0534	0.0053	< 0.0001
Denial rate for home purchase loan (sqrt)							0.1015	0.0133	< 0.0001	0.0304	0.0092	0.0009
Relative median property value (log)												
Historical redlining score	-0.1945	0.0318	< 0.0001							-0.1945	0.0318	< 0.0001
Proportion population under 18	-2.7287	0.3405	< 0.0001							-2.7287	0.3405	< 0.0001
Proportion population over 65	0.3587	0.3008	0.233							0.3587	0.3008	0.233
Population density (standardized)	0.1717	0.0158	< 0.0001							0.1717	0.0158	< 0.0001
Homeownership rate												
Historical redlining score				-0.0773	0.0049	< 0.0001				-0.0773	0.0049	< 0.0001
Proportion population under 18				0.4175	0.0593	< 0.0001				0.4175	0.0593	< 0.0001
Proportion population over 65				1.2273	0.0956	< 0.0001				1.2273	0.0956	< 0.0001
Population density (standardized)				-0.0723	0.0059	< 0.0001				-0.0723	0.0059	< 0.0001
Denial rate for home purchase loan (sqrt)												
Historical redlining score							0.0387	0.0050	< 0.0001	0.0387	0.0050	< 0.0001
Proportion population under 18							0.5618	0.0655	< 0.0001	0.5618	0.0655	< 0.0001
Proportion population over 65							0.2325	0.0633	0.0002	0.2325	0.0633	0.0002
Population density (standardized)							0.0121	0.0036	0.0007	0.0121	0.0036	0.0007
Intercepts												
Poor mental health prevalence	0.1223	0.0064	< 0.0001	0.1180	0.0055	< 0.0001	0.0711	0.0040	< 0.0001	0.1358	0.0065	< 0.0001
Relative median property value (log)	0.9602	0.1463	< 0.0001							0.9602	0.1463	< 0.0001
Homeownership rate				0.4420	0.0325	< 0.0001				0.4420	0.0325	< 0.0001
Denial rate for home purchase loan (sqrt)							0.1390	0.0287	< 0.0001	0.1390	0.0287	< 0.0001

Residual Variances												
Poor mental health prevalence	0.0006	0.0000	< 0.0001	0.0008	0.0001	< 0.0001	0.0008	0.0000	< 0.0001	0.0005	0.0000	< 0.0001
Relative median property value (log)	0.2576	0.0176	< 0.0001							0.2576	0.0176	< 0.0001
Homeownership rate				0.0305	0.0011	< 0.0001				0.0305	0.0011	< 0.0001
Denial rate for home purchase loan (sqrt)							0.0152	0.0010	< 0.0001	0.0152	0.0010	< 0.0001
Residual Covariances												
Relative median property value ~~ homeownership										0.0151	0.0027	< 0.0001
Relative median property value ~~ denial rate (sqrt)										-0.0256	0.0040	< 0.0001
Homeownership ~~ denial rate (sqrt)										-0.0047	0.0008	< 0.0001
Defined Parameters												
Indirect effects												
Relative median value (log)	0.0075	0.0016	< 0.0001							0.0063	0.0013	< 0.0001
Homeownership rate				0.0057	0.0008	< 0.0001				0.0041	0.0006	< 0.0001
Denial rate for home purchase loan (sqrt)							0.0039	0.0009	< 0.0001	0.0012	0.0004	0.002
Total indirect effect	0.0075	0.0016	< 0.0001	0.0057	0.0008	< 0.0001	0.0039	0.0009	< 0.0001	0.0116	0.0019	< 0.0001
Total effect	0.0140	0.0011	< 0.0001	0.0140	0.0014	< 0.0001	0.0140	0.0012	< 0.0001	0.0140	0.0016	< 0.0001
Proportion mediated	0.5365	0.0428	< 0.0001	0.4094	0.0411	< 0.0001	0.2806	0.0250	< 0.0001	0.8299	0.0748	< 0.0001
Observations	12047			12047			12047			12047		
AIC	-37459			-59420			-67616			-66787		

Table 3-4. SEM mediation analysis of historical redlining and poor mental health prevalence by features of contemporary housing markets, conditional on relative proportion of Black residents

	Model 2A			Model 2B			Model 2C			Model 2D		
	Estimate	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**	**Estimate**	**Std. Err.**	**p**
Regression Slopes												
Poor mental health prevalence												
Historical redlining score (direct effect)	0.0065	0.0011	< 0.0001	0.0083	0.0014	< 0.0001	0.0101	0.0012	< 0.0001	0.0024	0.0010	0.0220
Proportion population under 18	0.0770	0.0190	0.0001	0.2133	0.0101	< 0.0001	0.1253	0.0146	< 0.0001	0.0990	0.0173	< 0.0001
Proportion population over 65	-0.1259	0.0118	< 0.0001	-0.0487	0.0211	0.0211	-0.1634	0.0163	< 0.0001	-0.0696	0.0121	< 0.0001
Population density (standardized)	-0.0008	0.0010	0.4300	-0.0127	0.0023	< 0.0001	-0.0086	0.0016	< 0.0001	-0.0060	0.0015	0.0001
Relative median property value (log)	-0.0386	0.0030	< 0.0001							-0.0325	0.0027	< 0.0001
Homeownership rate				-0.0742	0.0078	< 0.0001				-0.0534	0.0053	< 0.0001
Denial rate for home purchase loan (sqrt)							0.1015	0.0133	< 0.0001	0.0304	0.0092	0.0009
Relative median property value (log)												
Historical redlining score	-0.2509	0.0417	< 0.0001							-0.2509	0.0417	< 0.0001
Relative proportion Black residents	-0.2635	0.0421	< 0.0001							-0.2635	0.0421	< 0.0001
Redlining score:Relative proportion Black residents	0.0579	0.0125	< 0.0001							0.0579	0.0125	< 0.0001
Proportion population under 18	-2.2435	0.3038	< 0.0001							-2.2435	0.3038	< 0.0001
Proportion population over 65	0.2987	0.2575	0.2460							0.2987	0.2575	0.2460
Population density (standardized)	0.1592	0.0163	< 0.0001							0.1592	0.0163	< 0.0001
Homeownership rate												
Historical redlining score				-0.0671	0.0053	< 0.0001				-0.0671	0.0053	< 0.0001
Relative proportion Black residents				-0.0216	0.0069	0.0017				-0.0216	0.0069	0.0017
Redlining score:Relative proportion Black residents				-0.0001	0.0021	0.9487				-0.0001	0.0021	0.9487
Proportion population under 18				0.5619	0.0729	< 0.0001				0.5619	0.0729	< 0.0001
Proportion population over 65				1.2535	0.0756	< 0.0001				1.2535	0.0756	< 0.0001
Population density (standardized)				-0.0771	0.0071	< 0.0001				-0.0771	0.0071	< 0.0001
Denial rate for home purchase loan (sqrt)												
Historical redlining score							0.0375	0.0074	< 0.0001	0.0375	0.0074	< 0.0001
Relative proportion Black residents							0.0341	0.0096	0.0004	0.0341	0.0096	0.0004
Redlining score:Relative proportion Black residents							-0.0047	0.0029	0.1113	-0.0047	0.0029	0.1113
Proportion population under 18							0.4390	0.0539	< 0.0001	0.4390	0.0539	< 0.0001
Proportion population over 65							0.2225	0.0474	< 0.0001	0.2225	0.0474	< 0.0001
Population density (standardized)							0.0159	0.0031	< 0.0001	0.0159	0.0031	< 0.0001
Intercepts												
Poor mental health prevalence	0.1223	0.0064	< 0.0001	0.1180	0.0055	< 0.0001	0.0711	0.0040	< 0.0001	0.1358	0.0065	< 0.0001
Relative median property value (log)	1.1841	0.1597	< 0.0001							1.1841	0.1597	< 0.0001

Homeownership rate				0.4177	0.0315	< 0.0001				0.4177	0.0315	< 0.0001
Denial rate for home purchase loan (sqrt)							0.1345	0.0307	< 0.0001	0.1345	0.0307	< 0.0001
Relative proportion Black residents	1.8223	0.0906	< 0.0001	1.8223	0.0906	< 0.0001	1.8223	0.0906	< 0.0001	1.8223	0.0906	< 0.0001
Residual Variances												
Poor mental health prevalence	0.0006	0.0000	< 0.0001	0.0008	0.0001	< 0.0001	0.0008	0.0000	< 0.0001	0.0005	0.0000	< 0.0001
Relative median property value (log)	0.2198	0.0136	< 0.0001							0.2198	0.0136	< 0.0001
Homeownership rate				0.0287	0.0016	< 0.0001				0.0287	0.0016	< 0.0001
Denial rate for home purchase loan (sqrt)							0.0137	0.0008	< 0.0001	0.0137	0.0008	< 0.0001
Relative proportion Black residents	4.1522	0.2548	< 0.0001	4.1522	0.2548	< 0.0001	4.1522	0.2548	< 0.0001	4.1522	0.2548	< 0.0001
Defined Parameters												
Conditional indirect effects												
Relative median value (log) [rel. Black M-0.5*SD]	0.0079	0.0017	< 0.0001							0.0066	0.0013	< 0.0001
Relative median value (log) [rel. Black M+0.5*SD]	0.0033	0.0013	0.0078							0.0028	0.0011	0.0078
Homeownership rate [rel. Black M-SD]				0.0050	0.0006	< 0.0001				0.0036	0.0004	< 0.0001
Homeownership rate [rel. Black M+SD]				0.0050	0.0006	< 0.0001				0.0036	0.0004	< 0.0001
Denial rate for home purchase loan (sqrt) [rel. Black M-0.5*SD]							0.0034	0.0008	< 0.0001	0.0010	0.0003	0.0022
Denial rate for home purchase loan (sqrt) [rel. Black M+0.5*SD]							0.0025	0.0005	< 0.0001	0.0007	0.0002	0.0018
Total indirect effect [rel. Black M-0.5*SD]	0.0079	0.0017	< 0.0001	0.0050	0.0006	< 0.0001	0.0034	0.0008	< 0.0001	0.0113	0.0016	< 0.0001
Total indirect effect [rel. Black M+0.5*SD]	0.0033	0.0013	0.0078	0.0050	0.0006	< 0.0001	0.0025	0.0005	< 0.0001	0.0071	0.0013	< 0.0001
Total effect [rel. Black M-0.5*SD]	0.0144	0.0017	< 0.0001	0.0132	0.0015	< 0.0001	0.0135	0.0016	< 0.0001	0.0136	0.0016	< 0.0001
Total effect [rel. Black M+0.5*SD]	0.0098	0.0013	< 0.0001	0.0133	0.0016	< 0.0001	0.0125	0.0014	< 0.0001	0.0095	0.0013	< 0.0001
Proportion mediated [rel. Black M-0.5*SD]	0.5489	0.0763	< 0.0001	0.3761	0.0490	< 0.0001	0.2538	0.0461	< 0.0001	0.8254	0.0731	< 0.0001
Proportion mediated [rel. Black M+0.5*SD]	0.3400	0.1065	0.0014	0.3771	0.0446	< 0.0001	0.1959	0.0323	< 0.0001	0.7502	0.1005	< 0.0001
Index of moderated mediation												
Relative median property value (log)	-0.0022	0.0005	< 0.0001							-0.0019	0.0004	< 0.0001
Homeownership rate				0.0000	0.0002	0.9486				0.0000	0.0001	0.9486
Denial rate for home purchase loan (sqrt)							-0.0005	0.0003	0.1446	-0.0001	0.0001	0.1480
Observations	12,047			12,047			12,047			12,047		
AIC	11977			-8809			-17560			-16482		

Chapter 4 | SITUATING ASSOCIATIONS BETWEEN HISTORICAL REDLINING PATTERNS AND NEIGHBORHOOD HEALTH INEQUITIES WITHIN BROADER CONTEXTS OF ANTI-BLACK STRUCTURAL RACISM

Abstract

Historical redlining practices carried out by the Home Owners Loan Corporation beginning in the 1930s have been highlighted as an important contributor to patterns of concentrated disadvantage and concentrated advantage in cities across the United States. To date, most studies of historical redlining and contemporary health outcomes focus on a single city or metropolitan area; few explicitly examine differences across geographic contexts or what factors might explain variation. In this study, we hypothesized core-based statistical areas (CBSAs) with higher degrees of contemporary institutionalized anti-Black racism in local housing markets would demonstrate stronger relationships between historical redlining patterns and neighborhood diabetes prevalence. First, we used confirmatory factor analysis to develop a novel composite index of institutionalized anti-Black racism in housing markets (IRH), which incorporated measures of racial residential segregation, discrimination in mortgage lending practices, and relative property values of neighborhoods with over- and under-representations of Black residents. We found CBSAs with larger total populations and relatively large Black populations, on average, have higher degrees of IRH. In multilevel regression analyses, we found the IRH index acts as a modifier of the relationship between historical redlining and neighborhood diabetes prevalence. The IRH index explained only 8.6 percent of variation across CBSAs but remained positive and statistically significant in sensitivity analyses using spatial regression approaches. Our findings suggest the relationship between historical redlining patterns and contemporary area-based health outcomes varies across geographic contexts, and this variation is partially due to differences in patterns of contemporary institutionalized racism in housing markets. Additional research is needed to further understand factors and processes by which impacts of historical structural racism are maintained or diminished.

Introduction

Formal recognition of structural racism as a public health crisis has stimulated increased attention to the historical contexts and processes that have established our current landscape of entrenched inequalities. Historical redlining practices carried out by the Home Owners Loan Corporation (HOLC) beginning in the 1930s have been highlighted as an important contributor to patterns of concentrated disadvantage and concentrated advantage in cities across the United States. Redlining essentially entailed the assignment of one of four letter grades (A-D) to urban neighborhoods in cities with at least 40,000 residents based on perceived risk for foreclosure, where "A" was "most desirable" and generally corresponded to more affluent white neighborhoods, whereas "D" was deemed "hazardous" and generally corresponded to neighborhoods with concentrations of Black and/or immigrant residents. Digitization of HOLC's "residential security maps" by the University of Richmond's Mapping Inequality Project has enabled researchers to link these historical "risk grades" to a range of contemporary conditions and outcomes. For example, researchers have found associations between historical redlining patterns and contemporary discrimination in mortgage lending, inequities in economic opportunities and conditions that support health, and disparities across a wide range of health outcomes (Krieger et al., 2020; Lee et al., 2021; Lynch et al., 2021a; Mehdipanah et al., 2023; Mujahid et al., 2021; Nardone, Casey, et al., 2020; Nardone, Chiang, et al., 2020). Relationships between historical redlining and health outcomes have been established in prior work; however, structural racism and its impacts on neighborhood health do not occur in a vacuum but are rather shaped by contemporary forces working at broader city and regional levels. These forces may maintain the legacy of historical redlining practices and their associations with contemporary health outcomes.

Historically, redlining practices and related forms of spatial racism (e.g., restrictive covenants) acted to exclude communities of color from housing markets. Although overt racial discrimination in housing has been outlawed since the passing of the Fair Housing Act in 1968, people of color and neighborhoods with concentrations of Black and/or Hispanic residents continue to experience inequities in mortgage lending opportunities and homeownership. In the words of sociologist Karl Taeuber, "Old habits never die, they just fade from view. So it is with housing discrimination. Old patterns never die, though sometimes they fade from view" (Taeuber, 1988). In general, there are two prevailing arguments in the population health literature about how and why historical redlining practices may have lasting impacts on downstream neighborhood conditions and outcomes. First, a "spatial marking" perspective argues the HOLC grades had direct influences on neighborhood reputations, lending patterns, economic opportunities, and property values (Aaronson et al., 2021; Faber, 2021). Conversely, a "structural" perspective argues the creation of the HOLC maps codified a system of beliefs that conflated neighborhood racial composition and value – but that the maps and risk grades themselves had little influence on lending decisions or investment patterns (Graetz & Esposito, 2021; Hillier, 2003). The reality is likely a combination of the two perspectives.

Prior studies have shown relationships between historical redlining patterns and contemporary neighborhood health outcomes differ across geographic contexts (Nardone, Chiang, et al., 2020). Drawing on the "spatial marking" and "structural" perspectives together, we considered whether this variation in the redlining-health relationship might be dependent on how contemporary housing markets are operating today to include or exclude communities of color. In other words, we suspected the relationship between historical redlining patterns and contemporary health at the neighborhood level would persist regardless of broader metropolitan characteristics – consistent with a spatial marking perspective. However, we also suspected this relationship would be stronger in metropolitan areas with a higher degree of contemporary institutionalized racism within the housing market – broadly consistent with a structural perspective. Few studies have examined the role of broader contextual features in shaping relationships between historical redlining and health outcomes, partly because most studies focus on a single city or metropolitan area. Contextualizing neighborhoods with histories of redlining within contemporary housing markets may suggest conditions or processes which maintain the legacy of historical redlining practices.

In this study, we examined whether and how associations between historical redlining patterns and neighborhood diabetes prevalence vary across metropolitan areas, and we explored whether conditions within contemporary housing markets might explain this variation. Historically, redlining affected many different racial, ethnic, and cultural groups (Markley, 2022). We chose to focus our analysis on anti-Black racism, however, as the Black population was the largest population by far to be targeted by historical redlining practices and other forms of spatial racism during the 20th century and today experiences the greatest inequities in lending opportunities and homeownership (Namin et al., 2022; *Quarterly Residential Vacancies and Homeownership, Second Quarter 2021*, 2021). As described in Camara Jones' levels of racism framework, institutionalized racism "often manifests as inherited disadvantage" (Jones, 2000). Because Black families had the most limited housing choices and homeownership opportunities in the early and mid-20th century, future generations ultimately had less inherited wealth to build from relative to other groups. As such, we created a novel composite measure of institutionalized anti-Black racism in housing markets as a possible metropolitan/micropolitan area-level modifier of the relationship between historical redlining and neighborhood diabetes prevalence. We anticipated associations between historical redlining patterns and contemporary outcomes would be dependent on how housing markets are operating today to include or exclude Black communities. This study contributes to two related bodies of literature. First, our construction of a novel index of institutionalized anti-Black racism in housing markets aligns with calls to explicitly name and measure structural racism in health inequities research (Groos et al., 2018; Hardeman et al., 2018). Second, our examination of historical redlining and neighborhood health within contemporary housing markets contributes to our understanding of the relevance of local context in maintaining the harmful legacy of historical redlining practices and other forms of spatial racism.

Structural racism measurement

In response to calls for greater attention to the explicit naming and measurement of structural and institutional racism, researchers have begun to develop novel measures for use in the study of racial and ethnic health inequities (Hardeman et al., 2018). In a systematic review of methods used to quantify structural racism, Groos et al. (2018) identified several approaches public health researchers have taken, for example, by quantifying perceptions of structural racism within social institutions or by examining disparate socioeconomic status, law enforcement involvement, or political participation across groups as indicators of institutionalized racism (Groos et al., 2018). Some scholars, though relatively few, have developed multidimensional measures of structural racism at different geographic levels drawing on multiple domains and sources of data (Alson et al., 2021; Chambers et al., 2018; Chantarat et al., 2021; Dougherty et al., 2020; Lukachko et al., 2014). For example, Lukachko et al. (2014) developed four domains of structural racism at the state level, including political participation, employment and job status, educational attainment, and judicial treatment, and found Black residents and white residents of states with high structural racism had higher and lower risks of myocardial infarction, respectively (Lukachko et al., 2014). Dougherty et al. (2020) developed a county-level measure of structural racism which incorporated seven indicators related to housing, education, poverty, incarceration, and healthcare and found a significant association between structural racism and body mass index across U.S. counties (Dougherty et al., 2020). Chambers et al. (2018) examined both traditional measures (e.g., Black-white dissimilarity index) and novel measures (e.g., Black-to-white ratio in elected office) of structural racism in California and found associations with birth outcomes among Black and white women (Chambers et al., 2018). Finally, Chantarat et al. (2021) developed a multidimensional measure of structural racism at the public use microdata area-level, applying latent class analysis to measures of residential segregation and inequities in homeownership, educational attainment, employment, and income (Chantarat et al., 2021).

Others have developed measures of structural or institutional racism related to housing, for example, by utilizing various indicators of racial residential segregation and in some cases measures of mortgage lending discrimination (Beyer et al., 2019; Gee, 2002; Mendez et al., 2011, 2012, 2014; Zhou et al., 2017). However, most of these studies have tended to rely on singular indicators and examine only one or two metropolitan areas in their analyses. None have developed measures which incorporate multiple dimensions of racial exclusion from housing markets, or which can be compared across geographic contexts. Multidimensionality is important because structural racism is complex and manifests in many ways. Housing-related measures used as proxies for structural racism in prior studies, such as residential segregation or mortgage lending discrimination, are – alone – ultimately narrow in their conceptualization. Despite the use of residential segregation as a proxy for structural racism in several prior studies, for example, recent studies argue segregation is a consequence of structural racism but is insufficient as a proxy (Riley, 2018; Sewell, 2016). In recognition, scholars have called for innovation in the measurement and operationalization of structural racism in health inequities research (Groos et al., 2018). The present study broadens the scope of structural racism measurement by developing a novel composite index of institutionalized anti-Black racism within local housing markets which incorporates multiple dimensions and which can be compared across U.S. metropolitan/micropolitan areas. We chose to focus our measure on housing market dynamics, as we conceptualize housing and the processes by which residential stratification occurs as being upstream to subsequent exposures and experiences within residential contexts. Further, features of the housing market, including inequitable homeownership opportunities and property values, may be acting as barriers to wealth accumulation and social mobility, which have important implications for health across generations.

Institutionalized racism in housing markets

In this study, institutionalized racism is conceptualized as the common cause of inequities across multiple processes within housing markets. Although fair housing legislation prohibits racial discrimination in the sale and rental of housing, Black Americans continue to face inequities in homeownership, mortgage lending, and property values. In 2020, roughly 45 percent of African Americans owned their homes compared to 75 percent of white Americans (*Quarterly Residential Vacancies and Homeownership, Second Quarter 2021*, 2021). These disparities in homeownership rates stem from historical structures that excluded Black families from housing markets, and their persistence offers evidence of continued institutionalized racism within housing systems. In support, only about half of the gap in Black-white homeownership can be explained by differences in income, educational attainment, marital status, credit scores, and age distribution (Choi et al., 2019). Nationwide, Black applicants in 2020 were three times as likely to be denied a loan for home purchase and twice as likely to be denied for refinance relative to non-Hispanic white applicants (Liu et al., 2021). Black applicants are also disproportionately targeted for high-cost loans and other predatory lending practices (Barwick, 2010). Further, homes in majority Black neighborhoods are undervalued by over 20 percent relative to homes in neighborhoods with fewer than one percent Black residents, even after adjusting for structural features and neighborhood amenities (Perry et al., 2018). Neighborhood racial composition is a bigger predictor of property values today than it was in 1980 (Howell & Korver-Glenn, 2021). The devaluation of Black property has impeded the accumulation of wealth among Black households across generations and has important implications for inequities in other systems (e.g., school funding). Relatedly, the racial wealth gap has seen little improvement since 1980; on average, Black families today have one-sixth of the wealth held by their white counterparts (Derenoncourt et al., n.d.). Further, many major cities have seen only minor declines, if any, in Black-white residential segregation over the last 50 years (Rugh & Massey, 2014). Despite a general movement away from overt segregationist ideology and declines in segregation among cities with relatively small Black populations, many major cities with large Black populations remain highly segregated, and more than 20 metropolitan areas in the U.S. are considered hypersegregated (Massey, 2016; Massey & Tannen, 2015). Racial residential segregation acts as a driver of racialized inequities across many other systems (e.g., education, law enforcement, health care) because it concentrates disadvantage in segregated non-white neighborhoods (Massey & Denton, 1993) and has been used as a proxy for structural racism in several previous studies (Groos et al., 2018).

Historical redlining and health

Researchers have found associations between historical residential redlining in the 1930s and present-day health inequities, showing neighborhoods which were graded by HOLC as high risk for lending and investment experience significantly worse health today across a range of outcomes (Krieger et al., 2020; Lee et al., 2021; Lynch et al., 2021; Mujahid et al., 2021; Nardone, Casey, et al., 2020; Nardone, Chiang, et al., 2020). Studies suggest these lasting consequences of historical redlining and other forms of spatial racism may occur through pathways of systematic neighborhood disinvestment and siting of hazardous environmental exposures (Aaronson et al., 2021; Faber, 2021), conflation of neighborhood racial composition with property values (Graetz & Esposito, 2021), institutionalization of mortgage lending discrimination and relatedly, inequitable opportunities for homeownership and accumulation of capital (Woods, 2012), and finally, established patterns of racial residential segregation as well as, consequently, the concentration of social and economic disadvantage (Rothstein, 2017). Although the use of the HOLC "residential security maps" to inform lending decisions was deemed unconstitutional in the late 1940s, redlining practices and their predecessors – including racial zoning, segregation in public housing, and racially restrictive covenants – ultimately normalized exclusion from and discrimination within housing markets on the basis of race.

Today, although many studies have connected historical redlining patterns to contemporary outcomes at the neighborhood level, researchers have yet to thoroughly explore the broader contexts within which these neighborhoods are situated. Most previous studies have focused on the neighborhood level alone, and many have examined only one or two metropolitan areas in their analyses. As such, there has been little exploration of how the relationship between historical redlining and health outcomes may vary across metropolitan/micropolitan areas or how differences might relate to contemporary housing market dynamics. To our knowledge, only two studies to-date have examined intersections of historical and contemporary forms of institutionalized racism in housing in their association with neighborhood health outcomes (Lynch et al., 2021; McClure et al., 2019). These studies, however, were limited to individual cities and examined features of contemporary housing markets at the neighborhood level alone. Fair housing audit studies conducted over the last 50 years have found the frequency and patterns of housing market discrimination differ across metropolitan areas (G. Galster, 1990; Quillian et al., 2020). This cross-metropolitan variation is not well-understood but has been linked to Black-white housing-price segregation, interracial income gaps, and larger shares of noncollege-educated white residents (G. C. Galster & Keeney, 1988).

To our knowledge, the present study is the first to situate relationships between historical redlining patterns and neighborhood health outcomes within their broader context of contemporary housing markets, features of which may be maintaining the legacy of historical redlining practices. We anticipated there may be a stronger relationship between historical redlining patterns and adverse health outcomes in areas with a greater degree of contemporary institutionalized anti-Black racism. This relationship may suggest neighborhoods are more impacted today by histories of redlining and disinvestment when the broader context in which they are situated continues to exclude communities of color from housing markets. We focused our analysis on neighborhood prevalence of diagnosed diabetes as prior work has found the association between historical redlining and neighborhood diabetes prevalence differs significantly across cities (Nardone, Chiang, et al., 2020). Importantly, diabetes and related risk factors (e.g., obesity, physical activity, fruit and vegetable intake) have been linked to neighborhood conditions, including social and physical environments (Arcaya et al., 2016) that are, in turn, influenced by place-based investments and land use patterns.

Data and methods

We carried out this study in two distinct stages. First, we used confirmatory factor analysis (CFA) to construct a novel composite index of institutionalized anti-Black racism at the core-based statistical area (CBSA) level. We chose to construct the index at the CBSA level, as metropolitan/micropolitan areas are generally close approximations to housing market areas (*Housing Market Area*, 2022). We constructed the index for 408 CBSAs, after applying a set of inclusion criteria, described below. In the next stage of our analysis, we aimed to assess variation across CBSAs in the association between historical redlining patterns and contemporary neighborhood diabetes prevalence. Specifically, we were interested in whether differences in this documented relationship depended, in part, on the degree of contemporary institutionalized anti-Black racism within local housing markets. For this stage of our analysis, we used an ecological design and multilevel framework, nesting census tracts within their corresponding CBSA.

Confirmatory factor analysis

We created a novel composite index of institutionalized anti-Black racism in local housing markets at the CBSA level using confirmatory factor analysis (CFA). In alignment with our conceptualization of institutionalized racism in housing markets, we included several indicators used in prior studies, each selected to represent a different dimension of inequity among Black Americans relative to their non-Hispanic white counterparts. Specifically, we included: (1) Black-to-white odds of loan denial for home purchase; (2) Black-to-white odds of obtaining a high-cost loan, defined as having a rate spread greater than 1.5 (Lynch et al., 2021); (3) a measure of Black property devaluation, adapted from Howell & Korver-Glenn (2021) and Perry, Rothwell, & Harshbarger (2018); (4) the Black-to-white homeownership rate ratio; (5) the Black-white dissimilarity index; and finally, (6) the Black isolation index (*Appendix B. Measures of Residential Segregation*, 2021).

We chose to use CFA over other methods of dimension reduction (e.g., exploratory factor analysis, principal components analysis) because we wanted to explicitly test our theoretical model, which conceptualizes institutionalized anti-Black racism as the common cause of inequities in contemporary lending patterns, homeownership rates, and property values, as well as the maintenance of racial residential segregation. As the CFA procedure assumes multivariate normality, we utilized variable transformations to achieve normality or approximate normality. Table 4-1 below details the indicators included in our initial CFA model, including their method of construction, variable transformation used, and original data source.

Table 4-1. Indicators included in initial confirmatory factor analysis for contemporary institutionalized anti-Black racism in housing markets

Indicator	Definition/construction	Variable transformation	Original data source
Black-to-white odds of loan denial for home purchase	Odds of denial for home purchase loan among non-Hispanic Black applicants (denials divided by originations) divided by odds of denial for home purchase loan among non-Hispanic white applicants; limited to CBSAs with at least 10 non-Hispanic Black applicants and at least 10 non-Hispanic white applicants	Square-root transformation	Home Mortgage Disclosure Act database (2013-2017)
Black-to-white odds of obtaining a high-cost loan	Odds of obtaining a high-cost loan, defined as having a rate spread greater than 1.5, among non-Hispanic Black applicants (high-cost loans divided by non-high-cost loans) divided by odds of obtaining a high-cost loan among non-Hispanic white applicants; limited to CBSAs with at least 10 non-Hispanic Black applicants and at least 10 non-Hispanic white applicants	Raised to 0.75 power	Home Mortgage Disclosure Act database (2013-2017)
Black property devaluation	Average of median property values of census tracts with a disproportionate share of Black residents (relative to the CBSA) divided by the average of median property values of census tracts in which Black residents are underrepresented.	Cube root transformation	American Community Survey 5-year estimates (2013-2017)
Black-to-white homeownership rate ratio	Ratio of Black homeownership rate to non-Hispanic white homeownership rate (homeownership rate is calculated as the number of owner-occupied units divided by the total number of occupied housing units)	Raised to 1.45 power	American Community Survey 5-year estimates (2013-2017)
Black-white dissimilarity index	A measure of evenness in the distribution of non-Hispanic Black and non-Hispanic white residents across neighborhoods within a core-based statistical area (CBSA) (*Appendix B. Measures of Residential Segregation*, 2021)	None	American Community Survey 5-year estimates (2013-2017)
Black isolation index	A measure of exposure, representing the extent to which Black residents are exposed only to one another (*Appendix B. Measures of Residential Segregation*, 2021)	Box Cox transformation (lambda = 0.22)	American Community Survey 5-year estimates (2013-2017)

Our analytic sample for this stage of analysis included CBSAs which contained at least 50,000 residents, had complete data, and contained at least two percent non-Hispanic Black residents (thereby retaining the top three quartiles after applying the other inclusion criteria). We also excluded CBSAs which had extreme outliers (values below Q1-3*IQR or above Q3+3*IQR) for any of our CFA variables. These criteria yielded 408 out of 927 possible CBSAs. We carried out the CFA modeling procedure using the *lavaan* package in R. In all models we standardized all transformed variables and set the factor variance equal to one (variance standardization method). Finally, we computed the composite index by calculating factor scores using the weighted sum scores method (DiStefano et al., 2009). We conceptualize this index as representing the degree of institutionalized anti-Black racism within local housing markets; thus, we refer to this measure as the "IRH index" in subsequent analyses. For descriptive purposes, we created a categorical IRH index by dividing the 408 CBSAs into five even quintiles, where the first quintile corresponds to the bottom 20 percent of IRH values, and the fifth quintile corresponds to the top 20 percent.

The indicators included in the initial CFA warrant a few important considerations. First, the Black isolation index is dependent on the absolute size of the Black population; as such, in sensitivity analyses we created the IRH index with different combinations of these variables, including and excluding Black isolation. This issue is discussed further in our limitations section. Next, in constructing Black-to-white odds of loan denial for home purchase and Black-to-white odds of obtaining a high-cost loan, we did not account for differences in loan amount, income, or other loan or applicant characteristics. We chose not to adjust for these factors as, even if some part of the inequity between Black and white applicants could be explained by differences in income, for example, the inequity is still a reflection of structural or institutionalized racism even if inequities in multiple systems (e.g., housing, education, employment) are at play. Finally, our indicator of Black property devaluation is based on median property values stratified by the size of the Black population within a census tract relative to that of the CBSA (i.e., location quotient), where neighborhoods were categorized as having a ratio below one (meaning Black residents are underrepresented) or above one (meaning Black residents are overrepresented); it was not possible to assess property values of Black homeowners and non-Black homeowners directly. Perry, Rothwell, & Harshbarger (2018), our inspiration for this measure, compared the average of median property values of neighborhoods with 50 percent or more Black residents to that of neighborhoods with less than one percent Black residents. We chose to modify the measure in order to maintain our sample size, as the original method restricts analysis to CBSAs which contain at least one neighborhood with 50 percent or more Black residents and at least one neighborhood with less than one percent Black residents.

Multilevel analysis

In the next stage of our analysis, we aimed to examine variation in the relationship between historical redlining patterns and neighborhood diabetes prevalence across CBSAs and to assess whether this variation relates to the degree of contemporary institutionalized anti-Black racism (i.e., our composite IRH index) within the broader contexts in which neighborhoods are situated. The analytic sample for this stage of our analysis included census tracts which had at least 20 percent overlap with areas historically appraised by HOLC and were contained within a CBSA that had an associated IRH index value. In total, this sample included 12,668 census tracts across 133 CBSAs (out of a possible 12,864 tracts across 143 CBSAs).

In this stage of our analysis, the primary outcome of interest was census tract prevalence of diagnosed diabetes, obtained from the 2020 release of the Centers for Disease Control and Prevention (CDC) PLACES Project, which provides model-based small-area estimates for health outcomes, behavioral risk factors, and utilization of preventive healthcare services. The original source of these data was the Behavioral Risk Factor Surveillance System (BRFSS) for 2017-2018 (CDC, 2022). Diabetes prevalence was defined as the proportion of residents who reported they had ever been diagnosed with diabetes, excluding gestational diabetes (LLCP 2018 Codebook Report, 2019). On the neighborhood level, the primary predictor of interest was a continuous redlining score created based on the relative area of a census tract assigned each historical HOLC risk grade. We obtained these continuous "historic redlining scores" from Meier and Mitchell's Historic Redlining Scores project (2021), which utilized digitized versions of the historical HOLC "residential security maps" to create continuous and interval measures normed to the 2010 census tract boundaries. These scores are bounded between 1-4, where a score of 1 indicates a census tract was contained within an area assigned an “A” grade by HOLC, and a score of 4 indicates a census tract was contained within an area assigned a “D” grade by HOLC, or in other words, redlined. On the CBSA level, the primary predictor of interest was our novel IRH index. Tract-level covariates included the proportion of the population under age 18, proportion of the population over age 65, log-transformed population density, and the tract-to-CBSA relative proportion of Black residents (i.e., location quotient). CBSA-level covariates included log-transformed total population, log-transformed median income, proportion of Black residents, and fixed effects for U.S. Census region. We obtained tract- and CBSA-level covariates from the American Community Survey 5-year estimates for 2013-2017.

We built multilevel linear models regressing neighborhood diabetes prevalence on the tract- and CBSA-level predictors described above, nesting census tracts within CBSAs. Our primary interest in these multilevel models was the cross-level interaction between historical redlining score and the IRH index. These analyses were completed using the *lme4* package in R. Finally, we assessed the degree of spatial autocorrelation using global Moran's I (I =0.7323, $p<0.0001$) , and, in subsequent sensitivity analyses, we built spatial error regression models with queen contiguity and CBSA fixed effects to account for spatial dependence in model residuals.

Results

We present our results in two sections. First, we discuss the results of our confirmatory factor analysis and creation of our novel composite index of institutionalized anti-Black racism in local housing markets (IRH index). We also examine the distribution and characteristics of CBSAs across IRH quintiles. Second, we share the results of our multilevel analysis which examined whether the IRH index acts as a CBSA-level modifier of the relationship between historical redlining score and neighborhood diabetes prevalence.

CFA and creation of IRH index

Our initial CFA model for institutionalized racism in local housing markets included the six indicators described previously. Summary statistics for the raw variables are shown in Table 4-2. After running the initial CFA model, we retained indicators with standardized factor loadings with an absolute value greater than 0.4. Under this criterion, we eliminated the Black-to-white homeownership rate ratio and Black-white dissimilarity index. Our subsequent model, containing the remaining four variables, achieved factor loadings above 0.4 (abs), a Comparative Fit Index of 0.904 and Standardized Root Mean Square Residual of 0.090, within acceptable ranges for model fit. The results for our initial and final CFA models are shown in Table 4-3 below.

Table 4-2. Summary statistics for raw variables included in confirmatory factor analysis (n=408)

Variable	Mean	SD	Min	Max
Black-white dissimilarity index	0.4954	0.1094	0.1663	0.7977
Black isolation index	0.2663	0.1756	0.0408	0.7088
Black-to-white homeownership rate ratio	0.5416	0.1449	0.1104	0.8967
Black-to-white odds of loan denial for home purchase	2.1151	0.6609	0.5519	5.4946
Black-to-white odds of obtaining a high-cost loan	1.9945	0.6235	0.3474	4.7970
Black property devaluation	0.7471	0.1868	0.3173	1.3763

Table 4-3. Confirmatory factor analysis results, initial and final models (n=408)

Indicator	Standardized factor loading	p-value	CFI
Initial model			0.717
Black-white dissimilarity index	0.213	< 0.001	
Black isolation index	0.541	< 0.001	
Black-to-white homeownership rate ratio	0.104	0.046	
Black-to-white odds of loan denial for home purchase	0.891	< 0.001	
Black-to-white odds of obtaining a high-cost loan	0.899	< 0.001	
Black property devaluation	-0.497	< 0.001	
Final model			0.904
Black isolation index	0.534	< 0.001	
Black-to-white odds of loan denial for home purchase	0.899	< 0.001	
Black-to-white odds of obtaining a high-cost loan	0.896	< 0.001	
Black property devaluation	-0.486	< 0.001	

We used the standardized factor loadings from the final CFA model as weights in constructing our novel measure of institutionalized racism in housing markets (IRH index) at the CBSA level. The final index has a range of -6.84 to 8.50, with a mean of zero and standard deviation of 2.31. Higher IRH values correspond to higher degrees of inequity among Black residents within a CBSA. For example, the highest IRH value corresponds to the Georgetown, SC micropolitan area, where Black isolation is 0.44 and Black residents are 5.5 times as likely as their non-Hispanic white counterparts to be denied a loan for home purchase and 4.4 times as likely to obtain a high-cost loan. Owner-occupied properties in neighborhoods with overrepresentations of Black residents are also valued at only 35 percent that of properties in neighborhoods where Black residents are underrepresented (relative to the Black population of the CBSA). Conversely, the lowest IRH value corresponds to the Sierra Vista-Douglas, AZ metropolitan area, where Black isolation is 0.07, and Black residents are more than 20 percent less likely to be denied a loan for home purchase and more than 50 percent less likely to obtain a high-cost loan than their non-Hispanic white counterparts. Further, neighborhoods with overrepresentations of Black residents have, on average, 38 percent higher property values compared to neighborhoods where Black residents are underrepresented. A complete list of IRH values and untransformed indicator variables by CBSA is provided in Appendix Table 4-7. Table 4-4 below shows the Pearson's correlation coefficients for the composite IRH index and its component variables.

Table 4-4. Correlation matrix of CFA variables and composite IRH index (n=408)

	Black isolation index	Black-to-white odds of loan denial for home purchase	Black-to-white odds of obtaining a high-cost loan	Black property devaluation
Black isolation index	1.00			
Black-to-white odds of loan denial for home purchase	0.47	1.00		
Black-to-white odds of obtaining a high-cost loan	0.45	0.81	1.00	
Black property devaluation	-0.54	-0.40	-0.43	1.00
Composite IRH index	0.70	0.90	0.90	-0.66

Figure 4-1 below shows the geographic distribution of the 408 CBSAs, shaded by IRH quintile. In general, CBSAs included in our analysis are heavily concentrated in the eastern half of the United States and on the west coast. This patterning is expected given our inclusion criteria and migration history of the Black population in the U.S. Although our IRH index does not cover all areas of the country and excludes CBSAs with relatively small Black populations, the 408 CBSAs included in our analysis are home to roughly 85 percent of non-Hispanic Black Americans.

Table 4-5 below shows average characteristics of CBSAs in each of the five IRH quintiles. Expectedly, the IRH component indicators show a graded relationship with IRH quintile. CBSAs within higher IRH quintiles, on average, contain relatively large Black populations compared to CBSAs in the lower IRH quintiles. As Black isolation is dependent on the absolute size of the Black population, we expectedly see higher degrees of isolation in areas with larger Black populations. In these areas, we also see substantially greater inequities in lending patterns and property valuation. For example, while Black residents of CBSAs in IRH quintile 1 are approximately 30 percent more likely than their white counterparts to be denied a loan for home purchase and approximately 20 percent more likely to obtain a high-cost loan, Black residents of CBSAs in quintile 5 are nearly three times as likely to be denied or to obtain a high-cost loan. Among CBSAs in quintile 1, owner-occupied housing units in neighborhoods where Black residents are overrepresented compared to the CBSA overall are, on average, valued at 92 percent that of units in neighborhoods where Black residents are underrepresented. Conversely, among CBSAs in quintile 5, owner-occupied housing units in neighborhoods with overrepresentations of Black residents are, on average, valued at only 59 percent that of units in neighborhoods where Black residents are underrepresented.

A few notable trends emerged in examining average demographic characteristics of CBSAs across IRH quintiles. First, mean total population increases with IRH quintile, suggesting larger metropolitan areas may have more deeply entrenched racial inequities in housing market processes. As discussed above, the relative size of the Black population increases with IRH quintile. Conversely, the relative sizes of the non-Hispanic white and Hispanic populations decrease with IRH quintile. This pattern is likely reflective of regional differences in the distribution of Black and Hispanic residents. For example, CBSAs on the west coast and in the southwest have relatively large concentrations of Hispanic residents, and these areas also tend to have lower IRH values. Finally, we found average socioeconomic and housing conditions of CBSAs are largely consistent across IRH quintiles, although median home values and median incomes are slightly higher among CBSAs in quintile 5 relative to those in quintile 1. This pattern is logically consistent given CBSAs in quintile 5 are, on average, larger metropolitan areas and therefore likely to have higher costs of living. For comparison, Table 4-8 in the Appendix provides the same information for the sample of CBSAs included in our subsequent regression analyses (n=133), detailed below.

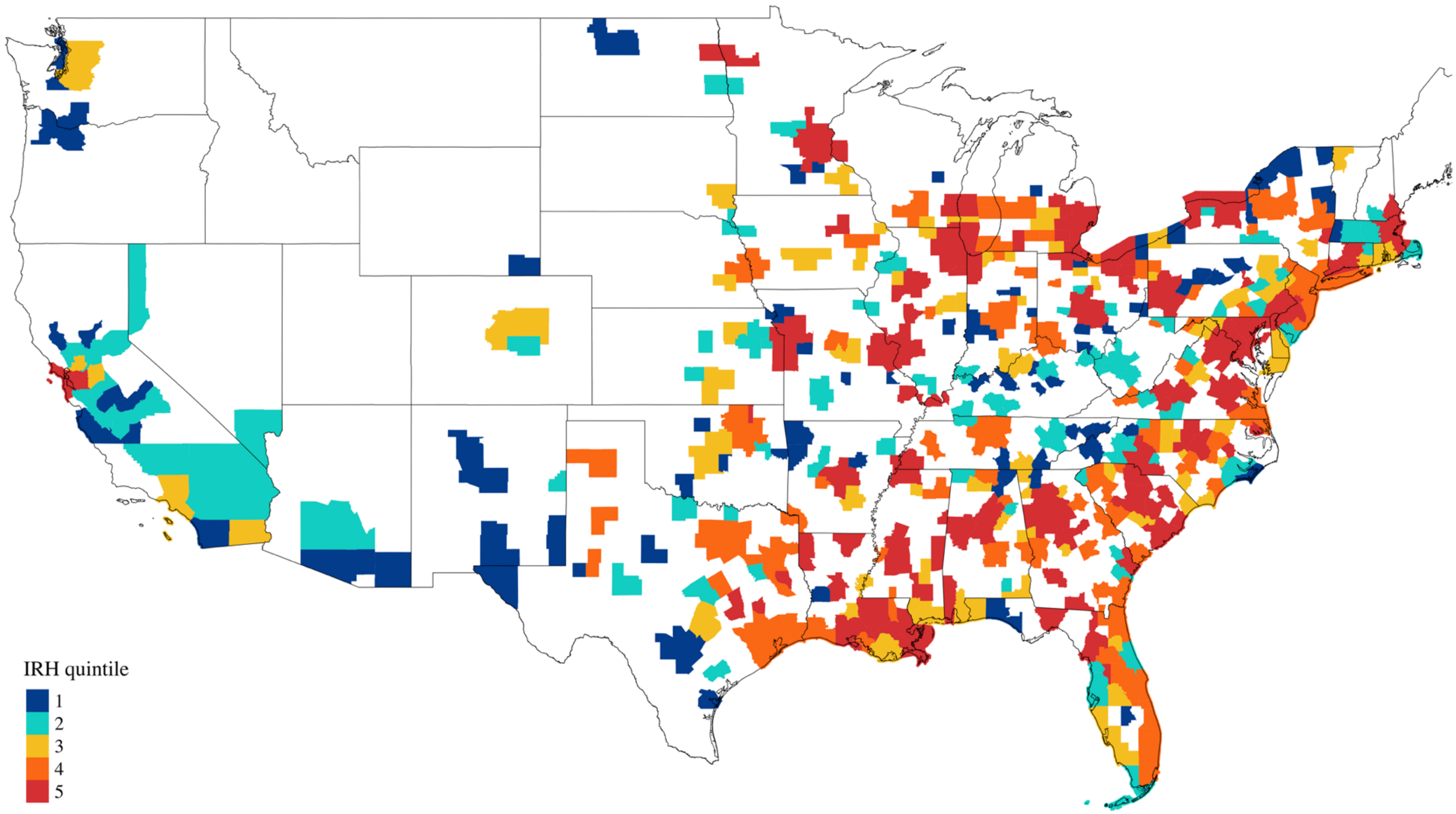

Figure 4-1. Map of IRH index by quintile (n=408)

Not shown: Anchorage, AK Metro Area (quintile 2); Fairbanks, AK Metro Area (quintile 2)

Table 4-5. Average CBSA-level characteristics by IRH quintile (n=408)

	IRH quintile									
	1 (n=82)		**2 (n=81)**		**3 (n=82)**		**4 (n=81)**		**5 (n=82)**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
IRH component indicators										
Black isolation index	0.105	0.053	0.171	0.104	0.265	0.153	0.349	0.137	0.442	0.161
Black-to-white odds of loan denial for home purchase	1.312	0.339	1.837	0.273	2.134	0.264	2.368	0.342	2.925	0.603
Black-to-white odds of obtaining a high-cost loan	1.205	0.365	1.768	0.265	2.017	0.300	2.248	0.345	2.735	0.492
Black property devaluation	0.921	0.161	0.818	0.154	0.739	0.149	0.671	0.142	0.587	0.127
Demographic characteristics										
Total population	253,019	513,986	444,486	829,765	549,891	1,535,344	874,515	2,521,708	1,097,529	1,710,687
Proportion non-Hispanic Black residents	0.045	0.028	0.086	0.076	0.143	0.129	0.179	0.119	0.221	0.132
Proportion non-Hispanic white residents	0.779	0.200	0.754	0.165	0.718	0.166	0.698	0.145	0.678	0.133
Proportion non-Hispanic Asian residents	0.020	0.023	0.028	0.044	0.027	0.033	0.022	0.021	0.030	0.035
Proportion Hispanic residents	0.143	0.190	0.123	0.132	0.100	0.117	0.095	0.097	0.065	0.052
Socioeconomic & housing conditions										
Median home value ($)	151,711	69,491	172,007	108,346	165,128	75,055	143,965	49,845	172,615	88,139
Homeownership rate	0.656	0.061	0.655	0.067	0.665	0.061	0.663	0.058	0.654	0.062
Poverty rate	0.159	0.036	0.151	0.037	0.153	0.051	0.159	0.038	0.156	0.042
Median income ($)	49,280	7,799	51,696	10,914	52,024	10,471	49,896	8,409	54,145	12,236

Multilevel analysis

In the final stage of our analysis, we aimed to situate associations between historical redlining patterns and neighborhood diabetes prevalence within the broader context of contemporary housing markets. Table 4-9 in the Appendix shows summary statistics for our regression variables. Table 4-6 below details each step in our modeling approach. First, we built an intercept-only model (Model 1), nesting census tracts within CBSAs, to assess whether diabetes prevalence varied across CBSAs. We found the intercept variance was statistically significant and intraclass correlation was 0.3046, suggesting approximately 30 percent of the total variance in diabetes prevalence is on the CBSA level. We added our primary tract-level predictor of interest, redlining score, and selected tract-level covariates to our subsequent model (Model 2) and found redlining score was statistically significant, where a one-point increase in redlining score corresponds to a 1.54 percentage point increase in neighborhood diabetes prevalence [95% CI: 1.47-1.61]. We also found the inclusion of our tract-level predictor and covariates explained approximately 20 percent of the intercept variance and 60 percent of the residual variance in diabetes prevalence.

In Model 3, we added our primary CBSA-level predictor of interest – the IRH index – and selected CBSA-level covariates, as well as fixed effects for U.S. Census region. At this stage of our analysis, the IRH index was not statistically significant; however, the inclusion of our CBSA-level predictors explained an additional 60 percent of the variance in diabetes prevalence across CBSAs. In Model 4, we added random slopes to allow the effect of redlining score to vary across CBSAs and found the slope variance was small but statistically significant. Finally, in Model 5, we added a cross-level interaction term between historical redlining score and the IRH index to assess whether and to what extent the association between historical redlining score and neighborhood diabetes prevalence depends on the degree of contemporary institutionalized anti-Black racism in housing markets. We found the cross-level interaction was statistically significant and positive, where a one-point increase in the IRH index corresponds to a 0.0017 increase in the slope magnitude of redlining score [95% CI: 0.0006-0.0028]. This finding suggests the IRH index acts as a CBSA-level modifier of the association between historical redlining and neighborhood diabetes prevalence. In other words, part of the reason the "effect" of historical redlining score on diabetes prevalence is different across CBSAs is because CBSAs differ in degree of contemporary institutionalized anti-Black racism in housing markets, where a higher IRH value corresponds to a larger effect of historical redlining on diabetes prevalence. Figure 4-2 visualizes the cross-level interaction, showing the relationship between historical redlining score and neighborhood diabetes prevalence at two levels of the IRH index (min = -4.23, max = 6.6). In comparing Models 4 and 5, we found the cross-level interaction term explains roughly 8.6 percent of the slope variance.

In sensitivity analyses, we built spatial error regression models with CBSA fixed effects to account for spatially correlated residuals. We found the magnitude of the cross-level interaction term between historical redlining score and the IRH index was reduced relative to Model 5; however, the estimate remained positive and statistically significant (see Appendix Table 4-10).

Table 4-6. Multilevel regression results for diabetes prevalence on historical redlining score and novel IRH index

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Estimate (SE)	(95% CI)	Estimate (SE)	(95% CI)	Estimate (SE)	(95% CI)	Estimate (SE)	(95% CI)	Estimate (SE)	(95% CI)
Constant	0.1311	(0.1259, 0.1363)	0.0686	(0.0637, 0.0736)	0.8699	(0.6147, 1.1253)	0.7845	(0.5186, 1.0499)	0.7811	(0.5160, 1.0458)
	(0.0026)		(0.0025)		(0.1293)		(0.1296)		(0.1294)	
Tract-level predictors										
Redlining score			0.0154	(0.0147, 0.0161)	0.0153	(0.0146, 0.0160)	0.0183	(0.0163, 0.0204)	0.0162	(0.0138, 0.0186)
			(0.0004)		(0.0004)		(0.0010)		(0.0012)	
Proportion population under age 18			0.0143	(0.0138, 0.0147)	0.0143	(0.0138, 0.0148)	0.0141	(0.0136, 0.0146)	0.0141	(0.0136, 0.0146)
			(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Proportion population over age 65			0.0164	(0.0158, 0.0171)	0.0164	(0.0157, 0.0170)	0.0162	(0.0156, 0.0169)	0.0162	(0.0156, 0.0169)
			(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Population density			0.0018	(0.0013, 0.0023)	0.0018	(0.0013, 0.0023)	0.0021	(0.0016, 0.0026)	0.0021	(0.0016, 0.0026)
			(0.0003)		(0.0003)		(0.0002)		(0.0002)	
Relative proportion Black residents			0.0113	(0.0110, 0.0115)	0.0113	(0.0110, 0.0115)	0.0112	(0.0110, 0.0115)	0.0112	(0.0110, 0.0115)
			(0.0001)		(0.0001)		(0.0001)		(0.0001)	
CBSA-level predictors										
IRH index					-0.0012	(-0.0038, 0.0014)	-0.0008	(-0.0035, 0.0018)	-0.0050	(-0.0089, -0.0013)
					(0.0013)		(0.0013)		(0.0019)	
Log total population					0.0024	(-0.0011, 0.0060)	0.0026	(-0.0009, 0.0062)	0.0026	(-0.0009, 0.0061)
					(0.0018)		(0.0018)		(0.0018)	
Log median income					-0.0777	(-0.1027, -0.0528)	-0.071	(-0.0964, -0.0446)	-0.0697	(-0.0955, -0.0439)
					(0.0126)		(0.0126)		(0.0126)	
Proportion Black residents					0.1136	(0.0657, 0.1618)	0.0714	(0.0183, 0.1241)	0.0716	(0.0187, 0.1242)
					(0.0244)		(0.0248)		(0.0248)	
Region (ref = Northeast)										
Midwest					-0.0020	(-0.0106, 0.0065)	-0.0024	(-0.0110, 0.0061)	-0.0021	(-0.0107, 0.0064)
					(0.0043)		(0.0043)		(0.0043)	
South					0.0059	(-0.0045, 0.0162)	-0.0045	(-0.0059, 0.0148)	0.0043	(-0.0060, 0.0146)
					(0.0052)		(0.0052)		(0.0052)	
West					-0.0002	(-0.0141, 0.0137)	-0.0020	(-0.0159, 0.0120)	-0.0025	(-0.0165, 0.0115)
					(0.0070)		(0.0070)		(0.0070)	
Cross-level interactions										
Redlining score::IRH									0.0017	(0.0006, 0.0028)
									(0.0005)	
Random effects										
Intercept variance	0.0009	(0.0007, 0.0011)	0.0007	(0.0005, 0.0009)	0.0003	(0.0002, 0.0004)	0.0007	(0.0005, 0.0011)	0.0007	(0.0004, 0.0010)
Slope variance							0.0001	(0.0001, 0.0001)	0.0001	(0.0001, 0.0001)
Correlation							-0.80	(-0.87, -0.69)	-0.78	(-0.86, -0.66)
Residual variance	0.0020	(0.0019, 0.0020)	0.0008	(0.0008, 0.0008)	0.0008	(0.0008, 0.0008)	0.0007	(0.0007, 0.0008)	0.0007	(0.0007, 0.0008)
Number of tracts	12,668		12,668		12,668		12,668		12,668	
Number of CBSAs	133		133		133		133		133	

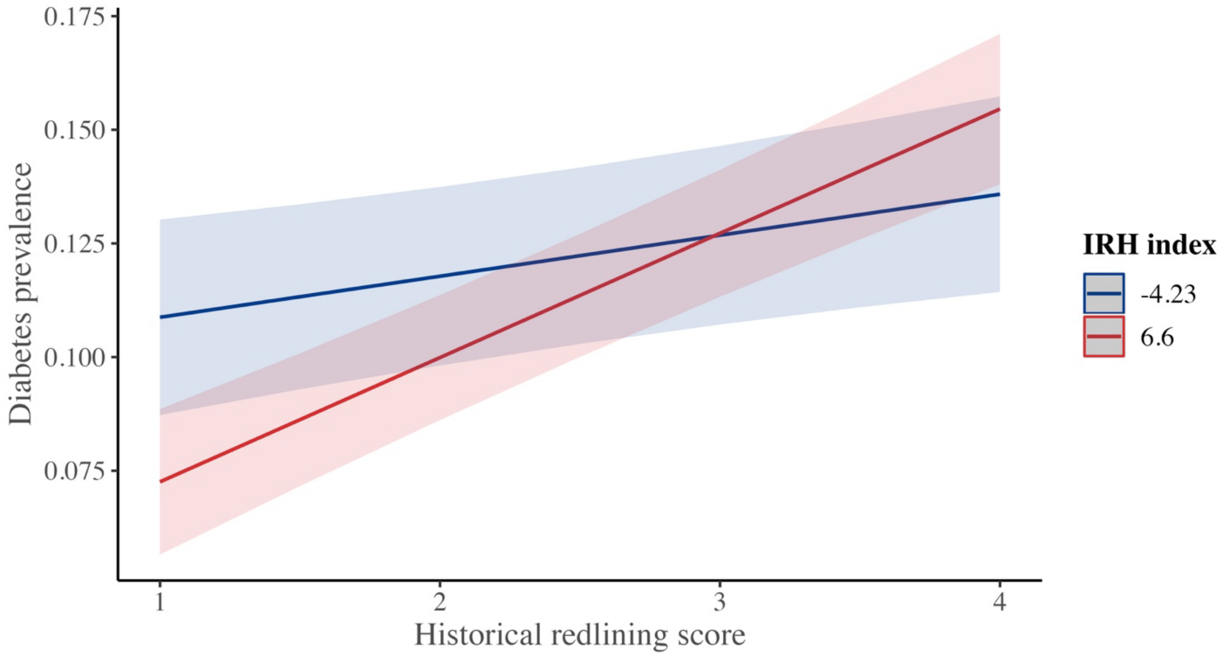

Figure 4-2. Association between historical redlining score and neighborhood diabetes prevalence at two levels of IRH index (min = -4.23, max = 6.6)

Discussion

In this study we created a novel index of institutionalized anti-Black racism in local housing markets using confirmatory factor analysis. We hypothesized that inequities within the urban housing landscape ultimately stem from this same underlying cause. In our final CFA model, we found strong associations between Black isolation, Black-to-white odds of loan denial for home purchase, Black-to-white odds of obtaining a high-cost loan, Black property devaluation, and our latent factor of interest. Our descriptive analyses suggested larger metropolitan/micropolitan areas and those with relatively large Black populations experience higher degrees of institutionalized anti-Black racism in contemporary housing markets. This finding suggests that, among CBSAs with the most segregated concentrations of Black residents, Black residents experience the most severe inequities in access to credit, predatory lending, and property values. Given the Black population was the largest group to be targeted by historical redlining practices beginning in the 1930s, we anticipated the legacy of redlining would be strongest in CBSAs with continued exclusion of Black families from housing markets. We assessed whether documented associations between historical redlining patterns and neighborhood diabetes prevalence depended, in part, on the degree of contemporary institutionalized anti-Black racism in housing. In our multilevel models we found our novel IRH index acted as a CBSA-level modifier of the relationship between redlining score and diabetes prevalence, suggesting contemporary forms of institutionalized racism in housing markets may be, in part, maintaining the legacy of historical redlining practices; however, the index explained relatively little (8.6 percent) of the slope variance across CBSAs.

Our novel IRH index makes valuable contributions to the growing area of structural racism measurement in terms of both our methodological approach and findings. Previous studies have developed measures of structural or institutional racism related to housing and identified associations with a range of health outcomes. Like our approach, many of these studies utilized the Home Mortgage Disclosure Act database to construct measures of discrimination in mortgage lending practices. For example, Gee (2002) developed a measure of contemporary redlining, defined as areas with high rates of loan denial relative to white applicants among Chinese Americans living in Los Angeles. They found lending discrimination at individual and neighborhood levels was associated with poor health (Gee, 2002). Similarly, Mendez et al. examined contemporary redlining, operationalized as tract-level odds of mortgage denial among African American and Hispanic applicants relative to white applicants, and found associations between residence in a redlined neighborhood and general health and stress level during pregnancy as well as preterm birth outcomes among a longitudinal cohort of pregnant women in Philadelphia County, PA (Mendez et al., 2011, 2012, 2014). Zhou et al. (2017) developed two indices of discrimination in mortgage lending, including the Black-to-white odds of loan denial and a place-based measure of lending discrimination based on differential denial rates across neighborhoods, and found a significant relationship between neighborhood mortgage lending discrimination and cancer incidence among Black women in two Wisconsin metropolitan areas (Zhou et al., 2017). Finally, Beyer et al. (2019) examined the relationship between metro-level measures of lending discrimination, racial residential segregation, including Black isolation and Black-white dissimilarity, and the degree of Black-white cancer disparities in the 100 largest metropolitan areas in the U.S. They found a positive association between lending discrimination against Black buyers and the gap in Black-white cancer mortality; however, racial residential segregation was not consistently associated with Black-white cancer disparities (Beyer et al., 2019).

These studies suggest mortgage lending discrimination and racism in housing markets more generally are associated with adverse health outcomes among communities of color, and this trend has been observed in diverse geographic areas across the U.S. Our approach builds from these prior studies, particularly in our measurement of lending discrimination, but captures multiple dimensions of inequity affecting Black Americans. For example, in addition to indicators of lending discrimination, we included measures of racial residential segregation and property devaluation in alignment with Perry, Rothwell, and Harshbarger (2018), who found properties in majority Black neighborhoods are valued lowest, relative to neighborhoods with less than one percent Black residents, in the most segregated metropolitan areas. Our study is the first to link racial residential segregation, inequities in lending opportunities, and property devaluation in a single composite index which can be compared across U.S. metropolitan and micropolitan areas. With a focus on inequities within urban housing markets, our novel IRH index may point to places where Black Americans are facing the greatest barriers to wealth accumulation and social mobility, which have implications for health across generations.

Our study also contributes to the growing body of literature examining the lasting impacts of historical redlining practices and other forms of spatial racism on contemporary health outcomes and inequities. Previous studies have identified associations between historical redlining patterns and disparities across a wide range of health outcomes, suggesting historically redlined neighborhoods experience worse health today compared to neighborhoods graded more favorably (Krieger et al., 2020; Lee et al., 2021; Lynch et al., 2021; Mujahid et al., 2021; Nardone, Casey, et al., 2020; Nardone, Chiang, et al., 2020). In alignment, we found historical redlining score is a significant predictor of contemporary neighborhood diabetes prevalence. Most previous studies have focused on a single city or metropolitan area; few have explicitly examined differences across geographic contexts. For example, Nardone et al.

(2020) examined associations between historical redlining patterns and urban health outcomes in nine major U.S. cities. City-specific analyses revealed substantial differences by city and outcome of interest. The correlation between HOLC risk grade and diabetes prevalence, for example, ranged from 0.07 in Chicago to 0.42 in Miami. In alignment, our findings suggest the relationship between historical redlining and contemporary diabetes prevalence varies across CBSAs. To our knowledge, our study is the first to examine factors which might begin to explain geographic variation in the relationship between redlining and health. Findings from our multilevel analyses suggest outcomes may be worse among residents of historically redlined neighborhoods within metropolitan/micropolitan areas with a higher degree of contemporary institutionalized anti-Black racism. However, as our IRH index explained only 8.6 percent of the slope variance, there are factors at play which have yet to be identified.

Broadly, our findings lend support to a structural interpretation of the impact of historical redlining practices on contemporary conditions and outcomes. This is not to say redlining did not contribute directly to neighborhood conditions and outcomes, as suggested by a spatial marking perspective. However, we found metropolitan/micropolitan areas with histories of HOLC appraisal (i.e., which had an associated "residential security map") far more frequently had IRH values within quintile 5 relative to our overall sample of CBSAs. Further, our regression findings suggest the relationship between redlining patterns and neighborhood diabetes prevalence is dependent on contemporary housing markets dynamics. Together, these findings suggest historical redlining may have contributed to lasting patterns of racialized and place-based discrimination in mortgage lending and property appraisal practices – and that the consequences for neighborhood health are most apparent in areas where Black Americans face the greatest degrees of exclusion from and discrimination within contemporary housing markets.

Limitations

While our study makes valuable contributions to the literature in these areas, several important limitations should be considered in interpreting our findings. First, our novel IRH index is comprised of four indicators of anti-Black racism, each of which has their own limitations. As discussed previously, our use of Black isolation as a measure of racial residential segregation is dependent on the absolute size of the Black population within a CBSA; thus, CBSAs with larger Black populations are inherently more likely to have higher isolation values, making it more difficult to understand whether this indicator is really a reflection of anti-Black racism or a reflection of the size of the Black population. However, in sensitivity analyses, we removed Black isolation from the IRH index; we also recreated the IRH index with Black-white dissimilarity in place of Black isolation. In both cases, our results were highly consistent with our original findings. Our indicators drawn from the Home Mortgage Disclosure Act (HMDA) database are also limited in that we did not account for differences in loan amount, income, or other loan or applicant characteristics. However, as discussed above, we chose not to adjust for these factors as the inequity is still a reflection of structural or institutionalized racism even if inequities in multiple systems (e.g., housing, education, employment) are at play. Finally, in constructing our measure of Black property devaluation, we were not able to assess property values of Black and white households directly; rather, we stratified neighborhood median property values by the relative proportion of Black residents (i.e., location quotient above or below one). Considering these challenges, researchers should work to develop novel data sources and indicators that allow for better tracking of equity issues within housing markets over time.

Our subsequent multilevel analysis of variation in associations between historical redlining patterns and neighborhood diabetes prevalence also has several important limitations. First, we chose to construct our novel IRH index specifically to examine anti-Black racism in housing markets, as the Black population was the largest group to be targeted by historical redlining practices and still today experiences the greatest degree of inequity in homeownership rates and wealth. However, recent studies have shown many racial and ethnic populations were affected by redlining practices (Markley, 2022), historically redlined neighborhoods today vary widely in their racial/ethnic composition, and further, associations between redlining and health are dependent on the contemporary racial/ethnic composition of a neighborhood (see Chapter 2). Therefore, situating associations between historical redlining patterns and contemporary diabetes prevalence within the context of institutionalized anti-Black racism may obscure contextual factors affecting other groups. This may also explain why relatively little of the slope variance corresponding to historical redlining score was accounted for by the IRH index. However, our findings suggest the influences of anti-Black institutionalized racism in housing markets are broad enough that they have place-based effects as measures in this ecological study. Future studies should examine individual-level outcomes stratified by race/ethnicity and placed within both neighborhood and broader metropolitan/micropolitan area contexts.

Conclusion

Although overt discrimination in housing has been outlawed, racial inequities in mortgage lending opportunities, homeownership, property values, and wealth have persisted. In many ways, these inequities stem from historically established structures, including historical redlining practices, which normalized the exclusion of communities of color from housing markets. Our novel IRH index identifies the places where Black Americans may be facing the greatest barriers to wealth accumulation and social mobility, which have important implications for health across generations. Although our IRH index explained relatively little of the CBSA-level variation in associations between historical redlining patterns and neighborhood diabetes prevalence, we suspect continued forms of racism and exclusion – whether on other geographic levels (e.g., neighborhoods) or within other sectors (e.g., education, employment) – are maintaining the legacy of historical redlining practices. Our analysis shows that there is unexplained variation across CBSAs in the relationship between historical redlining patterns and neighborhood diabetes prevalence. Further research is needed to understand factors and processes by which impacts of historical structural racism are maintained or diminished. Importantly, programmatic and policy approaches to addressing persistent wealth and health inequities affecting Black Americans should consider both historical and contemporary processes of exclusion and discrimination within housing markets.

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Appendix C

Table 4-7. IRH index and untransformed indicator values by CBSA (n=408)

CBSA code	CBSA name	Black isolation index	Black-to-white odds of loan denial	Black-to-white odds of high-cost loan	Black property devaluation	IRH index (raw)	IRH index (scaled, 0-100)
23860	Georgetown, SC Micro Area	0.44	5.49	4.40	0.35	8.50	100.00
45540	The Villages, FL Metro Area	0.36	5.12	4.80	0.77	7.10	90.87
33340	Milwaukee-Waukesha-West Allis, WI Metro Area	0.65	3.83	4.11	0.44	6.60	87.67
45940	Trenton, NJ Metro Area	0.46	3.30	3.57	0.32	5.60	81.14
16980	Chicago-Naperville-Elgin, IL-IN-WI Metro Area	0.64	3.17	3.40	0.54	4.69	75.17
32820	Memphis, TN-MS-AR Metro Area	0.69	3.20	2.95	0.43	4.60	74.61
23540	Gainesville, FL Metro Area	0.37	3.76	3.27	0.61	4.44	73.56
12940	Baton Rouge, LA Metro Area	0.60	3.21	3.16	0.56	4.29	72.59
34860	Nacogdoches, TX Micro Area	0.34	3.64	3.78	0.84	4.27	72.42
46220	Tuscaloosa, AL Metro Area	0.60	3.15	3.10	0.54	4.23	72.18
17460	Cleveland-Elyria, OH Metro Area	0.64	2.79	3.06	0.49	3.99	70.59
19820	Detroit-Warren-Dearborn, MI Metro Area	0.69	2.77	2.61	0.37	3.89	69.95
41180	St. Louis, MO-IL Metro Area	0.62	3.05	2.91	0.55	3.88	69.88
12780	Bartlesville, OK Micro Area	0.08	3.71	3.39	0.50	3.85	69.69
27140	Jackson, MS Metro Area	0.69	2.84	2.76	0.48	3.78	69.25
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	0.55	2.83	2.98	0.50	3.78	69.25
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	0.54	2.98	3.19	0.65	3.73	68.89
43340	Shreveport-Bossier City, LA Metro Area	0.63	2.84	2.94	0.55	3.70	68.70
32940	Meridian, MS Micro Area	0.59	2.70	3.03	0.55	3.58	67.95
12580	Baltimore-Columbia-Towson, MD Metro Area	0.62	2.76	2.85	0.51	3.58	67.91
26660	Huntsville, TX Micro Area	0.25	3.98	3.04	0.81	3.56	67.78
33660	Mobile, AL Metro Area	0.61	3.05	2.67	0.56	3.51	67.47
14860	Bridgeport-Stamford-Norwalk, CT Metro Area	0.28	2.85	2.79	0.37	3.50	67.40
13820	Birmingham-Hoover, AL Metro Area	0.63	2.90	2.61	0.50	3.49	67.35
37140	Paducah, KY-IL Micro Area	0.28	3.44	3.19	0.75	3.41	66.85
33300	Milledgeville, GA Micro Area	0.52	2.78	2.69	0.49	3.34	66.35
35380	New Orleans-Metairie, LA Metro Area	0.64	2.80	2.85	0.62	3.31	66.15
11460	Ann Arbor, MI Metro Area	0.32	2.48	3.17	0.46	3.27	65.92
40380	Rochester, NY Metro Area	0.40	2.80	2.90	0.57	3.12	64.97
28100	Kankakee, IL Metro Area	0.40	3.10	2.85	0.68	3.10	64.81

24780	Greenville, NC Metro Area	0.45	3.26	2.75	0.76	3.01	64.23
12060	Atlanta-Sandy Springs-Roswell, GA Metro Area	0.59	2.49	2.64	0.50	2.98	64.03
40060	Richmond, VA Metro Area	0.51	2.75	2.63	0.57	2.93	63.68
40980	Saginaw, MI Metro Area	0.53	2.59	2.13	0.34	2.92	63.60
15380	Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	0.55	2.82	2.58	0.60	2.91	63.54
46660	Valdosta, GA Metro Area	0.52	2.94	2.64	0.67	2.89	63.41
32220	Marshall, TX Micro Area	0.34	3.06	2.45	0.53	2.84	63.09
44780	Sturgis, MI Micro Area	0.13	4.67	1.90	0.59	2.81	62.94
29180	Lafayette, LA Metro Area	0.46	2.81	2.66	0.62	2.80	62.85
44980	Sunbury, PA Micro Area	0.15	3.32	2.73	0.57	2.76	62.59
33740	Monroe, LA Metro Area	0.67	2.70	2.49	0.63	2.75	62.52
10500	Albany, GA Metro Area	0.69	2.78	2.37	0.62	2.73	62.41
45220	Tallahassee, FL Metro Area	0.48	2.82	2.29	0.51	2.70	62.20
44940	Sumter, SC Metro Area	0.57	2.61	2.55	0.59	2.68	62.10
22420	Flint, MI Metro Area	0.60	2.42	1.99	0.35	2.57	61.36
47940	Waterloo-Cedar Falls, IA Metro Area	0.31	2.48	2.90	0.59	2.50	60.86
22500	Florence, SC Metro Area	0.54	2.69	2.43	0.61	2.49	60.84
28140	Kansas City, MO-KS Metro Area	0.41	2.63	2.43	0.52	2.48	60.79
20500	Durham-Chapel Hill, NC Metro Area	0.42	2.58	2.54	0.56	2.47	60.69
44100	Springfield, IL Metro Area	0.37	2.48	2.67	0.55	2.45	60.59
39580	Raleigh, NC Metro Area	0.34	2.65	2.66	0.59	2.44	60.51
30780	Little Rock-North Little Rock-Conway, AR Metro Area	0.49	2.69	2.56	0.67	2.44	60.50
40220	Roanoke, VA Metro Area	0.40	3.00	2.53	0.72	2.43	60.46
18060	Columbus, MS Micro Area	0.58	2.89	2.26	0.67	2.42	60.36
24220	Grand Forks, ND-MN Metro Area	0.07	4.56	2.82	1.07	2.37	60.06
15940	Canton-Massillon, OH Metro Area	0.24	2.59	2.86	0.59	2.37	60.04
14460	Boston-Cambridge-Newton, MA-NH Metro Area	0.33	2.94	2.82	0.85	2.28	59.49
31420	Macon-Bibb County, GA Metro Area	0.63	2.27	2.07	0.42	2.26	59.31
42340	Savannah, GA Metro Area	0.54	2.31	2.40	0.53	2.25	59.23
31340	Lynchburg, VA Metro Area	0.32	2.65	2.73	0.69	2.20	58.95
25620	Hattiesburg, MS Metro Area	0.50	2.67	2.27	0.63	2.11	58.38
18140	Columbus, OH Metro Area	0.44	2.34	2.44	0.55	2.10	58.29
37900	Peoria, IL Metro Area	0.42	2.20	2.71	0.59	2.10	58.26
10780	Alexandria, LA Metro Area	0.57	2.54	2.41	0.70	2.09	58.19
16740	Charlotte-Concord-Gastonia, NC-SC Metro Area	0.43	2.30	2.46	0.55	2.05	57.97
16020	Cape Girardeau, MO-IL Metro Area	0.30	3.02	2.06	0.56	2.05	57.93
28020	Kalamazoo-Portage, MI Metro Area	0.29	2.90	2.44	0.69	2.04	57.91
19380	Dayton, OH Metro Area	0.55	2.60	2.06	0.57	2.03	57.83
25540	Hartford-West Hartford-East Hartford, CT Metro Area	0.37	2.58	2.53	0.69	1.97	57.41

17780	College Station-Bryan, TX Metro Area	0.19	2.53	2.75	0.60	1.96	57.35
26460	Hudson, NY Micro Area	0.17	3.32	2.56	0.81	1.96	57.34
45780	Toledo, OH Metro Area	0.44	2.18	2.32	0.49	1.93	57.19
41860	San Francisco-Oakland-Hayward, CA Metro Area	0.21	2.40	2.71	0.56	1.93	57.16
21020	Elizabeth City, NC Micro Area	0.39	2.76	2.21	0.64	1.92	57.11
29380	Lake City, FL Micro Area	0.29	2.76	2.64	0.77	1.92	57.11
35300	New Haven-Milford, CT Metro Area	0.31	2.60	2.45	0.63	1.91	57.04
17900	Columbia, SC Metro Area	0.53	2.45	2.34	0.67	1.91	57.03
38300	Pittsburgh, PA Metro Area	0.40	2.37	2.32	0.55	1.90	56.98
10420	Akron, OH Metro Area	0.39	2.40	2.25	0.53	1.87	56.79
33460	Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	0.23	2.64	2.71	0.71	1.87	56.75
33780	Monroe, MI Metro Area	0.06	3.30	2.89	0.77	1.86	56.70
16700	Charleston-North Charleston, SC Metro Area	0.40	2.23	2.22	0.47	1.85	56.66
21900	Fairmont, WV Micro Area	0.14	2.06	4.00	0.93	1.84	56.61
19500	Decatur, IL Metro Area	0.34	2.47	2.06	0.46	1.84	56.60
19060	Cumberland, MD-WV Metro Area	0.25	2.90	2.56	0.77	1.84	56.58
27260	Jacksonville, FL Metro Area	0.48	2.22	2.03	0.44	1.81	56.42
26300	Hot Springs, AR Metro Area	0.20	2.96	2.29	0.62	1.81	56.38
11100	Amarillo, TX Metro Area	0.18	2.64	2.51	0.58	1.80	56.33
24140	Goldsboro, NC Metro Area	0.44	2.53	2.48	0.76	1.79	56.27
34020	Morgan City, LA Micro Area	0.45	2.76	2.13	0.70	1.76	56.09
46180	Tupelo, MS Micro Area	0.36	2.46	3.03	0.97	1.76	56.07
45500	Texarkana, TX-AR Metro Area	0.39	3.15	1.93	0.72	1.75	56.03
41780	Sandusky, OH Micro Area	0.24	2.08	2.76	0.55	1.70	55.69
25940	Hilton Head Island-Bluffton-Beaufort, SC Metro Area	0.42	2.27	2.04	0.47	1.69	55.58
47260	Virginia Beach-Norfolk-Newport News, VA-NC Metro Area	0.50	2.30	2.29	0.64	1.68	55.57
34980	Nashville-Davidson--Murfreesboro--Franklin, TN Metro Area	0.38	2.38	2.41	0.65	1.67	55.49
26420	Houston-The Woodlands-Sugar Land, TX Metro Area	0.36	2.31	2.31	0.56	1.66	55.42
12260	Augusta-Richmond County, GA-SC Metro Area	0.53	2.17	2.20	0.57	1.62	55.17
38940	Port St. Lucie, FL Metro Area	0.32	2.22	2.33	0.52	1.60	55.03
49620	York-Hanover, PA Metro Area	0.16	2.55	2.59	0.61	1.60	55.02
36100	Ocala, FL Metro Area	0.27	2.97	2.50	0.90	1.59	54.99
20140	Dublin, GA Micro Area	0.50	2.73	2.27	0.87	1.59	54.94
35620	New York-Newark-Jersey City, NY-NJ-PA Metro Area	0.51	2.34	2.43	0.77	1.57	54.86
27380	Jacksonville, TX Micro Area	0.25	3.22	1.86	0.66	1.57	54.80
12020	Athens-Clarke County, GA Metro Area	0.35	2.24	2.65	0.72	1.54	54.63
33860	Montgomery, AL Metro Area	0.64	2.22	1.92	0.56	1.51	54.43
17980	Columbus, GA-AL Metro Area	0.63	2.12	2.05	0.57	1.50	54.36
19100	Dallas-Fort Worth-Arlington, TX Metro Area	0.34	2.31	2.34	0.62	1.49	54.28

23060	Fort Wayne, IN Metro Area	0.31	2.37	2.29	0.61	1.47	54.19
46980	Vicksburg, MS Micro Area	0.60	2.55	2.01	0.75	1.47	54.17
47380	Waco, TX Metro Area	0.28	2.62	1.94	0.53	1.47	54.17
11980	Athens, TX Micro Area	0.15	2.61	3.26	1.04	1.45	54.04
48980	Wilson, NC Micro Area	0.49	2.15	2.37	0.69	1.43	53.94
26900	Indianapolis-Carmel-Anderson, IN Metro Area	0.44	2.36	2.24	0.69	1.43	53.91
46340	Tyler, TX Metro Area	0.31	2.23	2.37	0.60	1.40	53.74
24860	Greenville-Anderson-Mauldin, SC Metro Area	0.31	2.40	2.45	0.73	1.38	53.60
29340	Lake Charles, LA Metro Area	0.58	2.38	2.01	0.69	1.38	53.59
49180	Winston-Salem, NC Metro Area	0.42	2.20	2.36	0.68	1.37	53.55
12220	Auburn-Opelika, AL Metro Area	0.35	2.65	2.18	0.76	1.35	53.36
27100	Jackson, MI Metro Area	0.31	2.15	2.07	0.48	1.27	52.90
43780	South Bend-Mishawaka, IN-MI Metro Area	0.30	2.12	2.20	0.52	1.27	52.87
48900	Wilmington, NC Metro Area	0.29	2.16	2.13	0.50	1.25	52.74
27060	Ithaca, NY Metro Area	0.06	3.61	2.80	1.15	1.24	52.65
49660	Youngstown-Warren-Boardman, OH-PA Metro Area	0.39	2.22	1.67	0.41	1.23	52.64
17140	Cincinnati, OH-KY-IN Metro Area	0.47	2.13	2.26	0.69	1.22	52.55
33100	Miami-Fort Lauderdale-West Palm Beach, FL Metro Area	0.51	1.83	2.16	0.53	1.21	52.47
23460	Gadsden, AL Metro Area	0.44	2.17	1.99	0.56	1.20	52.40
34740	Muskegon, MI Metro Area	0.50	1.65	2.07	0.43	1.15	52.12
31260	Lufkin, TX Micro Area	0.28	2.93	1.96	0.78	1.15	52.09
30620	Lima, OH Metro Area	0.28	1.99	2.14	0.47	1.14	52.01
42680	Sebastian-Vero Beach, FL Metro Area	0.30	2.08	2.03	0.48	1.12	51.88
40580	Rocky Mount, NC Metro Area	0.57	2.18	2.14	0.76	1.12	51.87
27780	Johnstown, PA Metro Area	0.14	2.40	2.42	0.62	1.09	51.69
17860	Columbia, MO Metro Area	0.14	2.35	2.82	0.79	1.08	51.66
13140	Beaumont-Port Arthur, TX Metro Area	0.51	2.31	2.03	0.75	1.05	51.46
36540	Omaha-Council Bluffs, NE-IA Metro Area	0.32	2.28	2.24	0.69	1.05	51.45
31540	Madison, WI Metro Area	0.10	2.92	2.53	0.86	1.04	51.36
35660	Niles-Benton Harbor, MI Metro Area	0.57	2.05	1.83	0.57	1.02	51.22
37340	Palm Bay-Melbourne-Titusville, FL Metro Area	0.23	2.25	2.18	0.59	0.98	50.99
26620	Huntsville, AL Metro Area	0.42	2.28	1.99	0.70	0.93	50.66
22180	Fayetteville, NC Metro Area	0.44	2.13	2.21	0.75	0.93	50.66
33260	Midland, TX Metro Area	0.13	2.71	2.04	0.61	0.93	50.65
12100	Atlantic City-Hammonton, NJ Metro Area	0.37	2.03	2.24	0.66	0.93	50.63
10580	Albany-Schenectady-Troy, NY Metro Area	0.30	2.26	2.11	0.66	0.90	50.45
12980	Battle Creek, MI Metro Area	0.32	2.38	1.74	0.55	0.89	50.42
24940	Greenwood, SC Micro Area	0.39	1.97	2.25	0.67	0.89	50.42
14140	Bluefield, WV-VA Micro Area	0.18	2.72	2.28	0.83	0.89	50.39

46540	Utica-Rome, NY Metro Area	0.19	2.01	2.69	0.71	0.88	50.32
41220	St. Marys, GA Micro Area	0.22	2.65	2.08	0.75	0.87	50.27
15260	Brunswick, GA Metro Area	0.43	1.73	2.09	0.52	0.86	50.17
23500	Gaffney, SC Micro Area	0.34	2.50	2.35	0.98	0.84	50.04
27180	Jackson, TN Metro Area	0.51	1.96	1.81	0.55	0.83	50.00
24340	Grand Rapids-Wyoming, MI Metro Area	0.27	2.24	2.23	0.72	0.81	49.87
30980	Longview, TX Metro Area	0.25	2.52	2.06	0.73	0.80	49.82
45060	Syracuse, NY Metro Area	0.36	2.38	1.91	0.70	0.80	49.82
46140	Tulsa, OK Metro Area	0.33	2.09	2.06	0.63	0.77	49.63
44420	Staunton-Waynesboro, VA Metro Area	0.13	2.31	2.57	0.74	0.77	49.62
32620	McComb, MS Micro Area	0.57	2.21	2.01	0.84	0.76	49.53
31180	Lubbock, TX Metro Area	0.21	2.36	2.11	0.66	0.75	49.49
48180	Waycross, GA Micro Area	0.38	1.93	2.16	0.65	0.75	49.47
16300	Cedar Rapids, IA Metro Area	0.10	2.94	2.10	0.73	0.74	49.43
36740	Orlando-Kissimmee-Sanford, FL Metro Area	0.36	1.98	2.12	0.64	0.74	49.39
25220	Hammond, LA Metro Area	0.42	2.60	1.76	0.79	0.73	49.38
41820	Sanford, NC Micro Area	0.28	2.13	2.22	0.70	0.71	49.25
40260	Roanoke Rapids, NC Micro Area	0.60	2.00	1.72	0.61	0.71	49.21
10900	Allentown-Bethlehem-Easton, PA-NJ Metro Area	0.10	2.48	2.48	0.74	0.69	49.10
34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC Metro Area	0.26	2.28	2.04	0.67	0.68	49.02
12420	Austin-Round Rock, TX Metro Area	0.14	2.20	2.27	0.61	0.65	48.80
15540	Burlington-South Burlington, VT Metro Area	0.08	2.33	3.07	0.95	0.64	48.79
31740	Manhattan, KS Metro Area	0.15	2.04	2.55	0.69	0.62	48.66
36660	Opelousas, LA Micro Area	0.57	2.31	2.13	1.04	0.62	48.62
37060	Oxford, MS Micro Area	0.26	2.88	2.37	1.24	0.61	48.54
45180	Talladega-Sylacauga, AL Micro Area	0.41	1.96	2.25	0.79	0.59	48.45
16580	Champaign-Urbana, IL Metro Area	0.26	2.62	1.82	0.75	0.58	48.34
40420	Rockford, IL Metro Area	0.30	2.10	1.86	0.57	0.56	48.27
16860	Chattanooga, TN-GA Metro Area	0.49	2.14	2.08	0.86	0.56	48.25
24660	Greensboro-High Point, NC Metro Area	0.48	1.82	2.08	0.69	0.54	48.10
27620	Jefferson City, MO Metro Area	0.19	2.61	2.13	0.86	0.53	48.03
48620	Wichita, KS Metro Area	0.28	2.28	1.98	0.73	0.49	47.81
15980	Cape Coral-Fort Myers, FL Metro Area	0.27	1.86	2.26	0.65	0.49	47.80
43900	Spartanburg, SC Metro Area	0.35	1.98	2.08	0.70	0.49	47.76
29620	Lansing-East Lansing, MI Metro Area	0.21	2.31	1.85	0.62	0.46	47.59
44660	Stillwater, OK Micro Area	0.07	2.70	2.40	0.83	0.46	47.57
23660	Galesburg, IL Micro Area	0.17	2.82	1.59	0.66	0.42	47.35
29860	Laurel, MS Micro Area	0.52	2.32	1.80	0.88	0.41	47.27
35840	North Port-Sarasota-Bradenton, FL Metro Area	0.24	1.89	1.97	0.53	0.41	47.26

28820	Kinston, NC Micro Area	0.56	2.00	1.91	0.81	0.39	47.12
39300	Providence-Warwick, RI-MA Metro Area	0.13	2.27	2.26	0.71	0.37	47.02
37860	Pensacola-Ferry Pass-Brent, FL Metro Area	0.35	1.81	1.98	0.61	0.37	46.99
19780	Des Moines-West Des Moines, IA Metro Area	0.15	2.25	2.12	0.66	0.37	46.98
21820	Fairbanks, AK Metro Area	0.09	2.46	2.61	0.91	0.36	46.93
29300	LaGrange, GA Micro Area	0.45	1.95	1.77	0.64	0.36	46.93
47580	Warner Robins, GA Metro Area	0.36	1.87	1.93	0.63	0.35	46.86
35020	Natchez, MS-LA Micro Area	0.63	2.31	1.38	0.72	0.34	46.79
38100	Picayune, MS Micro Area	0.25	2.14	2.22	0.82	0.33	46.77
34940	Naples-Immokalee-Marco Island, FL Metro Area	0.17	1.84	1.93	0.44	0.33	46.75
37260	Palatka, FL Micro Area	0.34	2.61	2.16	1.17	0.31	46.61
33140	Michigan City-La Porte, IN Metro Area	0.34	1.86	1.97	0.64	0.28	46.40
20220	Dubuque, IA Metro Area	0.11	2.38	1.92	0.60	0.27	46.32
39540	Racine, WI Metro Area	0.24	1.88	2.19	0.68	0.25	46.22
31900	Mansfield, OH Metro Area	0.29	2.09	1.73	0.62	0.23	46.07
40340	Rochester, MN Metro Area	0.12	2.31	2.22	0.75	0.22	46.02
15500	Burlington, NC Metro Area	0.30	1.99	2.03	0.74	0.20	45.88
36420	Oklahoma City, OK Metro Area	0.32	2.04	1.97	0.75	0.20	45.86
36700	Orangeburg, SC Micro Area	0.67	2.08	1.96	1.05	0.20	45.86
35980	Norwich-New London, CT Metro Area	0.13	2.10	2.14	0.64	0.18	45.76
40660	Rome, GA Metro Area	0.28	2.05	2.19	0.85	0.17	45.73
31300	Lumberton, NC Micro Area	0.36	2.17	1.93	0.85	0.17	45.66
28740	Kingston, NY Metro Area	0.12	2.21	2.31	0.77	0.16	45.66
20940	El Centro, CA Metro Area	0.10	2.39	2.40	0.88	0.15	45.56
31140	Louisville/Jefferson County, KY-IN Metro Area	0.45	1.74	1.72	0.60	0.13	45.45
19180	Danville, IL Metro Area	0.42	1.76	1.58	0.52	0.11	45.31
34620	Muncie, IN Metro Area	0.31	2.11	1.69	0.66	0.11	45.30
25060	Gulfport-Biloxi-Pascagoula, MS Metro Area	0.36	2.14	1.74	0.75	0.09	45.19
20100	Dover, DE Metro Area	0.32	2.19	2.11	0.97	0.09	45.16
25420	Harrisburg-Carlisle, PA Metro Area	0.34	1.95	1.76	0.65	0.08	45.14
20020	Dothan, AL Metro Area	0.42	2.00	1.72	0.73	0.07	45.04
26380	Houma-Thibodaux, LA Metro Area	0.29	2.25	2.06	0.94	0.06	44.98
39460	Punta Gorda, FL Metro Area	0.11	2.16	2.03	0.62	0.04	44.88
16820	Charlottesville, VA Metro Area	0.21	2.24	1.78	0.70	0.01	44.68
10300	Adrian, MI Micro Area	0.08	2.39	1.83	0.58	0.00	44.58
23580	Gainesville, GA Metro Area	0.14	2.27	2.05	0.78	-0.02	44.44
41540	Salisbury, MD-DE Metro Area	0.45	2.09	1.86	0.92	-0.03	44.42
21140	Elkhart-Goshen, IN Metro Area	0.18	2.47	1.70	0.74	-0.05	44.23
29460	Lakeland-Winter Haven, FL Metro Area	0.29	2.00	1.90	0.76	-0.05	44.23

45660	Tiffin, OH Micro Area	0.05	1.52	3.14	0.71	-0.10	43.96
19740	Denver-Aurora-Lakewood, CO Metro Area	0.18	1.96	2.12	0.75	-0.11	43.90
35260	New Castle, PA Micro Area	0.18	1.97	1.41	0.41	-0.11	43.89
42660	Seattle-Tacoma-Bellevue, WA Metro Area	0.14	2.01	2.06	0.68	-0.12	43.83
27500	Janesville-Beloit, WI Metro Area	0.12	2.16	1.72	0.56	-0.12	43.82
46700	Vallejo-Fairfield, CA Metro Area	0.21	1.97	1.96	0.72	-0.14	43.65
42540	Scranton--Wilkes-Barre--Hazleton, PA Metro Area	0.11	2.09	2.12	0.71	-0.15	43.63
38220	Pine Bluff, AR Metro Area	0.71	1.55	1.62	0.68	-0.16	43.53
31080	Los Angeles-Long Beach-Anaheim, CA Metro Area	0.27	1.73	2.05	0.71	-0.17	43.48
39740	Reading, PA Metro Area	0.09	2.00	2.05	0.62	-0.23	43.10
19460	Decatur, AL Metro Area	0.30	1.86	1.91	0.77	-0.23	43.06
20380	Dunn, NC Micro Area	0.25	2.08	2.05	0.93	-0.25	42.98
49020	Winchester, VA-WV Metro Area	0.09	2.44	2.40	1.04	-0.25	42.98
30700	Lincoln, NE Metro Area	0.09	2.11	2.01	0.65	-0.26	42.88
21500	Erie, PA Metro Area	0.23	1.68	1.57	0.47	-0.30	42.62
25180	Hagerstown-Martinsburg, MD-WV Metro Area	0.21	1.96	1.98	0.81	-0.33	42.46
44700	Stockton-Lodi, CA Metro Area	0.13	2.03	2.12	0.77	-0.33	42.45
43620	Sioux Falls, SD Metro Area	0.11	2.21	1.85	0.69	-0.33	42.44
19300	Daphne-Fairhope-Foley, AL Metro Area	0.21	2.32	1.72	0.85	-0.34	42.38
26980	Iowa City, IA Metro Area	0.14	2.47	1.78	0.84	-0.34	42.38
45300	Tampa-St. Petersburg-Clearwater, FL Metro Area	0.33	1.86	1.83	0.80	-0.35	42.30
40780	Russellville, AR Micro Area	0.06	2.38	2.22	0.86	-0.35	42.28
19660	Deltona-Daytona Beach-Ormond Beach, FL Metro Area	0.32	1.77	1.71	0.67	-0.35	42.28
19260	Danville, VA Micro Area	0.46	1.82	1.67	0.79	-0.36	42.24
43140	Shelby, NC Micro Area	0.31	2.16	1.78	0.93	-0.36	42.23
28940	Knoxville, TN Metro Area	0.28	1.75	1.69	0.64	-0.39	42.02
36140	Ocean City, NJ Metro Area	0.13	1.77	1.84	0.55	-0.42	41.83
21780	Evansville, IN-KY Metro Area	0.20	1.79	1.81	0.64	-0.43	41.79
27860	Jonesboro, AR Metro Area	0.23	2.10	2.03	0.98	-0.44	41.73
23420	Fresno, CA Metro Area	0.11	2.00	2.03	0.74	-0.49	41.42
48660	Wichita Falls, TX Metro Area	0.21	1.74	1.98	0.74	-0.51	41.26
34340	Mount Airy, NC Micro Area	0.07	2.49	2.37	1.13	-0.51	41.24
40900	Sacramento--Roseville--Arden-Arcade, CA Metro Area	0.15	1.75	1.93	0.64	-0.52	41.22
22520	Florence-Muscle Shoals, AL Metro Area	0.23	2.09	1.69	0.81	-0.53	41.13
43300	Sherman-Denison, TX Metro Area	0.12	1.88	1.94	0.66	-0.54	41.06
30460	Lexington-Fayette, KY Metro Area	0.25	1.82	1.63	0.66	-0.54	41.05
44140	Springfield, MA Metro Area	0.20	1.81	1.89	0.75	-0.58	40.79
12700	Barnstable Town, MA Metro Area	0.07	2.12	2.13	0.79	-0.59	40.72
21300	Elmira, NY Metro Area	0.20	1.69	1.74	0.61	-0.62	40.54

28580	Key West, FL Micro Area	0.13	1.67	2.26	0.79	-0.65	40.38
11500	Anniston-Oxford-Jacksonville, AL Metro Area	0.41	1.75	1.63	0.82	-0.68	40.15
44340	Statesboro, GA Micro Area	0.36	1.74	1.90	0.96	-0.71	39.93
49340	Worcester, MA-CT Metro Area	0.11	1.91	2.11	0.84	-0.76	39.62
32020	Marion, OH Micro Area	0.27	1.58	1.65	0.64	-0.77	39.55
41460	Salina, KS Micro Area	0.04	1.82	2.23	0.67	-0.79	39.41
43580	Sioux City, IA-NE-SD Metro Area	0.09	1.93	1.75	0.64	-0.80	39.36
44180	Springfield, MO Metro Area	0.07	1.90	2.01	0.69	-0.80	39.34
35100	New Bern, NC Metro Area	0.31	1.77	1.63	0.81	-0.85	39.04
20700	East Stroudsburg, PA Metro Area	0.19	1.87	1.84	0.85	-0.85	39.02
34900	Napa, CA Metro Area	0.08	2.63	1.76	0.98	-0.86	38.99
19340	Davenport-Moline-Rock Island, IA-IL Metro Area	0.21	1.65	1.74	0.70	-0.90	38.74
29940	Lawrence, KS Metro Area	0.06	2.44	1.76	0.84	-0.90	38.69
45820	Topeka, KS Metro Area	0.17	1.61	1.71	0.62	-0.90	38.69
47020	Victoria, TX Metro Area	0.09	1.59	2.01	0.62	-0.92	38.59
39060	Pottsville, PA Micro Area	0.19	1.71	1.46	0.58	-0.93	38.51
13780	Binghamton, NY Metro Area	0.11	1.78	1.95	0.75	-0.94	38.44
16620	Charleston, WV Metro Area	0.22	1.98	2.03	1.14	-0.96	38.31
37300	Palestine, TX Micro Area	0.30	2.12	1.46	0.95	-0.98	38.19
44220	Springfield, OH Metro Area	0.33	1.66	1.25	0.60	-0.99	38.10
10620	Albemarle, NC Micro Area	0.20	2.02	1.58	0.85	-1.00	38.03
42860	Seneca, SC Micro Area	0.16	1.90	2.04	1.02	-1.03	37.84
33700	Modesto, CA Metro Area	0.05	2.28	1.97	0.88	-1.03	37.84
17300	Clarksville, TN-KY Metro Area	0.29	1.74	1.54	0.79	-1.05	37.75
38060	Phoenix-Mesa-Scottsdale, AZ Metro Area	0.10	1.78	1.79	0.69	-1.07	37.63
28660	Killeen-Temple, TX Metro Area	0.30	1.70	1.45	0.74	-1.10	37.41
41060	St. Cloud, MN Metro Area	0.17	2.19	1.41	0.84	-1.12	37.31
29540	Lancaster, PA Metro Area	0.11	1.77	1.72	0.69	-1.15	37.09
32300	Martinsville, VA Micro Area	0.38	1.53	1.54	0.80	-1.17	36.97
16060	Carbondale-Marion, IL Metro Area	0.27	1.98	1.48	0.95	-1.23	36.57
14540	Bowling Green, KY Metro Area	0.17	1.99	1.63	0.93	-1.28	36.26
31700	Manchester-Nashua, NH Metro Area	0.05	2.01	1.97	0.86	-1.28	36.26
39900	Reno, NV Metro Area	0.04	2.11	1.62	0.68	-1.32	35.97
26740	Hutchinson, KS Micro Area	0.07	1.55	2.03	0.70	-1.36	35.69
47220	Vineland-Bridgeton, NJ Metro Area	0.30	1.53	1.46	0.75	-1.36	35.69
36860	Ottawa-Peru, IL Micro Area	0.10	2.40	1.54	1.01	-1.36	35.69
16540	Chambersburg-Waynesboro, PA Metro Area	0.08	2.00	1.93	0.98	-1.37	35.63
49780	Zanesville, OH Micro Area	0.09	1.71	1.57	0.64	-1.42	35.34
22580	Forest City, NC Micro Area	0.19	1.85	1.19	0.68	-1.42	35.29

39500	Quincy, IL-MO Micro Area	0.09	1.70	1.78	0.78	-1.51	34.76
11260	Anchorage, AK Metro Area	0.10	1.76	1.82	0.89	-1.59	34.24
26140	Homosassa Springs, FL Metro Area	0.04	2.36	2.00	1.21	-1.59	34.22
25980	Hinesville, GA Metro Area	0.44	1.38	1.44	0.85	-1.61	34.12
13220	Beckley, WV Metro Area	0.20	1.71	1.64	0.96	-1.63	33.98
29820	Las Vegas-Henderson-Paradise, NV Metro Area	0.18	1.52	1.55	0.77	-1.67	33.70
12860	Batavia, NY Micro Area	0.06	1.40	2.14	0.80	-1.71	33.44
34060	Morgantown, WV Metro Area	0.11	2.13	1.93	1.32	-1.72	33.38
17820	Colorado Springs, CO Metro Area	0.10	1.61	1.49	0.67	-1.74	33.21
25860	Hickory-Lenoir-Morganton, NC Metro Area	0.15	1.63	1.62	0.87	-1.75	33.18
21460	Enterprise, AL Micro Area	0.29	1.51	1.43	0.87	-1.75	33.17
26580	Huntington-Ashland, WV-KY-OH Metro Area	0.14	1.78	1.65	0.97	-1.76	33.11
41660	San Angelo, TX Metro Area	0.08	2.02	1.68	1.00	-1.77	33.02
40140	Riverside-San Bernardino-Ontario, CA Metro Area	0.12	1.64	1.67	0.89	-1.83	32.63
22020	Fargo, ND-MN Metro Area	0.09	2.04	1.49	0.94	-1.84	32.60
23980	Glasgow, KY Micro Area	0.08	1.30	2.37	0.98	-1.84	32.57
12540	Bakersfield, CA Metro Area	0.12	1.67	1.58	0.84	-1.86	32.46
13980	Blacksburg-Christiansburg-Radford, VA Metro Area	0.07	1.65	1.67	0.77	-1.86	32.45
41940	San Jose-Sunnyvale-Santa Clara, CA Metro Area	0.05	1.65	1.81	0.76	-1.87	32.38
27340	Jacksonville, NC Metro Area	0.21	1.49	1.44	0.81	-1.88	32.36
25500	Harrisonburg, VA Metro Area	0.07	2.08	1.84	1.17	-1.88	32.35
34780	Muskogee, OK Micro Area	0.26	1.58	1.22	0.79	-1.88	32.34
17580	Clovis, NM Micro Area	0.08	1.22	2.45	0.96	-1.89	32.27
41700	San Antonio-New Braunfels, TX Metro Area	0.16	1.69	1.51	0.91	-1.89	32.23
49700	Yuba City, CA Metro Area	0.04	1.88	1.99	1.02	-1.90	32.21
38900	Portland-Vancouver-Hillsboro, OR-WA Metro Area	0.08	1.71	1.72	0.90	-1.90	32.19
37460	Panama City, FL Metro Area	0.25	1.31	1.24	0.64	-1.92	32.04
42700	Sebring, FL Metro Area	0.22	1.58	1.30	0.82	-1.93	32.00
29020	Kokomo, IN Metro Area	0.17	1.46	1.34	0.70	-1.95	31.90
22100	Farmington, MO Micro Area	0.14	1.33	1.65	0.78	-2.01	31.49
22900	Fort Smith, AR-OK Metro Area	0.10	1.93	1.50	1.00	-2.01	31.49
11940	Athens, TN Micro Area	0.07	1.84	1.32	0.72	-2.02	31.43
31860	Mankato-North Mankato, MN Metro Area	0.05	1.63	1.95	0.97	-2.11	30.80
46060	Tucson, AZ Metro Area	0.06	1.69	1.60	0.84	-2.12	30.73
11780	Ashtabula, OH Micro Area	0.13	1.27	1.58	0.73	-2.14	30.65
10740	Albuquerque, NM Metro Area	0.05	1.71	1.81	0.92	-2.14	30.62
39020	Portsmouth, OH Micro Area	0.16	1.53	1.50	0.91	-2.15	30.56
31460	Madera, CA Metro Area	0.08	1.91	1.43	0.93	-2.16	30.53
25260	Hanford-Corcoran, CA Metro Area	0.11	1.84	1.33	0.91	-2.18	30.37

24020	Glens Falls, NY Metro Area	0.12	1.64	1.56	0.97	-2.19	30.29
36780	Oshkosh-Neenah, WI Metro Area	0.06	1.67	1.56	0.83	-2.19	30.27
45460	Terre Haute, IN Metro Area	0.12	1.30	1.62	0.78	-2.21	30.19
10700	Albertville, AL Micro Area	0.06	1.83	1.67	1.02	-2.23	30.06
10460	Alamogordo, NM Micro Area	0.07	2.01	1.53	1.09	-2.27	29.77
23180	Frankfort, KY Micro Area	0.18	1.37	1.58	0.95	-2.28	29.71
18880	Crestview-Fort Walton Beach-Destin, FL Metro Area	0.14	1.42	1.14	0.64	-2.31	29.52
41740	San Diego-Carlsbad, CA Metro Area	0.11	1.33	1.38	0.70	-2.37	29.14
14740	Bremerton-Silverdale, WA Metro Area	0.06	1.77	1.08	0.65	-2.41	28.85
43060	Shawnee, OK Micro Area	0.05	1.74	1.24	0.75	-2.53	28.07
48060	Watertown-Fort Drum, NY Metro Area	0.11	1.48	1.57	1.01	-2.55	27.96
11700	Asheville, NC Metro Area	0.15	1.53	1.42	1.03	-2.55	27.94
36980	Owensboro, KY Metro Area	0.08	1.66	1.11	0.74	-2.58	27.78
48540	Wheeling, WV-OH Metro Area	0.12	1.35	1.16	0.70	-2.62	27.51
33500	Minot, ND Micro Area	0.06	1.47	1.89	1.09	-2.65	27.33
38460	Plattsburgh, NY Micro Area	0.14	1.50	1.13	0.85	-2.76	26.57
32900	Merced, CA Metro Area	0.06	1.31	1.49	0.82	-2.85	25.97
31980	Marion, IN Micro Area	0.19	1.10	1.10	0.70	-2.87	25.86
41500	Salinas, CA Metro Area	0.11	1.19	1.48	0.89	-2.94	25.39
12180	Auburn, NY Micro Area	0.13	1.10	1.32	0.77	-2.97	25.18
36220	Odessa, TX Metro Area	0.09	1.31	1.64	1.07	-3.00	25.01
10180	Abilene, TX Metro Area	0.17	1.39	1.16	0.98	-3.04	24.78
48700	Williamsport, PA Metro Area	0.20	1.29	0.70	0.66	-3.08	24.50
17420	Cleveland, TN Metro Area	0.11	1.37	1.32	0.99	-3.10	24.38
41140	St. Joseph, MO-KS Metro Area	0.11	1.59	0.79	0.78	-3.13	24.18
39980	Richmond, IN Micro Area	0.09	1.55	0.98	0.84	-3.14	24.14
46100	Tullahoma-Manchester, TN Micro Area	0.08	1.41	1.39	1.02	-3.16	23.99
22220	Fayetteville-Springdale-Rogers, AR-MO Metro Area	0.05	1.57	1.44	1.07	-3.16	23.95
21060	Elizabethtown-Fort Knox, KY Metro Area	0.19	1.25	1.04	0.91	-3.24	23.47
34380	Mount Pleasant, MI Micro Area	0.04	1.16	1.86	1.03	-3.26	23.31
33980	Morehead City, NC Micro Area	0.13	1.03	1.04	0.76	-3.49	21.83
20180	DuBois, PA Micro Area	0.13	1.06	1.38	1.02	-3.54	21.47
36500	Olympia-Tumwater, WA Metro Area	0.06	1.48	1.13	0.98	-3.56	21.38
36020	Oak Harbor, WA Micro Area	0.11	0.93	1.02	0.68	-3.66	20.71
15660	Calhoun, GA Micro Area	0.06	1.38	0.95	0.81	-3.67	20.67
30020	Lawton, OK Metro Area	0.24	0.94	0.80	0.80	-3.78	19.95
19220	Danville, KY Micro Area	0.10	1.32	1.03	1.09	-3.93	18.97
19140	Dalton, GA Metro Area	0.05	1.57	0.99	1.10	-3.95	18.84
17060	Chillicothe, OH Micro Area	0.20	1.19	0.66	0.91	-3.97	18.72

44300	State College, PA Metro Area	0.17	1.21	0.99	1.24	-4.14	17.57
11900	Athens, OH Micro Area	0.04	1.44	1.16	1.19	-4.15	17.49
18580	Corpus Christi, TX Metro Area	0.07	1.05	1.24	1.05	-4.17	17.40
27740	Johnson City, TN Metro Area	0.09	1.07	1.07	1.00	-4.21	17.13
22780	Fort Leonard Wood, MO Micro Area	0.17	1.24	0.74	1.08	-4.22	17.09
21340	El Paso, TX Metro Area	0.08	1.20	1.13	1.15	-4.23	16.99
27460	Jamestown-Dunkirk-Fredonia, NY Micro Area	0.06	0.81	1.17	0.77	-4.24	16.94
35900	North Wilkesboro, NC Micro Area	0.08	1.55	0.56	0.96	-4.25	16.87
22060	Faribault-Northfield, MN Micro Area	0.11	0.87	0.76	0.70	-4.25	16.86
40080	Richmond-Berea, KY Micro Area	0.08	1.06	1.11	1.04	-4.30	16.56
24620	Greeneville, TN Micro Area	0.06	1.11	1.17	1.07	-4.30	16.53
16660	Charleston-Mattoon, IL Micro Area	0.08	0.85	1.32	1.02	-4.33	16.36
17340	Clearlake, CA Micro Area	0.05	0.82	1.16	0.82	-4.43	15.71
42620	Searcy, AR Micro Area	0.07	1.24	1.05	1.18	-4.44	15.60
42460	Scottsboro, AL Micro Area	0.06	0.73	1.26	0.87	-4.51	15.15
22860	Fort Polk South, LA Micro Area	0.27	0.83	0.79	1.07	-4.58	14.73
47660	Warrensburg, MO Micro Area	0.08	0.86	1.02	0.92	-4.60	14.58
26020	Hobbs, NM Micro Area	0.10	1.19	0.85	1.20	-4.71	13.86
23380	Fremont, OH Micro Area	0.06	0.61	1.19	0.80	-4.72	13.78
16940	Cheyenne, WY Metro Area	0.04	1.06	0.91	0.95	-4.79	13.33
14020	Bloomington, IN Metro Area	0.06	1.01	0.98	1.12	-4.92	12.47
26860	Indiana, PA Micro Area	0.11	1.12	0.58	1.07	-4.99	12.02
38340	Pittsfield, MA Metro Area	0.06	0.77	0.82	0.89	-5.23	10.45
34100	Morristown, TN Metro Area	0.06	0.98	0.43	0.94	-5.68	7.54
36300	Ogdensburg-Massena, NY Micro Area	0.08	0.76	0.51	1.17	-6.27	3.71
21420	Enid, OK Metro Area	0.06	0.55	0.35	0.74	-6.32	3.35
43420	Sierra Vista-Douglas, AZ Metro Area	0.07	0.77	0.43	1.38	-6.84	0.00

Table 4-8. Average characteristics by IRH quintile for CBSAs included in regression analyses (n=133)

	IRH quintile									
	1 (n=10)		**2 (n=20)**		**3 (n=24)**		**4 (n=34)**		**5 (n=45)**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
IRH component indicators										
Black isolation index	0.116	0.034	0.168	0.086	0.228	0.121	0.368	0.132	0.483	0.139
Black-to-white odds of loan denial for home purchase	1.490	0.184	1.800	0.119	2.080	0.212	2.260	0.232	2.700	0.321
Black-to-white odds of obtaining a high-cost loan	1.380	0.278	1.800	0.181	2.000	0.242	2.200	0.229	2.670	0.386
Black property devaluation	0.867	0.144	0.729	0.132	0.669	0.096	0.607	0.105	0.546	0.108
Demographic characteristics										
Total population	1,001,535	1,205,575	914,459	1,159,905	1,392,123	2,681,350	1,770,391	3,716,391	1,693,995	1,940,440
Proportion non-Hispanic Black residents	0.040	0.014	0.057	0.028	0.081	0.051	0.152	0.102	0.206	0.116
Proportion non-Hispanic white residents	0.723	0.293	0.768	0.185	0.748	0.158	0.705	0.160	0.683	0.127
Proportion non-Hispanic Asian residents	0.029	0.037	0.048	0.080	0.045	0.044	0.030	0.024	0.038	0.040
Proportion Hispanic residents	0.202	0.282	0.121	0.130	0.120	0.116	0.106	0.106	0.069	0.052
Socioeconomic & housing conditions										
Median home value ($)	181,090	125,999	196,875	157,780	193,712	99,723	155,838	61,430	189,549	104,727
Homeownership rate	0.645	0.055	0.651	0.050	0.651	0.060	0.659	0.053	0.655	0.038
Poverty rate	0.154	0.041	0.143	0.034	0.130	0.029	0.142	0.024	0.139	0.029
Median income ($)	51,849	10,334	56,072	13,872	57,818	8,932	54,200	7,399	58,266	11,598

Table 4-9. Summary statistics for untransformed regression variables

	Mean	SD
Tract-level predictors (n=12,681)		
Redlining score	2.958	0.780
Proportion population under age 18	0.216	0.079
Proportion population over age 65	0.129	0.060
Population density	17,374	23,266
Relative proportion Black residents	1.904	2.070
CBSA-level predictors (n=133)		
IRH index	1.031	1.825
Total population	1,489,763	2,521,493
Median income ($)	56,333	10,573
Proportion Black residents	0.135	0.108

Table 4-10. Spatial error regression results for diabetes prevalence on historical redlining score and novel IRH index

	Spatial error model		
	Estimate	SE	p-value
Constant	0.0865	0.0080	< 0.0001
Tract-level predictors			
Redlining score	0.0106	0.0005	< 0.0001
Proportion population under age 18	0.0097	0.0002	< 0.0001
Proportion population over age 65	0.0151	0.0003	< 0.0001
Population density	0.0008	0.0002	0.0013
Relative proportion Black residents	0.0107	0.0002	< 0.0001
Cross-level interactions			
Redlining score::IRH	0.0007	0.0002	0.0010
Number of observations	12,668		
Lambda	0.7109	0.0068	< 0.0001
AIC (error model)	-60,740		
AIC (OLS model)	-54,603		

Not shown: CBSA fixed effects

Chapter 5 | CONCLUSION

Collectively, the studies carried out in this dissertation add support to a burgeoning body of literature examining the harmful effects of historical to contemporary institutionalized racism in housing markets on community health and well-being. These studies utilized the historical "residential security maps" developed by the Home Owners' Loan Corporation in the mid-1930s as a reflection of existing patterns and practices within local housing markets at the time they were created. Consistent with prior literature, we found historically redlined neighborhoods today experience a greater burden of poor mental health and diagnosed diabetes relative to neighborhoods graded more favorably. As discussed previously, this dissertation was intended to probe these relationships between historical redlining and contemporary health outcomes and thereby expand upon current understandings of institutionalized racism in housing markets as an important driver of neighborhood health inequities. Broadly, the three empirical chapters examined: (1) the heterogeneity in associations between historical redlining patterns and neighborhood health outcomes based on contemporary neighborhood racial/ethnic composition; (2) neighborhood-level features of contemporary housing markets as mechanisms by which historical redlining may contribute to contemporary prevalence of poor mental health; and (3) how broader contexts of contemporary institutionalized anti-Black racism in local housing markets may reinforce associations between historical redlining patterns and contemporary prevalence of diagnosed diabetes. Below, I provide a brief summary the main findings of these studies and offer implications and future directions for research in this area.

In the first empirical chapter (Chapter 2), I found contemporary neighborhood racial/ethnic composition moderated the relationships between historical redlining patterns and neighborhood prevalence of poor mental health and diagnosed diabetes. The magnitude of these relationships was greater among majority non-Hispanic Black neighborhoods relative to majority non-Hispanic white neighborhoods. In other words, the discrepancy in outcomes between Black-majority and white-majority neighborhoods was most pronounced among historically redlined neighborhoods. Conversely, the magnitude of the relationship between historical redlining score and neighborhood prevalence of poor mental health was smaller among majority Hispanic neighborhoods relative to majority non-Hispanic white neighborhoods. In other words, the discrepancy in outcomes between Hispanic-majority and white-majority neighborhoods was least pronounced among historically redlined neighborhoods. Our findings suggest reparations for long histories of structural racism, exclusion, and violence must be contextualized to the particular communities targeted and the unique challenges they face. Further research is needed to better understand the present conditions within neighborhoods and communities marginalized through historical redlining practices, including specific attention to differential experiences and consequences across racial and ethnic strata. Our findings underscore the need for additional individual- and multi-level analyses that specifically examine effect modification by race/ethnicity as well as cross-level interactions between individual race/ethnicity and neighborhood conditions.

In the second empirical chapter (Chapter 3), I found a substantial portion of the association between historical redlining score and neighborhood prevalence of poor mental health can be explained by contemporary features of local housing markets – specifically, neighborhood property values, homeownership rates, and loan denial rates for home purchase. Further, I found the indirect effect of historical redlining on poor mental health via relative median property value was conditional on the tract-to-CBSA relative proportion of Black residents, where neighborhoods with relative overrepresentations of Black residents showed a reduced indirect effect via relative median property value, as well as a reduced total effect of historical redlining score. In other words, neighborhoods with relative underrepresentations of Black residents exhibited a stronger relationship between historical redlining score and relative median property value, and subsequently between historical redlining score and neighborhood prevalence of poor mental health. This finding suggests that properties in historically “A” graded (or “greenlined”) neighborhoods are valued more than those in neighborhoods graded less favorably – and most importantly, that this apparent benefit to property values is greater in neighborhoods where Black residents are underrepresented. Our findings suggest redlining practices and other exclusionary policies and practices may have contributed to the concentration of wealth in historically “A” graded neighborhoods – particularly those with underrepresentations of Black residents – in ways that may provide mental health benefits to the relative detriment of Black communities. Property appraisal processes must be fundamentally transformed so that racial composition is not considered in appraised values or used as a criterion in identifying comparable neighborhoods. Most importantly, racist ideologies conflating race and value must be dismantled to address the devaluation of assets in Black communities – and its consequences for individual, family, and community health and well-being.

Finally, in the third empirical chapter (Chapter 4), I developed a novel composite index of institutionalized anti-Black racism in housing markets (IRH), which incorporated measures of racial residential segregation, discrimination in mortgage lending practices, and relative property values of neighborhoods with over- and under-representations of Black residents. Confirmatory factor analysis suggested strong associations between Black isolation, Black-to-white odds of loan denial for home purchase, Black-to-white odds of obtaining a high-cost loan, Black property devaluation, and the latent factor of interest. This finding suggests that, among CBSAs with the most segregated concentrations of Black residents, Black residents experience the most severe inequities in access to credit, predatory lending, and property values. Our novel IRH index identifies the places where Black Americans may be facing the greatest barriers to wealth accumulation and social mobility, which have important implications for health across generations. In multilevel regression analyses, I found the IRH index acts as a CBSA-level modifier of the relationship between historical redlining and neighborhood diabetes prevalence, suggesting contemporary forms of institutionalized racism in housing markets may be, in part, maintaining the legacy of historical redlining practices. This analysis shows, however, that there is unexplained variation across CBSAs in the relationship between historical redlining patterns and neighborhood diabetes prevalence. Further research is needed to understand factors and processes by which impacts of historical structural racism are maintained or diminished. Importantly, programmatic and policy approaches to addressing persistent wealth and health inequities affecting Black Americans should consider both historical and contemporary processes of exclusion and discrimination within housing markets.

Broadly, the studies carried out in this dissertation add support to the growing body of literature tying historical redlining patterns and related forms of historical structural racism to contemporary health inequities. Our findings suggest there is heterogeneity in the relationships between historical redlining and neighborhood health outcomes, where the legacy of redlining may have differential effects across population strata and geographic contexts. Further research is needed to better understand the contexts and processes which perpetuate institutionalized racism in local housing markets and downstream impacts on health and well-being. As conveyed throughout this dissertation, our use of an ecological design at the neighborhood level has critical limitations and ultimately prevents causal inference. These studies, however, offer a strong foundation for generating hypotheses which can be tested in future research. As discussed, future research should draw on individual-level and longitudinal data to further our understanding of the impacts of historical to contemporary structural racism on health through neighborhoods contexts and broader social, economic, and political forces. Finally, this body of work aims to not only understand and draw attention to the consequences of historical to contemporary structural racism for health outcomes and inequities – but ultimately to support calls for accountability of the systems and institutions which perpetuate institutionalized racism.

VITA

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