

SEPARATE AND UNEQUAL: A SPATIALLY COMPREHENSIVE ANALYSIS OF
BLACK–WHITE HYPERTENSION DISPARITIES ACROSS THE UNITED STATES

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Geography—Doctor of Philosophy

2022

ABSTRACT

Introduction: It is estimated that hypertension accounts for 50% of the Black-white mortality disparity in the U.S. In seeking to explain this disparity, most studies highlight the role of racial residential segregation – an institutional mechanism designed to protect whites from social interaction with Blacks. Though research has unveiled a significant relationship between racial disparities in health and racial segregation, the socioeconomic characteristics of Black and white designated neighborhoods remain widely unaccounted and controlled for in disparities analysis.

Objective: The objectives of this study were twofold: first, simultaneously capture the racial, spatial, and socioeconomic structure of the United States; second, control for neighborhood characteristics in the analysis of Black-white hypertension

Methods: The Darden-Kamel Composite Socioeconomic Index and Index of Dissimilarity are used to simultaneously capture the racial, spatial, and socioeconomic structure of the U.S., and control for neighborhood characteristics. **Analysis:** A chi-square test of independence established the significance of the relationship between neighborhood high blood pressure (HBP) prevalence and neighborhood socioeconomic position (SEP). ANOVA and Tukey's HSD determined the significance of mean HBP prevalence difference across SEP. A two-proportion z test established the significance of Black-white hypertension proportional differences across SEP's 1 and 5. Finally, binomial regression coefficients at each level of SEP were compared to determine the significance of race/ethnicity a predictor of hypertension at each level of SEP. **Results:** After controlling for neighborhood SEP and adjusting for the interaction between race and sex predictors, regression analysis revealed that race/ethnicity is a statistically insignificant predictor of hypertension at each level of SEP.

ACKNOWLEDGEMENTS

The completion of this dissertation would not have been possible without God's everlasting Grace and favor, and the love, patience, and support of family, friends, and mentors. I extend much gratitude to my dissertation advisor and committee chair, Dr. Joe T. Darden. Dr. Darden's wisdom and support have helped me to navigate various aspects of academic life. As Dr. Darden settles into his retirement, I take great pride in being his last student and knowing that I have the blessing and validation of one of Geography's most legendary scholars as I start my academic career. To my committee members: Drs. Clifford Broman, Reneé Canady, and Igor Vojnovic, you all are leading examples of academic excellence! Going forward, I carry your example with me – only hoping to be as impactful as you all are in your respective fields. As for my mother, Cynthia, your strength and sacrifice has made ALL things possible. Very early in life I learned the value of hard work and commitment to completing whatever task lay before me. Those values are the foundations of my drive and spirit to push forward when facing the seemingly impossible. I've met many "impossible" moments through the course of my PhD journey, but I am sure that your prayers and the values you instilled in me as a child made all things possible. I am eternally grateful. To my brother Javon, thank you for constantly reminding me to stay calm and just breathe. Your humor and perspective are so valued. I thank my husband, Dr. Dennis Ikpe, who is a very talented scholar in his own right, for supporting me through this journey. We are kindred spirits and it has been an amazing experience to grow alongside you all these years. My children, Malik (7) and Mazi (17 mo.) – you two are my inspiration and your belief in me has sustained my motivation to keep pushing no matter what. Lastly, I want to thank the Department of Geography, Environment, and Spatial Science faculty, administrators and staff: Drs. Ashton Shortridge (Department Chair), Allen Arbogast (former Department Chair), Sandy

Marquart-Pyatt (Graduate Program Director), Nathan Moore (Former Grad Program Director), the current Geography Program Coordinator Joni Burns, and retired Geography Program Coordinator Sharon Ruggles. The pioneering Advancing Geography Through Diversity Program (AGTDP) and fellow AGTDP students have enriched my graduate experience. I thank both AGTDP and the American Association of Geographers (AAG) for sponsoring national and regional conference trips and research travel. With much gratitude and sincerity, I thank you all!

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION.....	1
CHAPTER 2: LITERATURE REVIEW	12
CHAPTER 3: DATA	27
CHAPTER 4: METHODS OF ANALYSIS	33
CHAPTER 5: DESCRIPTIVE STATISTICS.....	45
CHAPTER 6: ANALYSIS RESULTS	54
CHAPTER 7: SUMMARY AND CONCLUSIONS.....	84
BIBLIOGRAPHY.....	97

CHAPTER 1: INTRODUCTION

In the United States, hypertension—which is also referred to as high blood pressure (HBP)—is a highly prevalent vascular disease and a major public health concern. The American Heart Association (n.d.) defines Stage 1 hypertension as a systolic blood pressure greater than or equal to 130 mmHg, or diastolic blood pressure greater than or equal to 80 mmHg. Key behavioral risk factors of HBP include smoking, overweight and obesity, physical inactivity, excessive alcohol consumption, and poor diet (Li, 2016). The U.S. Centers for Disease Control and Prevention (CDC, n.d.-a) reported nearly 1 out of 2 adults in the United States have hypertension. Hypertension increases risk of heart disease and stroke, which are leading causes of death in the United States (CDC, n.d.-a). According to the National Institute of Diabetes and Digestive and Kidney Disease (NIDDK, n.d.), hypertension is the second-leading cause of kidney failure in the United States (Hsu & Tain, 2021; Luo et al., 2021; NIDDK, n.d.).

Hypertension Prevalence and Its Burden

HBP causes an accumulation of vascular scar tissue, which leads to constricted blood flow. Blood vessels throughout the body weaken over time, which impairs the function of the heart, brain, and kidneys (CDC, n.d.-c). When this happens, hypertensive patients often suffer from a combination of comorbidities, including heart disease (Ekström et al., 2020), stroke (Cipolla et al., 2018), anxiety or depression (Zhang et al., 2018), coronary artery disease, myocardial infarction, congestive heart failure, and peripheral vascular disease (Long & Dagogo-Jack, 2011).

Hypertension can be severely life altering, especially when it remains untreated for an extended period of time (Zhou, 2018). Hypertensive patients spend countless hours seeking medical care and subsequently experience mounting medical costs. In addition to the individual

financial burden, Benjamin et al. (2019) estimated hypertension care costs the United States \$55.9 billion per year, which includes the cost of health care services, medicines to treat HBP, and missed days of work.

National Hypertension Disparities

Measurable differences exist in hypertension prevalence along age, sex, and race and ethnicity. The CDC's National Center for Health Statistics reported in 2017–2018, the prevalence of hypertension increases with age, from 22.4% among adults aged 18–39, to 54.5% among those aged 40–59, and 74.5% among those aged 60 and over (Ostchega et al., 2020). Although the age-specific prevalence pattern is the same for men and women, men experience a higher prevalence of hypertension overall compared to women at 51.0% and 39.7%, respectively (Ostchega et al., 2020). Nationally, along race and ethnicity, hypertension prevalence is highest among non-Hispanic Black¹ populations (57.1%), compared to non-Hispanic white populations (43.6%) and Hispanics (43.7%; Ostchega et al., 2020). Overall, non-Hispanic Black men (57.2%) and women (56.7%) are disproportionately burdened by hypertension compared to their respective sexes and when compared to other race and ethnicity categories (Ostchega et al., 2020).

In addition to disproportionate Black–white hypertension prevalence, Black populations experience earlier onset and greater symptom severity compared to other racial groups (Mozaffarian et al., 2015; Musemwa & Gadegbeku, 2017). Researchers have also found the progression of prehypertension (i.e., systolic pressure from 120–139 millimeters of mercury [mm

¹ Throughout this dissertation, Black is capitalized, whereas white remains lowercase. For details on the intention behind this action, please see the Brookings Institution articles: (a) “Not Just a Typographical Change: Why Brookings is Capitalizing Black” (Lanham & Liu, 2019); and (b) “A Public Letter to the Associated Press: Listen to the Nation and Capitalize Black” (Lanham, 2020).

Hg] or a diastolic pressure from 80–89 mm Hg) to hypertension occurs more rapidly among Black individuals (Selassie et al., 2011). The “Coronary Artery Risk Development in Young Adults” study found that Black individuals have a higher incidence rate of heart failure before age 50 compared to white Americans (Kershaw et al., 2017), which is considered directly related to hypertension (Bibbins-Domingo et al., 2009; Musemwa & Gadegbeku, 2017). Overall, hypertension is thought to account for 50% of the Black–white mortality disparity in the United States (Musemwa & Gadegbeku, 2017).

The ongoing COVID-19 pandemic is an explicit example of why this investigation of racial health disparities is timely. Early in the COVID-19 pandemic, the CDC proposed that racial and ethnic minorities were disproportionately burdened by COVID-19 due to where they live, where they work, and a high prevalence of underlying health conditions (Aleligne et al., 2021; Benitez et al., 2020; Figueroa et al., 2020; Millett et al., 2020; Williams & Cooper, 2019). At the height of the COVID-19 pandemic, the social distance-driven advisory to work from home was a privilege afforded to mainly professional-class workers. In looking across race, Selden et al. (2020) found non-Hispanic white individuals were more likely to work from home (22.8%) than Black (13.3%) and Hispanic (12.5%, $p < 0.01$) individuals. The Department of Homeland Security (as cited by Kane & Tomer, 2021) outlined a list of 16 essential sectors representing 62% of the U.S. workforce. Compared to non-Hispanic white individuals, the Black population constitutes a large proportion of the essential workforce in health care (32%) and public transit (41%; Selden et al., 2020).

Increased COVID-19 mortality and complications occur with greater incidence in individuals with preexisting conditions, which include hypertension (58.9%), obesity (49.8%), diabetes and metabolic disease (41.5%), and cardiovascular disease (34.5%). These

comorbidities are disproportionately prevalent among the non-Hispanic Black population (Ferdinand et al., 2020). Non-Hispanic Black individuals represented 27.5% of all COVID-19 cases nationally in 2020 despite comprising only 13.4% of the population (Ferdinand et al., 2020). In May 2020, the CDC reported COVID-19 incidence among non-Hispanic Blacks individuals totaled 36.8% of newly reported cases (Ferdinand et al., 2020). The city of Chicago is approximately 29.2% Black (U.S. Census Bureau, n.d.-b). However, as of April 20, 2020, 45.6% of the confirmed COVID-19 cases were among Black residents, compared to only 20.4% of white residents (Illinois Department of Public Health, n.d.; Kim & Bostwick., 2020). COVID-19 mortality rates in Chicago revealed a similar pattern; 56% of the deaths at that time were among Black individuals, and 15.8% were White (Illinois Department of Public Health, n.d.; Kim et al., 2020). In 2020, despite Black Michigan residents comprising only 15% of the state's population, they represented 35% of people diagnosed with COVID-19, and accounted for 40% of all COVID-19 deaths statewide (Ray, 2020). The outlined COVID-19 disparities represent the fallout of an enduring tradition of systemic racism (Bharmal et al., 2015). America's housing system is one of many institutions that perpetuate systemic racism and oppression (Franz et al., 2022; Yu et al., 2021).

The history of racial residential segregation has been well documented across the United States. U.S. cities and their surrounding suburbs were largely shaped by residential segregation practices by white real estate brokers, apartment managers, and mortgage lenders who took actions to exclude Black populations from most of the predominantly white neighborhoods in central cities and from most surrounding suburban municipalities (Darden et al., 1987; Roberts et al., 2022; Sampson et al., 2022). Before the 1968 Fair Housing Act, these practices were

widespread and kept most Black individuals—even those who were middle class—out of predominantly white neighborhoods in U.S. cities and surrounding suburbs (Darden et al., 1987).

In conjunction with practices of outright Black exclusion, cities across the United States practiced what is known as redlining. During the Great Depression, the Home Owners Loan Corporation authorized maps that guided home lending institutions in preventing nonwhite racial and ethnic groups from establishing residence in white neighborhoods (Hillier, 2003). Predominantly Black neighborhoods were designated as undesirable for lenders and were outlined in red on these maps; this practice is now known as *redlining* (Bailey, 2017; Wilson, 2009). Those racially discriminative housing practices had an enduring legacy (Lynch et al., 2021; Sampson, 2022). As of 2022, many neighborhoods that were once redlined tend to be predominantly Black or Latinx, the most socioeconomically deprived, and home to residents with a high prevalence of poor self-rated health (Lynch et al., 2021; McClure et al., 2019; Williams & Collins, 2016). Redlining was a form of disinvestment (Sadler & Lafreniere, 2017) and various forms of neighborhood disinvestment remain in practice (Berglund, 2020; Chamberlain, 2018; Jang, 2020).

The applied methodology of this dissertation study offered an opportunity to examine the relationship between race-based residential segregation and neighborhood socioeconomic status and their combined effects on health. For many years, health disparities studies have investigated both individual and neighborhood-level factors relating to health outcomes (Coulon et al., 2016; Dubowitz et al., 2012; Jones, 2013; Kershaw et al., 2011; Mujahid et al., 2011; Robinette et al., 2017, 2021; Ross et al., 2008; Rukmana et al., 2021; Sadler et al., 2017). The goal was to investigate the significance of place in the observed national Black–white hypertension disparity prevalence gap. Because Black and white populations have been historically, and remain to

present day, residentially separated into different neighborhoods of unequal quality (Berkowitz et al., 2022; Darden et al., 2019), the practice of accounting and controlling for neighborhood characteristics in Black–white health disparities analysis is necessary (Darden et al., 2010).

Theoretical and Conceptual Framework: Neighborhood Effects

The overarching aim of this study was guided by the neighborhood effects theoretical and conceptual frameworks. Neighborhood effects is the belief that the characteristics of communities affect the life chances of individuals within them (Sharkey et al., 2014). Studies have shown Black–white neighborhood effects differ distinctly (Diez Roux, 2001). Differential neighborhood effects, which are the result of differing neighborhood characteristics, contribute to health disparities by race (Diez Roux, 2001).

There are four basic research approaches to the study of neighborhood effects: (a) concentrated poverty, (b) social processes and mechanisms, (c) social observation, and (d) space–time analyses (Darden et al., 2010). This study was conducted using the conceptual and theoretical framework of neighborhood effects first conceptualized by Wilson (1987) in his book, *The Truly Disadvantaged*. Wilson studied the influence of concentrated neighborhood poverty (i.e., fewer than 40% residents impoverished) on the creation and continued existence of a social underclass. Wilson argued this underclass is perpetually prevented from upward mobility because it is isolated from socioeconomic opportunities.

Continuing in the tradition of Wilson’s (1987) perpetual underclass arguments, Massey and Denton (1993) highlighted connections between residential segregation and concentrated poverty by proposing that those residing in segregated neighborhoods are most vulnerable to concentrated poverty (Moody, 2014). In 2008, researchers Ross and Mirowsky hypothesized that

the perpetual cycle of economic hardship (i.e., the state of belonging to a “perpetual underclass” [Wilson, 1987]) erodes one’s health (Moody, 2014).

Neighborhood effects on health scholarship was further validated with the U.S. Department of Housing and Urban Development’s Moving to Opportunity (MTO) program (Darden et al., 2010), which based its policy research on the idea that tenants living in neighborhoods of concentrated poverty and concentrated race have poor health outcomes (Acevedo-Garcia et al., 2004). MTO began in 1994 and was the first multisite experimental study of neighborhood effects. The program was designed to answer questions about what happens to families of low socioeconomic status when they are given the opportunity to move out of distressed public housing in the most impoverished neighborhoods of five very large metropolitan areas (i.e., Baltimore, Boston, Chicago, Los Angeles, and New York City). Using a randomized experimental design, researchers and policy analysts investigated the long-term effects of living in poor neighborhoods, and measured whether and how families who moved improved their lives in such areas as employment, earnings, educational attainment, and health compared to those left in their poverty-stricken neighborhoods. Though results were mixed regarding neighborhood effects on employment, earnings, and educational attainment, the researchers found large and statistically significant positive effects on the mental health of adults and girls who changed neighborhoods (Darden et al., 2010).

Focus of the Study

This dissertation study advanced knowledge of neighborhood effects on health by being the first to apply the Modified Darden-Kamel Composite Socioeconomic Index (Darden-Kamel Index; Darden et al., 2010) methodology to the simultaneous capturing of the racial, spatial, and socioeconomic structure of the entire United States. Additionally, the 2019 Medical Expenditure

Panel Survey (MEPS), which is a national health survey, was used to investigate disparities in hypertension diagnosis among non-Hispanic Blacks and whites who reside in similar and different SEP, which allowed for robust national population estimates. Though this study is grounded in the tradition of Wilson's (1987) conceptual framework of concentrated poverty, I did not solely focus on the effects of concentrated poverty on Black–white hypertension disparity. Rather, I focused on the composite effect of nine socioeconomic characteristics and their contribution to Black–white disparities in hypertension. Another important feature of this study is that it is spatially driven. Despite Black and white populations residing in different neighborhoods, the applied methodology allowed me to control neighborhood characteristics across the United States during analysis. The methods that were employed to control for neighborhood characteristics are outlined in Chapter 4 of this dissertation.

Black-white Differences in Neighborhood Characteristics

Despite widespread understanding of hypertension and its burden on the population, hypertension disparities analysis methods are varied (LaVeist et al., 2011; Morenoff et al., 2007; Smith et al., 2020; Thorpe et al., 2008). In this dissertation, I sought to establish the significance of controlling for those differences in neighborhood characteristics in the analysis of Black–white hypertension disparities and demonstrate the effect of doing so across the entire United States. Some investigations of health disparities place emphasis on the role of residential segregation and/or neighborhood socioeconomic status (SES; i.e., income, education, and occupation; Darden et al., 2010) but racial residential segregation and neighborhood SES variables do not thoroughly capture the composite effect of characteristics that simultaneously contribute to the overall context and experience of a neighborhood (Darden et al., 2010). Due to Black and white populations mostly residing in different neighborhoods of different

characteristic, I controlled for neighborhood characteristics in this dissertation by utilizing nine 2016-2020 American Community Survey (ACS) variables to compute a composite z score for most neighborhoods across the United States. Composite z scores, which are formally referred to as a composite socioeconomic index (CSI) scores, were sorted and split into quintiles along the 20th, 40th, 60th, and 80th percentile and subsequently assigned a neighborhood socioeconomic position (SEP) score based upon the quintile ranking. The indexing of neighborhoods across the entire United States allowed me to identify where non-Hispanic Blacks and whites are located across neighborhood SEP and ultimately investigate the significance of the relationship between neighborhood SEP and hypertension prevalence and the role of neighborhood SEP in the measured national Black–white hypertension disparity gap. Underscoring how Blacks and whites are distributed across neighborhood SEP and the significance of the composite effect of neighborhood characteristics will hopefully provide opportunities to consistently engage in discussions about systemic racism and increase the efficiency of health policy and interventions.

Study Objectives and Hypotheses

The overarching purpose of this study was to investigate the significance of place in the observed national Black-white hypertension disparity prevalence gap. Study objectives, however, were twofold: (a) simultaneously capture the racial, spatial, and socioeconomic structure of the United States; and (b) control for neighborhood characteristics in the analysis of Black–white hypertension disparities. The objectives of this study allowed for the investigation of the following hypotheses:

1. There is an inverse relationship between HBP prevalence and neighborhood SEP. The highest HBP prevalence rates will be in SEPs 1 and 2 (i.e., very low and low

- neighborhood characteristic) and the lowest HBP prevalence rates will be in SEPs 4 and 5 (i.e., high and very high neighborhood characteristic);
2. The mean neighborhood HBP prevalence rate at each level of SEP is significantly different, with the highest prevalence rates being in SEPs 1 and 2 and the lowest being in SEPs 4 and 5;
 3. The hypertension prevalence gap between non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1 will be similar² to the prevalence gap between non-Hispanic whites in SEP 5 and non-Hispanic Blacks in SEP 1;
 4. The non-Hispanic Black–white HBP prevalence gap narrows when non-Hispanic Blacks and whites live in neighborhoods of similar SEP.

Methods Employed

The use of the Darden-Kamel Index in conjunction with the Index of Dissimilarity (Massey & Denton, 1988) allowed for the simultaneous capturing of the racial, socioeconomic, and spatial structures of the entire United States in the analysis of racial disparities in hypertension. Simultaneously capturing the racial, socioeconomic and spatial structure of the entire United States laid the foundation for the control of neighborhood characteristics in hypertension disparities analyses.

Through the application of the Darden-Kamel Index, I used nine variables to analyze and quantify neighborhood characteristic across the United States. I controlled for neighborhood characteristic by calculating the neighborhood SEP of most U.S. census tracts (Darden et al., 2010). SEP includes socioeconomic status (SES) variables such as income, education and

² The non-Hispanic Black SEP 5 and non-Hispanic white SEP 1 proportional difference and the non-Hispanic white SEP 5 and non-Hispanic Black SEP 1 proportional difference are considered similar if their two-proportion difference z test 95% confidence intervals overlap.

occupation, plus additional variables related to socioeconomic characteristics of neighborhoods.

The nine 2016-2020 ACS variables used to compute Neighborhood SEP are percentage of poverty, percentage unemployed, median income, percentage of vehicle ownership, percentage professional and managerial jobs, percentage bachelors' degree or higher, median house value, median monthly rent, and percentage of home ownership. There are five levels of SEP: very high SEP (VHSEP), high SEP (HSEP), middle SEP (MSEP), low SEP (LSEP), and very low SEP (VLSEP): VHSEP = 5, HSEP = 4, MSEP = 3, LSEP = 2, VLSEP = 1. Controlling for neighborhood SEP presented a spatially comprehensive approach because most neighborhoods in a defined geographic area, for which a composite socioeconomic index (CSI) score can be calculated, were incorporated in analysis. The details around how SEP and the dissimilarity index score are computed are outlined in Chapter 4 of this dissertation.

CHAPTER 2: LITERATURE REVIEW

The objectives of this literature review are threefold: (a) highlight the methodologies and neighborhood characteristic variables used to investigate neighborhood characteristics as a pathway to adverse health outcomes; (b) outline and compare the methodologies used to control for neighborhood characteristics in hypertension disparities analysis; and (c) investigate the contribution of the Modified Darden-Kamel Composite Socioeconomic Index (Darden-Kamel Index) methodology to the study of health disparities. The intention of this review is to facilitate an understanding of how my dissertation's approach to the control of neighborhood characteristics not only offers a means of establishing neighborhood characteristics as a pathway to hypertension disparities, but also presents evidence to suggest that this method is a more comprehensive and efficient means of doing so when generating national population estimates.

I begin my review with Ross and Mirowsky's (2008) study that investigated the relationship between concentrated poverty and poor health outcomes. This study is a significant starting point in my review of literature because their study was indirectly inspired by the tradition of Wilson's (1987) conceptualization of concentrated neighborhood poverty (Moody, 2014). Additionally, this study marks a point in scholarship when some investigators began to consider the possibility that neighborhood socioeconomic characteristics not only have an impact on one's health, but possibly more of an impact on one's health than individual socioeconomic characteristics.

Similar to Ross and Mirowsky (2008), other researchers set out to investigate neighborhood characteristics as a pathway to adverse health outcomes. The studies outlined in the section titled "Neighborhood Characteristics and Health Outcomes" (Section 1) represent a sample of studies that investigate neighborhood characteristics as a pathway to adverse health

outcomes. Section 1 also provides a good overview of variables commonly used to define neighborhood characteristics: i.e. concentrated neighborhood poverty, walking environment, availability of healthy foods, perceived safety, social cohesion, segregation and hyper-segregation, neighborhood satisfaction, crime, income, housing age and condition, and vacancy. Some of the Section 1 studies examine hypertension outcomes, which is the investigated health outcome of this dissertation, whereas others investigate BMI, changes in blood lead level (BLL), and mental health.

Neighborhood Characteristics and Health Outcomes

Ross and Mirowsky (2008) performed their investigation in the city of Chicago researched whether neighborhood poverty affects health after adjusting for individual SES ($n = 2,592$). They hypothesized, “Neighborhood socioeconomic status has effects on residents' levels of physical functioning and impairment over and above their own sociodemographic characteristics” (Ross & Mirowsky, 2008, p. 9). Multilevel regression analysis revealed individuals reported better physical functioning in higher SES neighborhoods (regression coefficient = 0.027; $p < 0.001$) and neighborhood SES was a statistically significant predictor of physical impairment (regression coefficient = 0.036; $p < 0.001$; Ross & Mirowsky, 2008).

Mujahid et al. (2011) investigated cross-sectional associations between neighborhood features and hypertension and examined the sensitivity of results to various methods of estimating neighborhood conditions. Health data were sourced from the Multi-Ethnic Study of Atherosclerosis on 2,612 individuals 45–85 years of age. Participants were recruited between August 2000–July 2002 from six study sites (i.e., Baltimore, Maryland; Chicago, Illinois; Forsyth County, North Carolina; Los Angeles, California; New York, New York; and St. Paul, Minnesota). The researchers measured neighborhood (i.e., census tract) conditions potentially

related to hypertension (e.g., walking environment, availability of healthy foods, food outlet type, safety, social cohesion) using information from a separate phone survey conducted in the study neighborhoods.

For each neighborhood, Mujahid et al. (2011) estimated scale scores by aggregating residents' responses using simple aggregation (i.e., crude means) and empirical Bayes estimation (i.e., unconditional, conditional, and spatial). The estimates of neighborhood conditions were linked to each study participant based on census tract of residence. Two-level binomial regression methods were used to estimate adjusted associations between neighborhood conditions and hypertension. Analysis results revealed residents of neighborhoods with greater walkability, availability of healthy foods, safety, and social cohesion were less likely to be hypertensive after adjusting for site, age, sex, income, and education.

Dubowitz et al. (2012) analyzed cross-sectional associations between the availability of different types of food outlets in the 1.5 miles surrounding a woman's residence and census tract neighborhood socioeconomic status (NSES), body mass index (BMI), and blood pressure (BP). Data ($n = 60,775$ women) from the Women's Health Initiative Clinical Trial—a national study of postmenopausal women aged 50–79—were used along with six U.S. Census NSES variables at the census tract level. The researchers simultaneously modeled NSES and food outlets using linear and logistic regression models, adjusting for multiple sociodemographic factors, population density, and random effects at the tract and metropolitan statistical area level. Analysis results revealed as NSES increased from the 10th to the 90th percentile, systolic and diastolic BP were lower by 1.11 mm and 0.40 mm Hg, respectively (Dubowitz et al., 2012).

Jones (2013) examined how segregation and SES (individual and metropolitan) impacted hypertension outcomes for a sample of 200,102 individuals. Nationally representative individual-

level health data were used for analysis from the 2005 Behavioral Risk Factor Surveillance System (BRFSS) and 2005 American Community Survey (ACS) data. Multilevel analyses indicated both segregation and hyper-segregation are associated with hypertension, net of individual and spatial SES (Jones, 2013). Individual and metropolitan SES had independent effects on hypertension, but these effects also differed across segregation type. In segregated and hyper-segregated environments, highly educated and high-earning individuals seemed to be protected against hypertension. In extremely hyper-segregated areas (i.e., areas where very little interaction exists with non-Black residents), SES does not have any protective benefit. Findings revealed SES has differential effects across segregation types and hypertension in disadvantaged (i.e., extremely hyper-segregated) areas may be a function of structural constraints rather than SES (Jones, 2013).

Coulon et al. (2016) set out to investigate (a) whether neighborhoods do in fact account for meaningful variation in BP; (b) if there was a direct association between poverty and BP across neighborhoods; (c) if there were direct and interacting associations of perceived crime and neighborhood satisfaction on BP across individuals; and (d) finally, whether these individual associations differed across neighborhoods. The researchers hypothesized greater neighborhood poverty would be related to higher BP, and neighborhood satisfaction would buffer the negative association of high perceived crime on BP in three at-risk communities in South Carolina. Coulon et al. used a multilevel modeling approach to allow estimation of effects occurring at individual and neighborhood levels of analysis, and to account for the nesting of data within neighborhoods/block groups. Analysis results revealed neighborhood-level poverty was associated with elevated diastolic ($\gamma = 11.48$, $SE = 4.08$, $P = 0.008$) and systolic ($\gamma = 12.79$, $SE = 6.33$, $P = 0.052$) BP readings.

Sadler et al. (2017) investigated contextual neighborhood factors that were suspected of leading to increased blood lead level (BLL) risk following widespread lead-in-water contamination in Flint, Michigan. Using geocoded 2013 and 2015 BLL data and areal interpolation, Sadler et al. predicted BLLs at every residential parcel in Flint. Social and built environmental variables were spatially joined to link the parcels with neighborhood-level factors that were believed to influence BLLs. A comparison of BLLs before and during the Flint water crisis revealed the highest estimates of predicted BLLs during the water crisis and the greatest changes in BLLs in neighborhoods with the following characteristics: longest water residence time in pipes, oldest house age, and poorest average neighborhood housing condition.

Robinette et al. (2017) examined the relation between neighborhood income and the development of new chronic health conditions over a 10-year period. Robinette et al. hypothesized higher neighborhood income would be associated with a lower incidence of health conditions 10 years after an initial health assessment. Data came from the National Midlife in the United States (MIDUS) study. The MIDUS study was conducted in 1994 and follow-up studies were conducted in 2004 and 2014. Robinette et al.'s reported findings pertained to the 2004 and 2014 participants, who were drawn from random-digit dialing procedures (43.06%), oversampling in five metropolitan areas (18.92%), and some siblings and twins of the 1994 MIDUS study participants (38.03%). The 2004 and 2014 follow-up survey assessment measures were: (a) chronic health conditions (both mental and physical); (b) neighborhood socioeconomic status (SES; median household income at census tract level); (c) neighborhood tenure (number of years lived in their neighborhood or township); and (d) covariates (income from personal wages, pensions, social security, and government assistance; Robinette et al., 2017).

The MIDUS follow-up studies (as cited by Robinette et al., 2017) used multinomial logistic regression analyses, adjusting for individual income and sociodemographic variables, to investigate whether higher neighborhood income was associated with a lower incidence of health conditions 10 years after an initial health assessment. Findings indicated the odds of developing two or more new health conditions (i.e., no new health conditions as referent), was significantly lower (OR = 0.92, CI [0.86, 0.99]) for every \$10,000 increment in neighborhood income.

Pearson et al. (2019) examined the relationship between neighborhood vacancy and mental health with adjustment for length of residence and possible moderation by social (dis)integration in a sample of Flint, Michigan, residents. Pearson et al. used both survey and neighborhood vacancy data to investigate the effects of length of residence, neighborhood vacancy rates, and social disintegration on mental health measures. Pearson et al. (2019) also examined whether disintegration moderates the relationship between vacancy and which neighborhood characteristics predict social disintegration.

Regression modeling results revealed that short-term increases in neighborhood vacancy were associated with poor mental health after adjustment for individual covariates. Additionally, Pearson et al. (2019) found social integration diminishes the relationship between neighborhood vacancy and mental health outcomes. Results suggested social conditions of neighborhoods may be important, particularly in places that have experienced declines in the built environment. Finally, Robinette et al. (2021) examined whether perceived neighborhood cohesion (i.e., the extent to which neighbors trust and count on one another) buffered against the mental health effects of the 2020 COVID-19 global pandemic. The researchers surveyed U.S. adults ($n = 3,965$; M age = 39 years), measuring depressive symptoms, tendency to stay home more during than before the 2020 COVID-19 global pandemic, and perceived neighborhood cohesion. A

series of linear regressions indicated perceiving one's neighborhood as more cohesive was not only associated with fewer depressive symptoms, but also attenuated the relationship between spending more time at home during the pandemic and depressive symptoms. These relationships persisted even after considering several individual-level sociodemographic characteristics and multiple contextual features, including median household income, population density, and racial and ethnic diversity of the zip codes in which participants resided.

To summarize, the aforementioned studies outline connections between neighborhood characteristics and health outcomes. Neighborhood characteristics—such as age of housing stock, neighborhood poverty, vacancy, income, and social cohesion, among others—were found to be significantly associated with health outcomes across all aforementioned studies. As such, one can reasonably assume that exposure to adverse neighborhood characteristics can lead to poor health outcomes. Despite poor neighborhood characteristics being an established pathway to adverse health outcomes, this dissertation is the first to apply a spatially comprehensive approach to the capturing of neighborhood characteristics across the United States in order to account and control for the differing neighborhood characteristics of non-Hispanic Blacks and whites in disparities analysis. In the next section, which is titled “Neighborhood Characteristics and Hypertension Disparities” (Section 2), I highlight how some studies have attempted to control for the differing neighborhood characteristics of Blacks and whites in hypertension disparities analysis.

Neighborhood Characteristics and Hypertension Disparities

To investigate the role of neighborhood characteristic in Black–white hypertension disparities, Morenoff et al. (2007) analyzed the contribution of residential neighborhood sociodemographic context to social disparities in hypertension prevalence, awareness, treatment,

and control. Data from The Chicago Community Adult Health Study were used to estimate socioeconomic and racial–ethnic disparities in the prevalence, awareness, treatment, and control of hypertension, and to analyze how these disparities related to the areas in which people live. Census tracts were used as neighborhood proxies and factor analysis was used to develop a mean set of factors that capture the shared variance of neighborhood characteristics. The four factors were socioeconomic disadvantage, neighborhood affluence/gentrification, racial/ethnic/immigrant composition, and older age composition, and they were used to adjust social disparities in BP for neighborhood context. In total, 20 U.S. Census sociodemographic variables³ from the 2000 U.S. Census were used to define the “social context” of each neighborhood across the city of Chicago. Morenoff et al. found Black individuals and people with lower levels of education had significantly higher odds of hypertension than their respective comparison groups (i.e., white people and people with 16 or more years of education); yet, after adjusting for neighborhood context, these disparities diminished and became statistically insignificant (Morenoff et al., 2007).

Thorpe et al. (2008) set out to explore whether Black–white disparities in hypertension would persist if Blacks and whites are exposed to similar social environments. The researchers compared data from the Exploring Health Disparities in Integrated Communities-South West Baltimore (EHDIC-SWB) study with the National Health and Nutrition Examination Survey (NHANES, 1999–2004) to determine if race disparities in hypertension in the United States were attenuated in the EHDIC-SWB sample, which was based in a racially integrated southwest

³ Twenty variables from Morenoff et al.’s (2007) study: percentage families with income less than \$10k, families with income \$50k or higher, families in poverty, families on public assistance, unemployed in civilian labor force, families female headed, never married, less than 12 years of education, 16 or more years of education, professional/managerial occupation, non-Hispanic Black, Hispanic, foreign born, homes owner occupied, in same residence in 1995, 0–17 years old, 18–29 years old, 30–39 years old, 50–69 years old, 70+ years old.

Baltimore, Maryland community without race differences in income. After adjustment for potential confounders—various analytic models from EHDIC-SWB and NHANES 1999–2004 data—Thorpe et al. found the race odds ratio was between 29% and 34% smaller in the EHDIC-SWB sample. Thorpe et al. concluded social and environmental exposures explained a substantial proportion of the race difference in hypertension.

LaVeist, et al. (2011) set out to investigate whether racial health disparities in hypertension, diabetes, obesity among women, and use of health services persisted among (as reported in national studies) Black and white Americans living in integrated settings. LaVeist, et al. (2011) identified communities in the United States that contained at least 35% Black and at least 35% white residents; had a ratio of Black-to-white median income between 0.85 and 1.15; and had a ratio of Black-to-white high school graduation rates (among people aged 25 and above) between 0.85 and 1.15. Ultimately, 425 tracts met the inclusion criteria, and two adjoining tracts in southwest Baltimore, Maryland, were selected as the first study site. In-person interviews were conducted with adult residents (ages 18 and older) of the southwest Baltimore study site. Local survey response data were compared to national data from both the NHANES and Medical Expenditure Panel Survey (MEPS). Findings revealed nationally reported disparities in hypertension, diabetes, obesity among women, and use of health services either vanished or substantially narrowed among the subject population, with the exception of disparities in smoking: white residents were more likely than Black residents to smoke, underscoring the higher rates of ill health in white residents in the southwest Baltimore sample than seen in national data (LaVeist, et al., 2011).

Finally, Smith et al. (2020) investigated the impact of living in a gentrifying neighborhood on Black–white hypertension disparities. Data from the ACS were used to identify

gentrifying neighborhoods across the United States from 2006–2017. Health and demographic data were obtained for non-Hispanic Black and white respondents of the 2014 MEPS residing in gentrifying neighborhoods. Modified Poisson models were used to determine whether there was a difference in the prevalence of hypertension of individuals by their race and ethnicity for those who lived in gentrifying neighborhoods across the United States. When compared to white residents living within gentrifying neighborhoods, Black individuals living in gentrifying neighborhoods had a similar prevalence of hypertension after adjusting for 11 individual variables (Smith et al., 2020).

Though the aforementioned studies controlled for neighborhood characteristic in their analysis of Black–white hypertension disparities and presented strong evidence that Black–white hypertension disparities diminish when Black and white residents are exposed to similar neighborhood characteristics, their characterization of neighborhoods did not simultaneously capture the racial, socioeconomic, and spatial structure of a defined area. Furthermore, with the exception of Morenoff et al.’s (2007) study, the socioeconomic characteristics used to define a neighborhood were not applicable to most neighborhoods within a defined space – only gentrifying, racially integrated, and neighborhoods with similar income among Blacks and whites were analyzed. The applied Darden-Kamel Index methodology of this dissertation study, however, effectively included most U.S. neighborhoods in analysis and used aggregate population health data and a large national health survey to produce robust national population estimates. Population estimates are important for policy formation, evidence-based decision making, and monitoring progress towards achieving population level health goals (Spoorenberg, 2020).

Finally, although Morenoff et al. (2007) captured the socioeconomic characteristics of all neighborhoods within the city of Chicago, my study: (a) simultaneously captured the racial, socioeconomic, and spatial structure of the entire United States; and (b) unlike factor analysis, the Darden-Kamel Index derived neighborhood SEP scores provided a clear and single neighborhood SEP index score for each neighborhood included in analysis. Morenoff's et al. (2007) factor analysis approach produces four factor categories, and though these four factor categories are controlled for in the analysis of racial disparities in hypertension across the city of Chicago, one cannot easily assign meaning to each of the four categories. For instance, the neighborhood disadvantage factor category is not a neighborhood characteristic type on its own, as opposed to SEP 1 which equates to very low socioeconomic position (VLSEP). As seen in Chapter 4, there is no ambiguity around what it means to live in a VLSEP neighborhood. The factor category of neighborhood disadvantage cannot be explained in the same way. Additionally, the composite effect of the four factor categories, which essentially represents four uncorrelated variables, is not considered. The applied Darden-Kamel Index methodology of this study accounts for the composite effect of nine uncorrelated (Moody, 2014) variables on measurable Black-white hypertension disparities. The final section of this chapter, which is titled "A Spatially Comprehensive Analysis of Black-white Hypertension Disparities" outlines the results of two studies that applied the Darden-Kamel Index methodology to the analysis of Black-white health disparities in Metropolitan Detroit.

A Spatially Comprehensive Analysis of Black-white Hypertension Disparities

Racial residential segregation has been a barrier to the analysis of disparities among Black and white populations who are exposed to similar neighborhood characteristics because Blacks and whites, more often than not, live in different neighborhoods of different

characteristics (LaVeist, 2005). Despite the inherent spatial barriers posed by racial residential segregation, the Darden-Kamel Index allows for the control of neighborhood characteristics across space, thereby making possible the analysis of disparities among Black and white residents who are exposed to similar neighborhood characteristics.

In Darden et al.'s (2010) review of Black–white health outcome studies, they noted Black and white population groups living in the same neighborhood (i.e., integration) had more similar health outcomes than groups living in different neighborhoods (i.e., segregation). Researchers also suggest that patterns of integration and segregation alone are insufficient to explain health disparities by race. Socioeconomic characteristics of neighborhoods where Black and white populations reside must also be considered to explain health disparities (Bayer & McMillan, 2005; Polednak, 1993).

As such, Darden et al. (2010) proposed that assessment of neighborhood effects using census tract socioeconomic data as surrogates for neighborhood characteristic is an effective method to capture the racial, socioeconomic, and spatial structures of a metropolitan area and should be done to lay the foundation for the study of health disparities. To date, the Darden-Kamel Index has only been applied to the Detroit metropolitan area. With this dissertation, I expanded upon the highlighted findings of this section by applying the Darden-Kamel Index to the capturing of racial, socioeconomic, and spatial structures of the entire United States. Additionally, I use a national health survey dataset that allows for the calculation of national population estimates. Nationally representative population estimates are ideal for the formulation and implementation of effective health policies and interventions (Spoorenberg, 2020). Though the Darden-Kamel Index is one of many methods used to capture the socioeconomic structure of a metropolitan area, it is the only one that has been used to simultaneously capture the racial,

socioeconomic, and spatial structures of the entire United States and was the one used for this dissertation.

Darden et al.'s (2010) approach to the study of racial health disparities was significant because health policymakers have acknowledged health disparities exist between high-income white populations and low-income Black populations at various geographic scales, such as zip code and county level; however, analysis of how much health disparities vary depending on the comprehensive characteristics of neighborhoods is not as well known (Darden et al., 2010). The applied Darden-Kamel Index methodology is the most spatially comprehensive approach to the study of disparities because it can be used to capture the majority of neighborhoods within any defined geographic area, i.e. city, county, or metro area.

Grady and Darden (2012) presented a contemporary case study of racial disparities in low birth weight (i.e., infants born at $< 2,500$ g) in the Detroit metropolitan area. Specifically, they investigated the effect of racial clustering and SEP levels on low birth weight. Two-level hierarchical generalized linear models with a logit link function were used to predict low birth weight as a function of maternal and neighborhood-level characteristics. Grady and Darden found the levels of SEP in one's neighborhood was more important in predicting intrauterine growth restriction than the level of racial residential segregation. Additionally, very low SEP was associated with a significant reduction in Black–white intrauterine growth restriction disparities (Grady & Darden, 2012).

Moody (2014) investigated if average BLLs of children in the Detroit metropolitan area were related to composite socioeconomic characteristics of the neighborhoods in which they lived. Difference in mean testing revealed that Black and white children living in VLSEP neighborhoods experienced similar BLLs, whereas Black and white children only above age 6 in

VHSEP neighborhoods experienced similar BLLs. However, Black children in low, middle, and high SEP neighborhoods had significantly greater BLLs. Additionally, when Black children resided in neighborhoods of the very high SEP and white children resided in neighborhoods of very low SEP, white children's mean BLLs were greater than those of Black children (Moody 2014).

Grady and Darden's (2012) and Moody's (2014) studies were both conducted in metropolitan Detroit (i.e., Wayne, Oakland, and Macomb counties) and represent a sample of the first studies to simultaneously capture the racial, spatial, and socioeconomic structure of an entire metropolitan area. Their findings suggested that after controlling for neighborhood characteristics, Black–white disparities in intrauterine growth restriction and elevated BLLs decreased. However, in the case of Moody (2014), Black children in low, middle, and high SEP had significantly greater BLLs. The results of this dissertation study revealed some similarities to that of Grady and Darden (2012) and Moody (2014). A national scale application of the Darden-Kamel Index methodology is timely because diseases such as hypertension are among the most burdensome to U.S. population, both directly and indirectly as a leading comorbidity of heart disease, kidney disease, and COVID-19.

Despite Blacks and whites predominantly living in different neighborhoods, this study captures where Blacks and whites are distributed across neighborhood type (i.e., neighborhood SEP across the entire United States). Given that each SEP has a defined set of characteristics, it allows a clear sense of the exposures that the majority of each population are exposed to. Chapter 4 of this dissertation underscores the varied neighborhood level experiences of non-Hispanic Blacks and whites.

Scaling the application of the Darden-Kamel Index methodology to that of the national scale allows for national population estimates which are useful in terms of evidence-based public health policy planning and implementation (Spoorenberg, 2020). This study will hopefully elevate the United States prioritization of addressing major public health crises through a spatial lens. A spatially conscious approach to the analysis and interpretation of measured Black-white health disparities presents a unique opportunity for the United States to face its truth: neighborhoods that facilitate either good or bad health are by design (LaVeist, 2011; Sadler & Lafreniere, 2017). Acknowledgment of that truth comes with a choice to either perpetuate the cycle of health disparities or strategically intervene and disrupt the disproportionate exposure of marginalized populations to neighborhood conditions that contribute to the sustaining of Black - white health disparities.

CHAPTER 3: DATA

The United States consists of 50 states and the District of Columbia (DC). The U.S. Census Bureau (2020) reported a national population of 331,449,281 as of April 1, 2020. Of the total U.S. population, 12.1% identified as non-Hispanic Black and 57.80% identified as non-Hispanic white. The five states with the highest non-Hispanic Black populations were DC (40.91%), Mississippi (36.44%), Louisiana (31.18%), Georgia (30.60%), and Maryland (29.06%; U.S. Census, 2020). The five states reporting the highest percentage of non-Hispanic whites were Maine (90.16%), West Virginia (89.14%), Vermont (89.13%), New Hampshire (87.16%), and Montana (83.13%; U.S. Census, n.d.-a).

Though non-Hispanic Blacks and whites constitute larger population proportions in some states relative to others, I analyzed hypertension disparities among non-Hispanic Black and white populations at census tract levels across all 50 U.S. states and DC. This study was national in scope, but the geographic scale of analysis was at census tract level (i.e., neighborhood level). Despite a lack of scholarly consensus regarding whether census tract or block group analysis is best, the areal unit known as census tract has been found to most significantly capture sociodemographic characteristics of a neighborhood at a small scale (Darden et al., 2010; Krieger et al., 2003; Moody, 2014) while also consistently capturing socioeconomic gradients in health (Grady, 2006; Moody, 2014; Subramanian et al., 2005).

Neighborhood and census tract were used synonymously in this study, but technically, the U.S. Census Bureau (n.d.-e) defines a census tract as a “small, relatively permanent statistical subdivision of a county or statistically equivalent entity . . . [they] generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people” (para. 31). Census

tracts are a quantitative unit of sorts and served as the operational definition of *neighborhood* for this study.

This study focuses on the neighborhood characteristics and hypertension prevalence of America's non-Hispanic Black and white resident population. The American Community Survey (ACS) is an ongoing survey that captures the sociodemographic data of America's entire resident population. ACS gives communities the information they need to plan investments and services (U.S. Census, n.d.-c). The survey covers a broad range of topics on social, economic, demographic, and housing characteristics of the U.S. population. The 5-year estimates from the ACS are "period" estimates that represent data collected over a period of time. The primary advantage of using multiyear estimates is increased statistical reliability of the data for less populated areas and small population subgroups (U.S. Census, n.d.-c). The 5-year estimates are available for all geographies down to the block group level.

Neighborhood Data

The utilized 2016-2020 ACS 5-year estimate (U.S. Census, n.d.-d) dataset that was used for this study was prepared by Social Explorer (Social Explorer, n.d.). Nine census tract level socioeconomic variables (i.e., percentage of poverty, percentage unemployed, median income, vehicle ownership, professional and managerial jobs, bachelor's degree or higher, median house value, median monthly rent, and percentage home ownership) from the 2016–2020 ACS 5-year estimate dataset were used to compute a composite socioeconomic index (CSI) and neighborhood socioeconomic position (SEP) score for 78,342 (91.74%) of the total 85,395 U.S. census tracts. In total, 7,053 census tracts were not assigned a CSI and SEP score due to missing either one or more of the nine tract level ACS variables. Details on how CSI and SEP scores were computed are in Chapter 4 of this dissertation.

Hypertension Data

The hypertension data for this study was derived from two sources: Centers for Disease Control and Prevention (CDC) PLACES (n.d.-b) and the 2019 Medical Expenditure Panel Survey (MEPS) Household Component (HC) Full-Year Consolidated Files (Agency for Healthcare Research and Quality [AHRQ], 2022). The PLACES data are model-based population estimates. Multilevel regression and poststratification methods were used to link geocoded health surveys, such as the Behavioral Risk Factor Surveillance System (BRFSS), and high spatial resolution population demographic and socioeconomic data to estimate high blood pressure (HBP) prevalence among adults 18 years and older at census tract level. For this dissertation, I used 5-year (2016–2020) estimate ACS data in analyses with PLACES HBP population data. There were 70,338 PLACES tract-level data points with a calculated HBP prevalence rate. In total, 56,500 (80.32%) of the PLACES tracts were successfully matched by their Federal Information Processing Standards codes to an SEP. The PLACES adult HBP prevalence population-level data were used to perform a chi-square test of independence, analysis of variance (ANOVA) testing, and map analysis of HBP prevalence above the national rate of 47% (CDC, n.d.-a) across SEP.

MEPS is a longitudinal survey that collects information on healthcare use, expenditures, sources of payment, health insurance coverage, a respondent's health status, health behaviors, socioeconomic demographic characteristics, and employment status on noninstitutionalized civilian U.S. populations. MEPS consists of five interviews conducted over a 2.5-year period and is unique in its ability to link data on individuals and households (e.g., demographics, health status, employment, and income) to information on their use of health services (AHRQ, 2022).

The 2019 MEPS data of this study were restricted from public access. Though MEPS has public use files available for download, this dissertation required the census tracts of MEPS respondents to be matched to a computed neighborhood SEP score. I submitted an application to AHRQ in December of 2021 in order to access 2019 MEPS data at census tract level. The data access application was submitted shortly after completing the Institutional Review Board (IRB) process at Michigan State University. With the release of the 2020 ACS data in March 2021, I computed SEP scores for each U.S. census tract and sent the scores to AHRQ. After providing the AHRQ data center a file that contained the SEP scores of 78,342 census tracts, the AHRQ data center began the official processing of the application in April 2022. After the applications approval, AHRQ matched each 2019 MEPS survey participant's DUPERSID (panel specific unique record/observation ID) to an SEP score by geographic identifier (GEOID). Application processing and the creation of the merge file took approximately 8 weeks. After AHRQ matched 2019 observations to and SEP score by DUPERSID, all GEOIDs were stripped from the final merge file. The merge file allowed for the matching of observations to corresponding health information by DUPERSID. The DUPERSID had already been match to an SEP score by AHRQ staff, thus allowing observation health variables to be matched with an SEP score. In June 2022, access to the restricted 2019 MEPS HC files was granted.

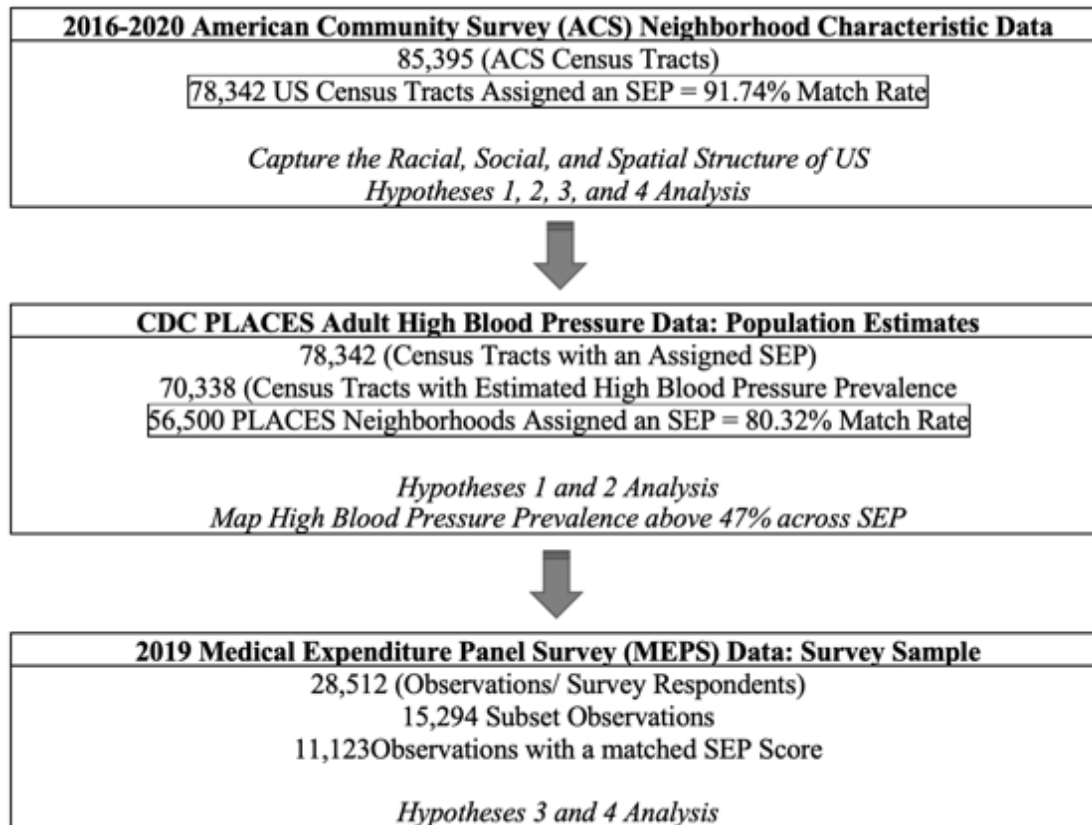
The matched file contained the DUPERSID of 28,512 respondents for the 2019 survey year. Of the 28,512 tracts, 11,123 were matched with an SEP score. I did not delete persons younger than age 18 and without an identified SEP score from the MEPS HC file; rather, the file remained intact for the duration of analysis as to appropriately account for the complex survey sampling design that was set based upon the entire survey year sample. Deleting cases could have resulted in inaccurate standard error calculations (AHRQ, 2022); therefore, no cases were

deleted from the dataset. Instead, the R Studio 4.2.1 survey package was used to carry out the `svydesign` (i.e., survey design) function to establish the survey sampling design, and the `subset` function was used to extract a survey sample for analysis. Further details on the functions carried out in R Studio 4.2.1 to clean the dataset in preparation for analysis are outlined in Chapter 4 of this dissertation. The MEPS survey sample was used to test Hypotheses 3 and 4 of this dissertation.

All of the proper nondisclosure data use agreement forms were approved to gain access to the 2019 MEPS data file from the U.S. Department of Health and Human Services AHRQ. The access and cost trends data center coordinator for AHRQ facilitated the processing of my application for data center access. Once granted access, all Hypotheses 3 and 4 analyses were conducted at the AHRQ data center in Rockville, Maryland because data files are not allowed to be removed from the AHRQ data center. Michigan State University's IRB issued an exempt status, IRB# STUDY00006804, for this work. Figure 1 provides a flow diagram of the 2020 ACS 5-year estimate, PLACES HBP population data, and MEPS survey sample data match rates and corresponding hypotheses.

Figure 1

Socioeconomic and Health Dataset Merge Flow Chart



CHAPTER 4: METHODS OF ANALYSIS

To test the outlined hypotheses, three datasets were used. I used the 2016–2020 American Community Survey (ACS), 2019 Centers for Disease Control and Prevention (CDC) PLACES high blood pressure (HBP) outcomes, and 2019 Medical Expenditure Panel Survey (MEPS) Household Component (HC) data.

Census Tracts as Neighborhoods

The Modified Darden-Kamel Composite Socioeconomic Index (Darden-Kamel Index) methodology was applied to capture the social and spatial characteristics of the entire United States; I used census tracts as neighborhood proxies for analysis. The Darden–Kamel Index (Darden et al., 2010) measures neighborhood-level socioeconomic status (SES). The highest score, 5, reflects very high neighborhood socioeconomic position (SEP), whereas a score of 1 reflects a very low neighborhood SEP. The Darden–Kamel Index extracts nine variables from the U.S. Census Bureau’s ACS 2016–2020 5-Year Estimate data. The variables used to calculate a composite socioeconomic index (CSI) were defined as follows:

- *Percentage of residents with a university degree* was the percentage of the population, 25 years of age and older, with at least a bachelor’s degree (i.e., 4 or more years of school beyond high school).
- *Median household income* was the median household income of the total number of family members 15 years and older, including those with no income in 2020.
- *Percentage of managerial and professional positions* was the percentage of workers 16 years and older at the top of the occupational hierarchy based on the occupational classification system used by the U.S. Census Bureau in 2020. This percentage was based on 23 major occupational groups stratified.

- *Median value of dwelling* was the median value of specified owner-occupied housing units. The value was the respondent's estimate of how much the property would sell for if it were for sale. This value included only one-family houses on less than 10 acres without a business or medical office on the property.
- *Median gross rent of dwelling* was calculated with median rent, which is the contract rent plus the estimated average monthly cost of utilities.
- *Percentage of homeownership*⁴ was calculated by dividing the number of owner-occupied housing units by the number of occupied housing units. Units were counted as owner occupied if the owner or co-owner lives in the unit, even if it is mortgaged or not fully paid for.
- *Percentage below poverty* was the percentage of families that fell below the U.S. poverty threshold for families of a particular size and income in 1999. I used the family size of four, which is the standard size used by U.S. Census Bureau to assess the SES of families.
- *Unemployment rate* was the percentage of all civilians 16 years and older who were neither at work nor with a job but who were not at work during the reference week or who were looking for work during the last 4 weeks and were available to start a job.
- *Percentage of households with vehicle*⁵ was calculated by subtracting the percent of occupied homes without a vehicle for each tract from 100%. The calculated difference was the percent of households with a vehicle. (Darden et al., 2010, p. 145)

⁴ The home ownership variable was calculated because the percentage of home ownership is not reported. The number of owner-occupied homes and number of occupied homes are reported. Dividing the number of owner-occupied homes by the number of occupied homes provided the utilized neighborhood homeownership rate.

⁵ The percent of households without a vehicle is reported as opposed to the percent of households with a vehicle. Therefore, the percentage of households with a vehicle was calculated by subtracting the percent of occupied homes without a vehicle for each tract from 100%.

CSI

The Darden–Kamel Index was used to sort and rank U.S. census tracts of residence according to their overall socioeconomic status. The CSI *z* score was calculated with the following formula (see Figure 2).

Figure 2

Composite Socioeconomic Index Formula

$$CSI_i + \sum_{j=1}^k \frac{V_{ij} - V_{jUSA}}{S(V_{jUSA})}$$

In this formula, CSI is the composite socioeconomic *z* score index for census tract *i*, the sum of *z* scores for the SES variables *j*, relative to the United States. SES; USA is U.S. area; *k* is the number of variables in the index; *V_{i j}* is the *j*th SEP variable for a given census tract *i*; *V_j USA* is the mean of the *j*th variable in the United States; and *S (V_j USA)* is standard deviation of the *j*th variable in the United States (Darden et al., 2010). After calculating the index score, the values were ranked from least to greatest, which allowed me to divide the United States into five levels (i.e., ranges of SEP) with boundaries at the 20th, 40th, 60th, and 80th percentiles (quintiles) of the CSI frequency distribution. This categorization allowed for the division of census tracts of residence into five socioeconomic characteristic groups with approximately equal proportions of the population in each group: 1 = very low socioeconomic position (VLSEP), 2 = low socioeconomic position (LSEP), 3 = middle socioeconomic position (MSEP), 4 = high socioeconomic position (HSEP), and 5 = very high socioeconomic position (VHSEP; Darden et al., 2010, 2019; Grady & Darden, 2012). After calculating the SEP scores across the United States, Table 1 details the spatial and social structures of the entire nation.

Table 1

Spatial and Social Structure of the United States, Based on the Modified Darden-Kamel Composite Socioeconomic Index (CSI): 2016–2020

SEP	Neighborhood characteristic	Bachelor's degree	% unemployed	% professional and managerial workers	Median household income	Median home value	Median gross rent	% below poverty	% with vehicle	% home ownership
5	Very high	32.57	3.6	17.81	117,715.52	574,567.14	1865.24	2.95	95.16	75.13
4	High	23.35	4.1	12.01	78,239.35	304,339.42	1276.1	4.91	94.89	71.08
3	Middle	17.36	4.69	9.56	62,209.02	222,390.01	1028.29	7.55	93.83	67.56
2	Low	13.32	5.98	8.24	50,385.41	174,330.24	894.49	12.04	91.51	61.73
1	Very low	9.95	10.56	8.1	35,483.6	140,492.84	805.38	25.09	81.57	45.8

Note. Mean characteristics of neighborhood calculated by Cordelia Martin-Ikpe from U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Dissimilarity Index

To capture the level of unevenness in the spatial distribution of Black and white populations across SEP, I used the Index of Dissimilarity. The Index of Dissimilarity was employed to measure the extent of residential segregation by census tracts grouped into quintiles based on socioeconomic characteristics (Darden et al., 2010; Moody, 2014). Mathematically, the Index of Dissimilarity was defined via the following formula (see Figure 3).

Figure 3

Dissimilarity Index Formula

$$D = 100(1/2) \left(\sum_{i=1}^k |x_i - y_i| \right)$$

In this formula, x_i is the proportion of the U.S. Black population residing in a given quintile (grouped census tracts) and y_i is the proportion of the U.S. white (non-Hispanic) population residing in the same quintile (grouped census tracts); k is the total number of grouped tracts in the United States (e.g., $k = 5$ when using quintiles); and D is the Index of Dissimilarity, which is equal to one half the sum of the absolute differences (i.e., positive and negative) between the proportion distributions of the Black and white population in the United States (Darden et al., 2010). The value of the index could be directly interpreted as the minimum proportion of one group (i.e., non-Hispanic Black residents) that would have to change its area of residence to achieve an identical spatial distribution with white residents (Massey & Denton, 1988). The U.S. non-Hispanic Black and white dissimilarity index score was 29.34%, which meant 29.34% of non-Hispanic Blacks would have to move to achieve spatial evenness across the United States. Table 2 details the spatial distribution of non-Hispanic Black and white populations across SEP.

Table 2*Non-Hispanic Black–White Dissimilarity Index: United States 2016–2020*

SEP	Neighborhood characteristic	Non-Hispanic Black	% Non-Hispanic Black	Non-Hispanic white	% Non-Hispanic white	Absolute % difference
5	Very high	3755359	10.02	45582386	24.68	14.65
4	High	5593035	14.93	43872540	23.75	8.82
3	Middle	6012142	16.04	40460321	21.9	5.86
2	Low	7672954	20.48	35153849	19.03	1.45
1	Very low	14438548	38.53	19651087	10.64	27.89
	Total	37472038	100	184720183	100	58.68
	Dissimilarity index					29.34

Note. $n = 222,192,221$

Dissimilarity Index calculated by Cordelia Martin-Ikpe from U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimate

Application of the Darden-Kamel Index and Index of Dissimilarity

The Darden-Kamel Index methodology, which is used to compute neighborhood SEP scores, was foundational to the objectives of this study. Non-Hispanic Black–white hypertension disparity gaps are observed and analyzed within the context of neighborhood SEP. Assigning a neighborhood SEP to neighborhoods across the United States streamlined a comprehensive means of accounting and controlling for neighborhood characteristic before analyzing racial disparities in hypertension. The Darden-Kamal Index on its own only controls for socioeconomic characteristics of neighborhood; however, I applied the Index of Dissimilarity in such a manner that races were stratified along SEP, which highlighted their spatial distribution across the United States within the context of SEP as opposed to conventional government boundaries.⁶ Irrespective of an individual’s zip code, city, county, or state, I analyzed their relative health differences within and across SEP. Based on dissimilarity index profiling, I was able to account for how individuals were stratified along SEP despite being racially segregated.

Research Questions 1 and 2: HBP and SEP

After having captured the spatial, social, and racial structures of the entire United States, I used CDC PLACES data to explore: (a) the significance of the relationship between neighborhood SEP and neighborhood HBP prevalence, and (b) discern whether mean HBP prevalence rates were significantly different across SEP. Investigation of Research Questions 1 and 2 were foundational to the Black–white hypertension disparities analysis because the application of the Darden-Kamal Index methodology was a novel approach to capturing neighborhood characteristics across the United States, making it necessary to establish the

⁶ Civil areas including states, counties, Federal, and Native American lands, and incorporated places such as cities and towns (USGS, n.d.).

significance of the relationship between neighborhood characteristic, as defined by the Darden-Kamel Index and HBP prevalence. Secondly, it was important to not lead with an assumption that HBP prevalence is significantly different across SEP.

Analysis of CDC PLACES Data

CDC PLACES data were downloaded from the CDC PLACES site and each neighborhood census tract with a corresponding SEP score was matched by a geographic identifier (GEOID) in R Studio 4.2.1. Hypothesis 1 (i.e., There is an inverse relationship between HBP prevalence and neighborhood SEP. The highest HBP prevalence rates will be in SEPs 1 and 2 [i.e., very low and low neighborhood characteristic] and the lowest HBP prevalence rates will be in SEPs 4 and 5 [i.e., high and very high neighborhood characteristic]) required the construction of a contingency table. Neighborhood HBP prevalence was split into four ranges across SEP: below 16%, 16%–31%, 32%–47%, and above 47%. The first two ranges are considered to be very low and low ranges, whereas the 32%–47% range captured neighborhoods closely aligned with the national average of 47% (CDC, n.d.-a). And finally, neighborhoods with an above national average HBP prevalence fell within the above 47% category. A count of neighborhoods falling within the outlined ranges across SEP was performed. The contingency table (see Table 3) outlines the number of U.S. neighborhoods that fall within each range of HBP prevalence across SEP. A chi-square test of independence was performed using the following contingency table to determine the significance of the relationship between SEP and HBP. The chi-square analysis results are presented in Chapter 6 of this dissertation.

Table 3*Number of Neighborhoods by HBP Prevalence and SEP: United States 2019*

HBP prevalence percentage	SEP 1	SEP 2	SEP 3	SEP 4	SEP 5
<16%	62	35	34	46	145
16–31%	2442	3555	5132	7191	9031
32–47%	7526	8036	6199	3355	1513
>47%	1781	234	80	72	31

Note. n = 56500

Calculated by Cordelia Martin-Ikpe from CDC PLACES HBP outcome data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

In addition to a chi-square test of independence, I also performed map analysis through the joining of a US Census tract shp. file and CDC PLACES HBP outcome data attributes in QGIS 3.26.1-Buenos Aires. Map analysis highlighted above the national average (47%) in relation to SEP and the non-Hispanic Black and white population densities across SEP. Map analysis findings are also presented in Chapter 6 of this dissertation.

Testing of Hypothesis 2 (i.e., The mean neighborhood HBP prevalence rate at each level of SEP is significantly different across SEP, with the highest prevalence rates being within SEPs 4 and 5 and the lowest being in SEPs 1 and 2) required the calculation of mean HBP prevalence across SEP. Those means were outlined in a box plot and an ANOVA test was performed to determine whether mean HBP prevalence across SEP was significantly different, and finally a post hoc test was performed to identify which pairs of HBP prevalence means across SEP were significantly different. The findings of this analysis are outlined in Chapter 6.

Research Questions 3 and 4: Black–white HBP Disparity

After establishing the significance of the connection between SEP and HBP and the significance of mean HBP difference across SEP, I analyzed Black–white HBP prevalence gaps within and across SEP using 2019 MEPS HC data. Using R Studio 4.2.1, SEP scores that had

been matched with a DUPERID (respondent ID) by GEOID were matched with 28,512 MEPS observations from the 2019 survey year. Of those 28,512 MEPS survey observations, 11,123 were successfully matched with an SEP score.

After matching neighborhood SEP and 2019 MEPS observation data, a duplicate copy of the matched SEP and MEPS data file was created and saved. The duplicate file was saved and later used for Hypotheses 3 and 4 testing, which required the application of survey weights and sub setting.

Unweighted MEPS Survey Sample

Before the dataset was weighted and subset for analysis, the descriptive statistics of the unweighted dataset were computed. The unweighted survey sample subset was produced after removing observations without an assigned SEP score, which left 11,123 observations. The 11,123 observations were used to compute the unweighted descriptive statistics of the survey sample. The unweighted survey sample subset descriptive statistics were computed using R Studio 4.2.1.

Weighted MEPS Survey Sample

The duplicate neighborhood SEP and 2019 MEPS observation match file was read into R Studio 4.2.1 as a .csv file. Due to the complex sampling design of MEPS, survey weights were applied when establishing the survey design in R Studio before calculating descriptive statistics and conducting statistical analysis. Person weight (PERWT19F), stratum (VARSTR), and the primary sampling unit (PSU; VARPSU) variables were used to establish the MEPS survey design in R Studio. PERWT19F represents the inverse probability of selection into the sample, adjusted for nonresponse with poststratification adjustments for age, race/ethnicity, and sex using the U.S. Census Bureau's population control totals. For each year, the sum of these weights was

equal to that year’s civilian, noninstitutionalized U.S. population (AHRQ, 2022). VARSTR is a variance sampling strata variable that represents the impact of the sample design stratification on the estimates of variance and standard errors. VARPSU is a variance PSU variable that represents the impact of the sample design clustering on the estimates of variance and standard errors(AHRQ, 2022).

After establishing the survey design, I used the R Studio 4.2.1 subset function to extract a survey sample containing persons 18 years of age and older, men and women, non-Hispanic Black and white individuals, those who responded *yes* or *no* to the hypertension diagnosis question, and finally persons with an assigned SEP score. The R Studio functions that were used to establish the survey design, subset the analysis sample, and perform regression analysis, are outlined in Table 4.

Table 4

R Studio 4.2.1 Functions and Codes Used to Establish the Survey Design, Subset the Survey Sample for Descriptive and Hypothesis Testing Analysis, and Perform Regression Modeling of Each SEP

Function	Code
svydesign (Survey design)	<code>svyds <- svydesign(id=~VARPSU, weights=~PERWT18F,strata=~VARSTR, nest=TRUE, survey.lonely.psu = “adjust”, data=data)</code>
subset (Survey sample)	<code>svysample<-subset(svyds, AGE>17) svysample<-subset(svysample,SEX==“0” SEX==“1”) svysample<-subset(svysample,HIBPDX==“0” HIBPDX==“1”) svysample<-subset(svysample,RACETHX==“0” RACETHX==“1”) svysample<- subset(svysample,SEP==“1” SEP==“2” SEP==“3” SEP==“4” SEP==“5”)</code>

Six duplicates of the file were created and set aside for regression analysis. Descriptive statistics were computed for the weighted and subset survey sample. After computing the descriptive statistics, the weighted subset sample was used to test the following hypotheses:

- Hypothesis 3: Though non-Hispanic Blacks in SEP 5 will have a lower hypertension prevalence rate than whites in SEP 1, the hypertension prevalence gap between non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1 will be less than the prevalence gap between non-Hispanic whites in SEP 5 and non-Hispanic Blacks in SEP 1.
- Hypothesis 4: The non-Hispanic Black–white hypertension prevalence gap narrows when non-Hispanic Blacks and whites live in neighborhoods of similar SEP.

Binomial Regression and Proportional Z Testing

The six regression files were used to further subset the data by each level of SEP. A regression model was created for each level of SEP in addition to a regression model for observations across SEP. The regression modeling required the hypertension variable to be set as the dependent variable, whereas age, sex, and race were the liner model predictor variables. Hypothesis 3 was tested by using the SEP specific datasets to first compute Black–white proportional differences in hypertension outcomes, next perform a proportional z test, and finally determine whether there was any overlap in the proportional difference confidence intervals among non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1. Hypothesis 4 was tested by comparing the non-Hispanic Black and white liner model coefficient results across each level of SEP. Before regression and proportional z testing are performed, I presented descriptive statistics in Chapter 5 provide a profile of the MEPS study sample. The descriptive statistic tables that outline race composition across SEP quintile and by SEP quintile are especially informative. Where MEPS study sample Blacks and whites reside across SEP largely mirrors the dissimilarity table (see Table 2) presented earlier in this chapter.

CHAPTER 5: DESCRIPTIVE STATISTICS

Centers for Disease Control and Prevention (CDC) PLACES census tract boundaries were derived from the U.S. Bureau of the Census (2010) population dataset. High blood pressure (HBP) data were sourced from the 2019 Behavioral Risk Factor Surveillance System (BRFSS) survey. Census and BRFSS data were used by the CDC PLACES initiative to generate small-area estimates of neighborhood HBP prevalence among individuals aged 18 and older (CDC, n.d.-b). The CDC PLACES dataset was used to test Hypotheses 1 and 2 of this dissertation.

Of the 70,338 CDC PLACES neighborhood tracts, 55,500 (80.32%) were successfully matched with a socioeconomic position (SEP) score. Of the total neighborhood-level HBP prevalence tracts, 11,811 (20.90%) neighborhoods belonged to SEP 1, 11,860 (20.99%) belonged to SEP 2, 11,445 (20.26%) belonged to SEP 3, 10,664 (18.87%) belonged to SEP 4, and 10,720 (18.97%) belonged to SEP 5. Mean HBP prevalence rates across SEP were calculated using R Studio 4.2.1. Table 5 shows mean HBP prevalence by neighborhood SEP and their associated standard deviations.

Table 5

Mean HBP Prevalence Percentage Among Adults Age 18 and Over by Neighborhood SEP

Mean HBP prevalence by SEP	Mean prevalence %	SD
SEP1	38.5	7.97
SEP2	34.8	5.99
SEP3	32.4	5.31
SEP4	30.0	5.25
SEP5	27.4	5.02

Note. $n = 56,500$

Calculated by Cordelia Martin-Ikpe from CDC PLACES HBP outcome data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Medical Expenditure Panel Survey

The 2019 Medical Expenditure Panel Survey (MEPS) Household Component (HC) survey file had a total of 28,512 observations. Of the 28,512 MEPS observations, 15,294 cases were eligible for analysis because the respondents were age 18 or older, identified as male or female, were non-Hispanic Black or white, and responded *yes* or *no* to having been diagnosed with hypertension unrelated to pregnancy. In total, 11,123 (73%) of the 15,294 observations were matched with a neighborhood SEP score. The weighted and unweighted descriptive statistics in the following sections summarize the 11,123 observations that were successfully matched with an SEP score. I developed aggregate summaries of the study population across SEPs 1–5, along with stratifying the data by SEP quintile and across SEP quintile.

Age

The unweighted survey sample included 3,300 adults (29.61%) between the ages of 18 and 39, 4,777 adults (31.23%) between the ages of 40 and 59, and 5,988 adults (39.15%) aged 60 and older. The unweighted mean age was 52.12 years. The weighted survey sample represented 45,561,981 (29.67%) adults age 18–39, 42,960,842 (32.19%) adults age 40–59, and 44,951,550 (33.68%) adults aged 60 years and older. The weighted mean age was 49.78 years.

Sex

The unweighted survey sample consisted of 5,248 men (47.18%) and 5,875 women (52.82%). The weighted survey sample consisted of 64,351,771 men (48.21%) and 69,122,602 women (51.79%).

Race and Ethnicity

The unweighted survey sample consisted of 8,935 (80.33%) non-Hispanic white respondents and 2,188 (19.67%) non-Hispanic Black respondents. The weighted survey sample

consisted of 112,542,435 (84.32%) non-Hispanic white respondents and 20,931,938 (15.68%) non-Hispanic Black respondents.

Essential Hypertension

Essential hypertension was defined as a hypertension diagnosis unrelated to pregnancy (Agency for Healthcare Research Quality [AHRQ], 2022). The unweighted survey sample included 4,336 (38.98%) hypertensive and 6,787 (61.02%) nonhypertensive individuals. The weighted survey sample included 45,562,803 (34.14%) hypertensive and 87,911,570 (65.86%) nonhypertensive individuals. Table 6 shows the unweighted survey sample descriptive statistics, and Table 7 shows the weighted survey sample statistics.

Table 6

Unweighted Survey Sample Descriptive Statistics

Variable	<i>n</i> (%)	<i>M</i>	<i>SD</i>
Age		52.17 years	18.51 years
18–39 years	3,300 (29.67)		
40–59 years	3,447 (30.99)		
60+ years	4,376 (39.34)		
Sex		.53	.50
Male	5,248 (47.18)		
Female	5,875 (52.82)		
Race/Ethnicity		.20	.40
Non-Hispanic white (nH-white)	8,935 (80.33)		
Non-Hispanic Black (nH-Black)	2,188 (19.67)		
Hypertension		.39	.49
Hypertensive	4,336 (38.98)		
Non-hypertensive	6,787 (61.02)		

Note. *n* = 11,123

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Table 7*Weighted Survey Sample Descriptive Statistics*

Variable	<i>n</i> (%)	<i>M</i>	<i>SD</i>
Age		49.69 years	18.41 years
18–39 years	45,561,981 (34.14)		
40–59 years	42,960,842 (32.19)		
60+ years	44,951,550 (33.68)		
Sex		.52	.5
Male	64,351,771 (48.21)		
Female	69,122,602 (51.79)		
Race/Ethnicity		.16	.36
Non-Hispanic white (nH-white)	112,542,435 (84.32)		
Non-Hispanic Black (nH-Black)	20,931,938 (15.68)		
Hypertension		.34	.47
Hypertensive	45,562,803 (34.14)		
Non-hypertensive	87,911,570 (65.86)		

Note. *n* = 133,474,373

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Tables 8 (unweighted) and 10 (weighted) are stratified by neighborhood SEP quintile. Tables 9 (unweighted) and 11 (weighted) are stratified across SEP quintile. The non-Hispanic Black and white variable categories of Tables 9 and 11 outline the difference in non-Hispanic Black and white population distributions by and across SEP quintile. The non-Hispanic Black population of Tables 9 and 11 decreases as SEP increases, whereas the non-Hispanic white population increases as SEP increases. The population distributions by race in Tables 9 and 11 follow the same pattern as the U.S. dissimilarity index table (see Table 2) in Chapter 4. The similarity among Tables 2, 9, and 11 underscore the spatial distribution of non-Hispanic Black and white populations across SEP. Tables 2, 9, and 11 suggest that Blacks and whites are often exposed to very different neighborhood characteristics.

Table 8*Unweighted Survey Sample by Quintile*

Variable	SEP 1		SEP 2		SEP 3		SEP4		SEP5	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
Age										
18–39 years	665	32.14	666	31.42	748	30.48	648	28.06	573	26.39
40–59 years	655	31.66	609	28.73	750	30.56	721	31.23	712	32.8
60+ years	749	36.2	845	39.86	956	38.96	940	40.71	886	40.81
Total	2,069	100	2,120	100	2,454	100	2,309	100	2,171	100
Sex										
Male	919	44.42	989	46.65	1,195	48.7	1,110	48.07	1,035	47.67
Female	1,150	55.58	1,131	53.35	1,259	51.3	1,199	51.93	1,136	52.33
Total	2,069	100	2,120	100	2,454	100	2,309	100	2,171	100
Race/Ethnicity										
Non-Hispanic Black	1,016	49.11	447	21.08	311	12.67	240	10.39	174	8.01
Non-Hispanic white	1,053	50.89	1,673	78.92	2,143	87.33	2,069	89.61	1,997	91.99
Total	2,069	100	2,120	100	2,454	100	2,309	100	2,171	100
Hypertension										
Hypertensive	980	47.37	880	41.51	935	38.1	867	37.55	674	31.05
Non-hypertensive	1,089	52.63	1,240	58.49	1,519	61.9	1,442	62.45	1,497	68.95
Total	2,069	100	2,120	100	2,454	100	2,309	100	2,171	100

Note. *n* = 11,123

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Table 9*Unweighted Survey Sample Counts and Percentages Across SEP*

Variable	SEP 1		SEP 2		SEP 3		SEP 4		SEP 5		Total/across SEP 1–5
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	
Age											
18–39 years	665	20.15	666	20.18	748	22.67	648	19.64	573	17.36	3,300
40–59 years	655	19	609	17.67	750	21.76	721	20.92	712	20.66	3,447
60+ years	749	17.12	845	19.31	956	21.85	940	21.48	886	20.25	4,376
Sex											
Male	919	17.51	989	18.85	1,195	22.77	1,110	21.15	1,035	19.72	5,248
Female	1,150	19.57	1,131	19.25	1,259	21.43	1,199	20.41	1,136	19.34	5,875
Race/Ethnicity											
Non-Hispanic Black	1,016	46.44	447	20.43	311	14.21	240	10.97	174	7.95	2,188
Non-Hispanic white	1,053	11.79	1,673	18.72	2,143	23.98	2,069	23.16	1,997	22.35	8,935
Hypertension											
Hypertensive	980	22.6	880	20.3	935	21.56	867	20	674	15.54	4,336
Non-hypertensive	1,089	16.05	1,240	18.27	1,519	22.38	1,442	21.25	1,497	22.06	6,787

Note. *n* = 11,123

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Table 10*Weighted Survey Counts and Percentages Sample by Quintile*

Variable	SEP 1		SEP 2		SEP 3		SEP 4		SEP 5	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
Age										
18–39 years	7,521,230	36.07	8,732,666	36.82	10,433,103	35.21	950,3845	32.15	9,371,137	31.54
40–59 years	6,784,533	32.54	6,975,342	29.41	9,434,894	31.84	9,809,763	33.18	9,956,310	33.51
60+ years	6,545,584	31.39	8,009,573	33.77	9,765,711	32.95	10,248,544	34.67	10,382,138	34.95
Total	20,851,347	100	23,717,581	100	29,633,708	100	29,562,152	100	29,709,585	100
Sex										
Male	9,771,477	46.86	11,282,347	47.57	14,719,274	49.67	14,256,506	48.23	14,322,166	48.21
Female	11,079,870	53.14	12,435,234	52.43	14,914,434	50.33	15,305,646	51.77	15,387,419	51.79
Total	20,851,347	100	23,717,581	100	29,633,708	100	29,562,152	100	29,709,585	100
Race/Ethnicity										
Non-Hispanic Black	8,751,192	41.97	4,152,381	17.51	3,018,251	10.19	2,725,954	9.22	2,284,160	7.69
Non-Hispanic white	12,100,155	58.03	19,565,200	82.49	26,615,457	89.81	26,836,198	90.78	27,425,425	92.31
Total	20,851,347	100	23,717,581	100	29,633,708	100	29,562,152	100	29,709,585	100
Hypertension										
Hypertensive	8,783,014	42.12	8,754,476	36.91	10,094,405	34.06	9,759,976	33.02	8,170,932	27.5
Non-hypertensive	12,068,333	57.88	14,963,105	63.09	19,539,303	65.94	19,802,176	66.98	21,538,653	72.5
Total	20,851,347	100	23,717,581	100	29,633,708	100	29,562,152	100	29,709,585	100

Note. *n* = 133,474,373

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Table 11*Weighted Survey Sample Counts and Percentages Across Neighborhood SEP*

Variable	SEP 1		SEP 2		SEP 3		SEP 4		SEP 5		Total/Across SEP 1–5
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	
Age											
18–39 years	7,521,230	16.51	8,732,666	19.17	10,433,103	22.9	9,503,845	20.86	9,371,137	20.57	45,561,981
40–59 years	6,784,533	15.79	6,975,342	16.24	9,434,894	21.96	9,809,763	22.83	9,956,310	23.18	42,960,842
60+ years	6,545,584	14.56	8,009,573	17.82	9,765,711	21.72	10,248,544	22.8	10,382,138	23.1	44,951,550
Sex											
Male	9,771,477	15.18	11,282,347	17.53	14,719,274	22.87	14,256,506	22.15	14,322,166	22.26	64,351,770
Female	11,079,870	16.03	12,435,234	17.99	14,914,434	21.58	15,305,646	22.14	15,387,419	22.26	69,122,603
Race/Ethnicity											
Non-Hispanic Black	8,751,192	41.81	4,152,381	19.84	3,018,251	14.42	2,725,954	13.02	2,284,160	10.91	20,931,938
Non-Hispanic white	12,100,155	10.75	19,565,200	17.38	26,615,457	23.65	26,836,198	23.85	27,425,425	24.37	112,542,435
Hypertension											
Hypertensive	8,783,014	19.28	8,754,476	19.21	10,094,405	22.15	9,759,976	21.42	8,170,932	17.93	45,562,803
Non-hypertensive	12,068,333	13.73	14,963,105	17.02	19,539,303	22.23	19,802,176	22.53	21,538,653	24.5	87,911,570

Note. *n* = 133,474,373

Calculated by Cordelia Martin-Ikpe from 2019 MEPS data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Though unweighted and weighted descriptive statistics were outlined, the weighted descriptive statistics were used in conjunction with hypotheses testing results to present the analysis interpretations outlined in Chapters 6 and 7. A summary of weighted descriptive analysis was most pertinent to an overall profile of the MEPS study population used for analysis. The primary conclusions that could be drawn from the weighted descriptive statistics were: (a) the study population was mostly middle age, non-Hispanic white, non-hypertensive, and female; (b) as it pertained to age and sex by SEP and across SEP the distribution of adults, middle-age adults, seniors, and males and females were, to an extent, evenly distributed; and (c) when looking at race and ethnicity across SEP, nearly 42% of the non-Hispanic Black population resides in SEP 1, while nearly 50% of the non-Hispanic white population resides in SEP 5. The weighted descriptive analysis by quintile also revealed an inverse pattern: as SEP increased, the non-Hispanic white proportion increased, while the non-Hispanic Black population decreased. Finally, in looking at hypertension prevalence across SEP quintile, hypertension prevalence was highest in SEP 3 and lowest in SEP 5; however, within SEP quintile, hypertension prevalence was greatest in SEP 1.

CHAPTER 6: ANALYSIS RESULTS

Hypothesis testing was performed in two stages. The first stage, which involved the testing of Hypotheses 1 and 2, used the Centers for Disease Control and Prevention (CDC) PLACES dataset. Hypotheses 1 and 2 did not address Black–white disparities in hypertension, but they did help to establish the foundation of this study by: (a) verifying whether the Modified Darden-Kamel Composite Socioeconomic Index (Darden-Kamel Index) derived neighborhood socioeconomic position (SEP) is a pathway to neighborhood high blood pressure (HBP) prevalence rates and (b) determining whether mean HBP prevalence is significantly different across SEP.

Hypotheses Testing and Results

A chi-square of independence was performed to test Hypothesis 1. After performing the chi-square test of independence to determine the significance of the relationship between SEP and HBP. Hypothesis two was tested by an analysis of variance (ANOVA), and a Tukey’s HSD (post hoc) test to determine whether mean HBP prevalence rates were significantly different across SEP. ANOVA and Tukey’s HSD testing were important to establish whether there was a need to control neighborhood SEP in hypertension disparities analysis. The assumption was, if mean HBP at each level of SEP differed significantly, there would be a need to control for neighborhood SEP to adjust for the analysis of HBP prevalence differences across SEP.

The second stage of hypotheses testing required the use of the restricted 2019 Medical Expenditure Panel Survey (MEPS) Household Component (HC) dataset. Hypotheses 3 and 4 addressed Black–white disparities in hypertension. Hypothesis 3 made a prediction relating to Black–white hypertension prevalence gaps (i.e., disparity) across SEP, specifically SEPs 1 and 5. Hypothesis 3 was tested by performing a two-proportion z test. The Black–white proportional

difference confidence intervals of SEP 5 non-Hispanic Blacks and SEP 1 non-Hispanic whites were compared to the proportional difference confidence intervals of SEP 5 non-Hispanic whites and SEP 1 non-Hispanic Blacks. I compared the two proportional difference confidence intervals to determine whether the hypertension disparity among SEP 5 Blacks and SEP 1 whites mirrored the hypertension disparity between SEP 5 whites and SEP 1 Blacks. Due to the enduring legacies of racial residential segregation, Blacks are more likely to live in neighborhoods of lower socioeconomic position compared to whites, even when Blacks are of equal socioeconomic standing (Darden et al., 2010; LaVeist, 2005). Due to the recognized Black-white differences in neighborhood characteristics, it is safe to assume that because there is no widely applied means of controlling for Black-white neighborhood characteristic differences, most disparities analyses compare the health outcomes of SEP 4 and 5 whites to SEP 1 Blacks. The assumption of my study is that after controlling for neighborhood SEP, the disparity gap among SEP 5 Blacks and SEP 1 whites would be similar to the disparity gap among SEP 5 whites and SEP 1 Blacks. If the two sets of proportional differences are found to be similar (overlapping of their 95% confidence intervals) it is an indication that the observed national disparity is largely due to the fact that Blacks are disproportionately exposed to neighborhoods of low socioeconomic position. If nearly 50% of the non-Hispanic Black population lived in SEP 4 and 5 neighborhoods (which is currently not the case) the present-day national disparity may not be as pronounced. However, in reality, the overwhelming majority of Blacks in America live in SEP 1 neighborhoods and my utilized approach to the study of Black-white disparities in hypertension highlights the role of that disproportion distribution in the measured national Black-white hypertension disparity.

Hypothesis 4 assessed Black–white hypertension prevalence gaps among Blacks and whites who reside in the same SEP. Hypothesis 4 was tested through binomial regression

modeling in R Studio 4.2.1. I ran three model types for all five levels of neighborhood SEP as well as across SEPs 1–5. In total, 18 separate models were run. Hypothesis 4 investigated whether the Black–white hypertension prevalence gaps at each level of SEP were less than the uncontrolled/across SEPs 1–5 Black–white hypertension prevalence gap. The assumption was the uncontrolled/across SEPs 1–5 Black–white hypertension prevalence gap represents how health disparities are typically analyzed, with no account or control of neighborhood SEP. Additionally, I assumed after controlling for neighborhood SEP, the Black–white hypertension prevalence gaps at each level of SEP would be less than the uncontrolled hypertension prevalence gap because Blacks and whites living in neighborhoods of similar SEP should have more similar hypertension prevalence rates. The regression coefficients of Models 1–5 were compared to the uncontrolled/across SEPs 1–5 coefficients. Coefficient comparisons were made across all three model types (i.e., a, b, and c). Model type *a* was fitted with race/ethnicity as the only predictor of a positive hypertension diagnosis. Model type *b* was fitted with race/ethnicity, age, and sex as predictors of a positive hypertension diagnosis. Model type *c* was fitted with race/ethnicity, age, and sex as predictors (with interaction commands between all three predictors) of a positive hypertension diagnosis.

Hypothesis 1: Neighborhood SEP and HBP Prevalence

Hypothesis 1 was: There is an inverse relationship between HBP prevalence and neighborhood SEP. The highest HBP prevalence rates will be in SEPs 1 and 2 (very low and low neighborhood characteristic) and the lowest HBP prevalence rates will be in SEPs 4 and 5 (high and very high neighborhood characteristic).

A chi-square test of independence was performed to test the statistical significance of the association between SEP and neighborhood HBP prevalence. Neighborhood HBP prevalence

rates were split into four categories, < 16%, 16–31%, 32–47% and > 47%. A count of neighborhoods falling within those four defined ranges across SEP were calculated. Table 12 outlines a clear pattern: SEPs 4 and 5 had the least number of neighborhoods falling into the highest HBP prevalence ranges, whereas SEPs 1 and 2 had the greatest number of neighborhoods falling into the highest HBP prevalence ranges. Chi-square analysis revealed a statistically significant relationship between neighborhood HBP prevalence and SEP, $X^2 (12, n = 56500) = 16299, P = 2.2e16 (p < 0.0001)$.

Table 12

Number of Neighborhoods by High Blood Pressure Prevalence and Socioeconomic Position: United States 2019

HBP prevalence %	SEP 1	SEP 2	SEP 3	SEP 4	SEP 5
< 16	62	35	34	46	145
16–31	2442	3555	5132	7191	9031
32–47	7526	8036	6199	3355	1513
> 47	1781	234	80	72	31

Note. n = 56500

Calculated by Cordelia Martin-Ikpe from CDC PLACES HBP outcome data and U.S. Census Bureau 2016–2020 American Community Survey (ACS) 5-year estimates.

Chi-square test results supported Hypothesis 1. This finding is important because the significance of the relationship between HBP prevalence and SEP was necessary to establish from the onset of the study because the applied neighborhood indexing methodology was a novel approach to capturing neighborhood characteristics across the U.S. Prior to this study, no study has undertaken the task of doing so.

Map analysis of HBP above the national average of 47% in relation to neighborhood SEP and non-Hispanic Black and white population density across SEP further emphasized the significance of the relationship between HBP and neighborhood characteristics. Figures 4–18

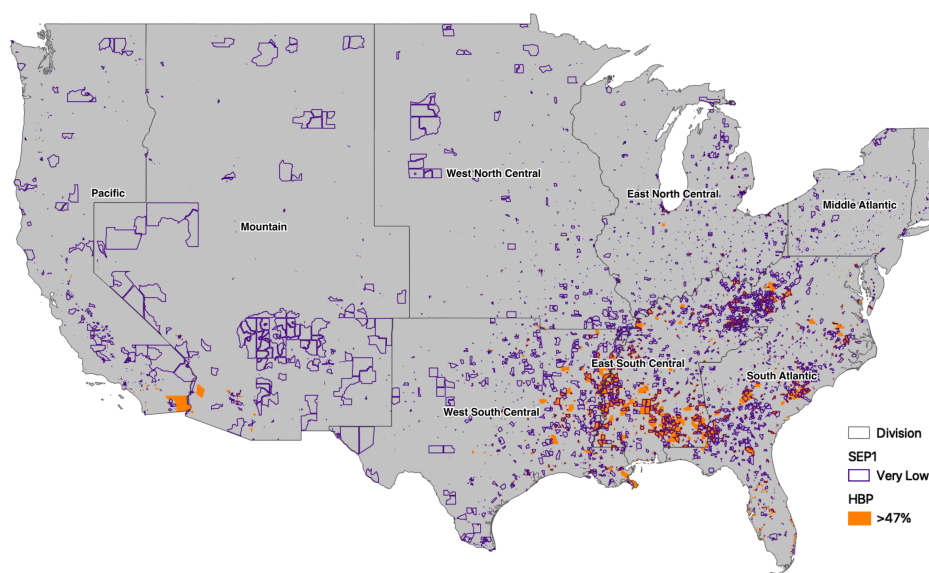
were generated using Q-GIS 3.26. Three shape (shp.) geographic boundary files were utilized: United States (Q-GIS Projection – European Petroleum Survey Group (EPSG):3857), U.S. Census Division, and a U.S. Census Tract boundary file (U.S. Census, n.d.-f). CDC PLACES geographic attribute data were matched and joined to the U.S. Census Tract shp. file attribute data by the Federal Information Processing Standard (FIPS) codes. 2016-2020 American Community Survey (ACS) population data geographic attributes were also matched and joined to the U.S. Census Tract shp. file attributes by FIPS codes. Joining both the CDC PLACES dataset and ACS 5-year estimate dataset to the U.S. Census Tract shp. file allowed for the mapping of neighborhood HBP prevalence above the national average of 47% and non-Hispanic Black and white population densities across SEP. Figures 4–6 (SEP1), 7–9 (SEP2), 10–12 (SEP3), 13–15 (SEP4), and 16–18 (SEP5) display neighborhood SEP 1, 2, 3, 4, and 5 tracts in relation to neighborhood HBP above the national average of 47% in relation to white and Black population densities by neighborhood SEP. Figures 4–6 display Neighborhood SEP 1 tracts and SEP 1 white and Black population densities in relation to neighborhoods with HBP prevalence above the national average of 47%. There was prominent overlap between neighborhoods of very low SEP and neighborhoods with a HBP prevalence above the 47% national average. In looking at racial densities across SEP, the findings were the same. Regardless of race, the non-Hispanic Black and white SEP 1 population densities overlapped the most with neighborhood HBP prevalence rates above 47% compared to those of non-Hispanic Black–white SEP 4 and 5 population densities.

Overall the map analysis supports the result of chi-square testing. As SEP increases, there is less overlapping among SEP 4 and 5 neighborhoods with above average HBP prevalence neighborhoods. Figures 4–18 do not highlight the racial disparity in HBP prevalence but do provide a visual representation of above-average HBP prevalence in relation to neighborhood

SEP and racial density across SEP. Though the racial disparity in hypertension cannot be analyzed in these maps once can begin to consider what percent of the total Black and white populations are represented in each SEP density map. For instance, the SEP 1 Black and white population density maps are not equal in their representation of each population. Approximately 11% of the total non-Hispanic white population is represented in the SEP 1 white population density map, whereas nearly 40% of the total non-Hispanic Black population is represented in the SEP 1 Black population density map. The SEP 5 population density maps by race represent an inverse distribution pattern. The non-Hispanic white population density map represents approximately 25% of their total population, whereas the SEP 5 non-Hispanic Black population density map represents about 10% of their total population. Given what we know about the overlap between SEP 1 neighborhoods and neighborhoods with above average HBP prevalence, it is safe to assume that a greater proportion (roughly 40%) of non-Hispanic Blacks reside in neighborhoods with the highest levels of HBP prevalence.

Figure 4

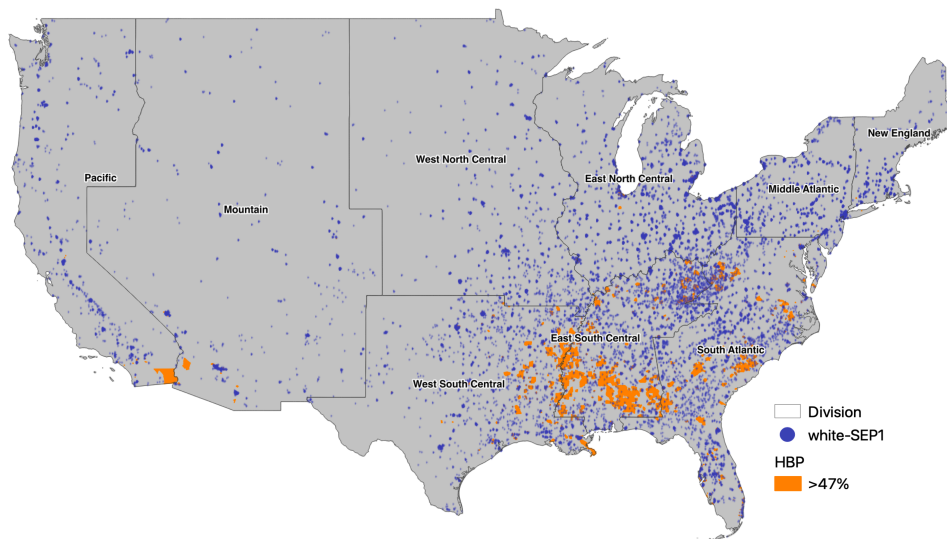
SEP 1 Neighborhoods and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 5

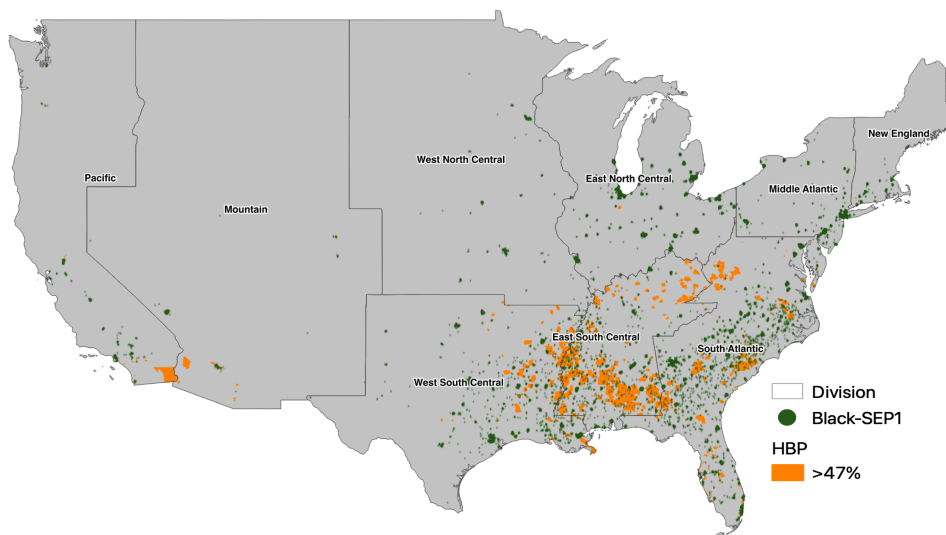
SEP1 Non-Hispanic White Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 6

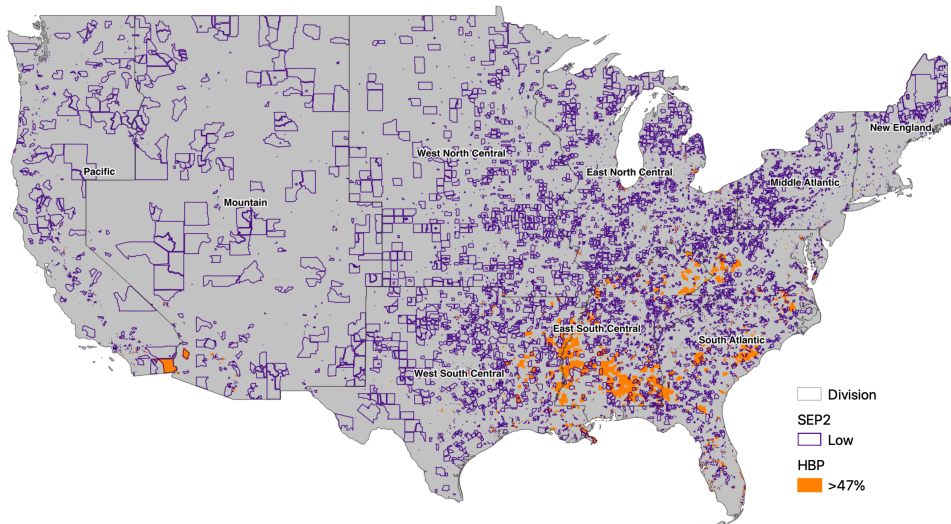
SEP1 Non-Hispanic Black Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 7

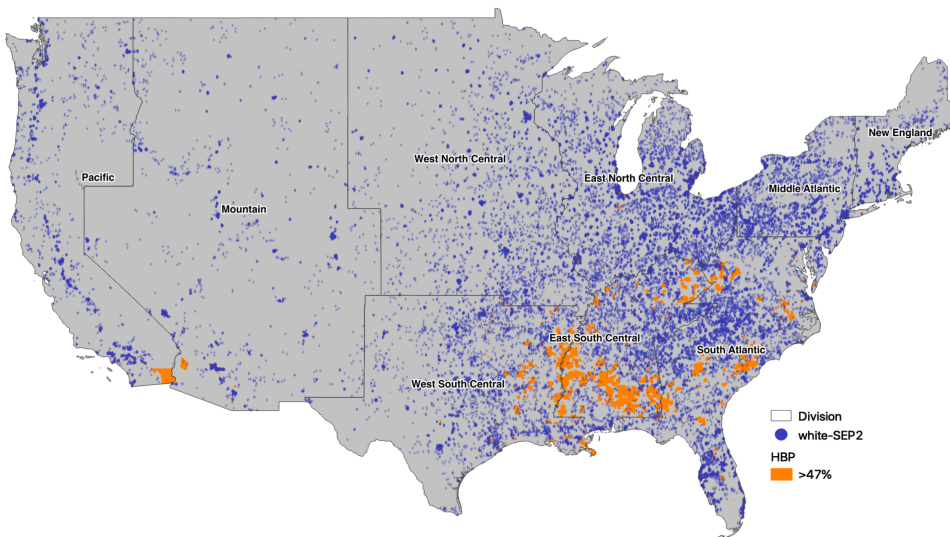
SEP 2 Neighborhoods and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 8

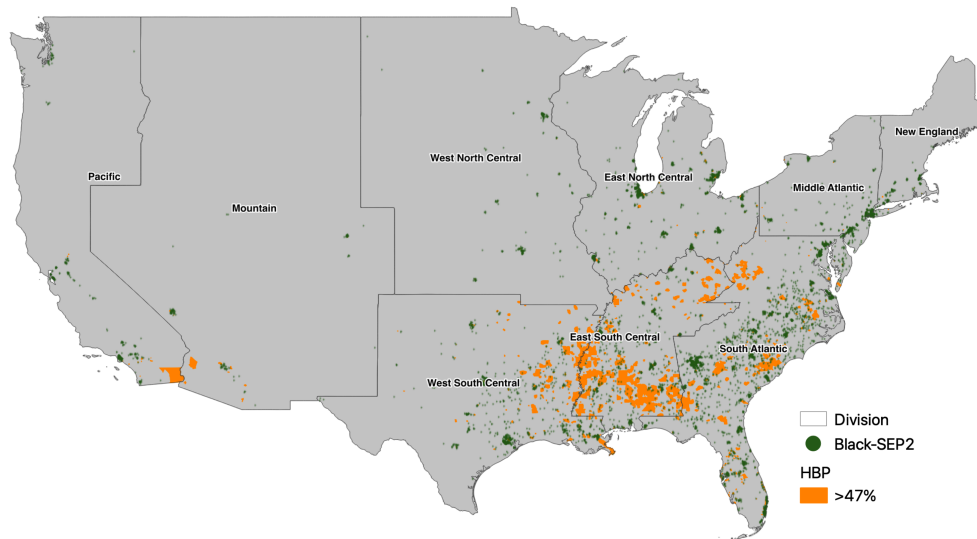
SEP 2 Non-Hispanic White Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 9

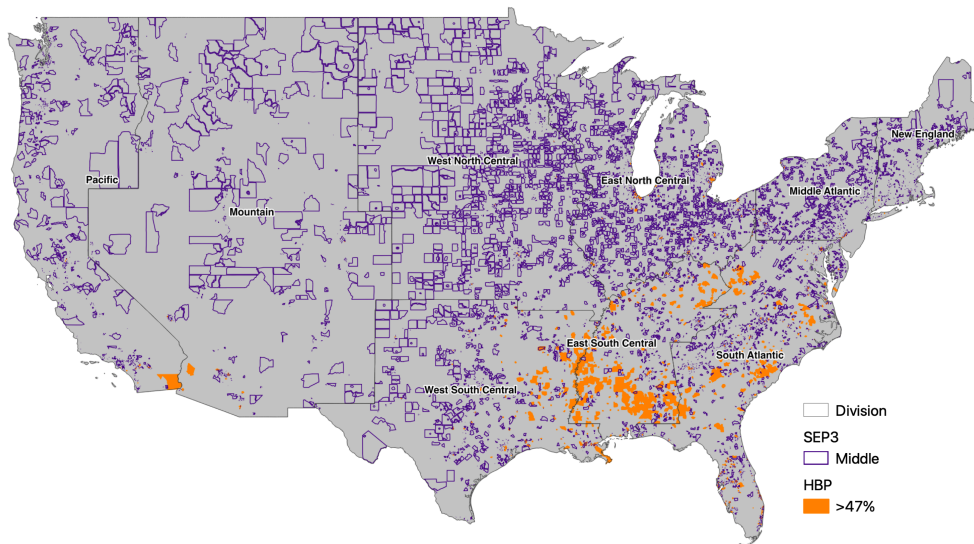
SEP 2 Non-Hispanic Black Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 10

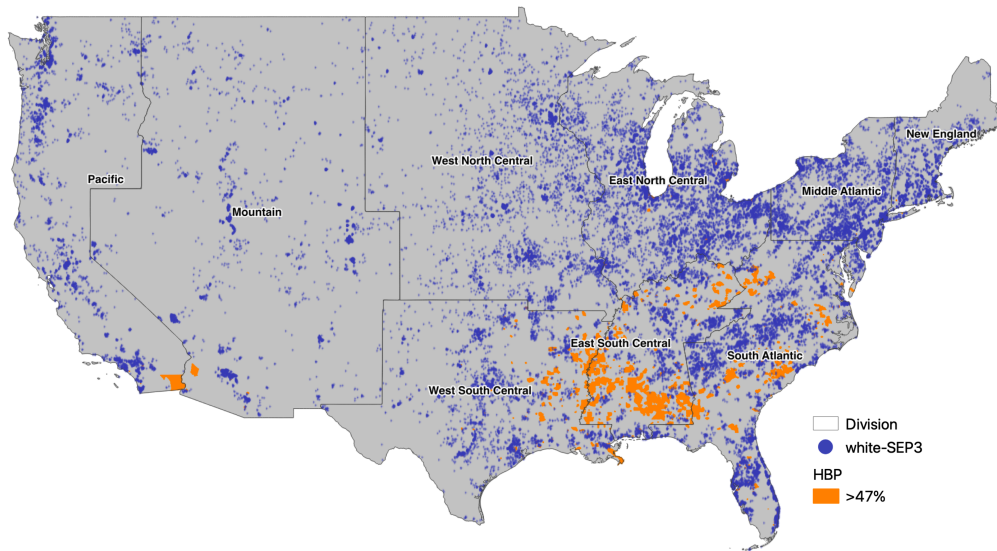
SEP 3 Neighborhoods and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 11

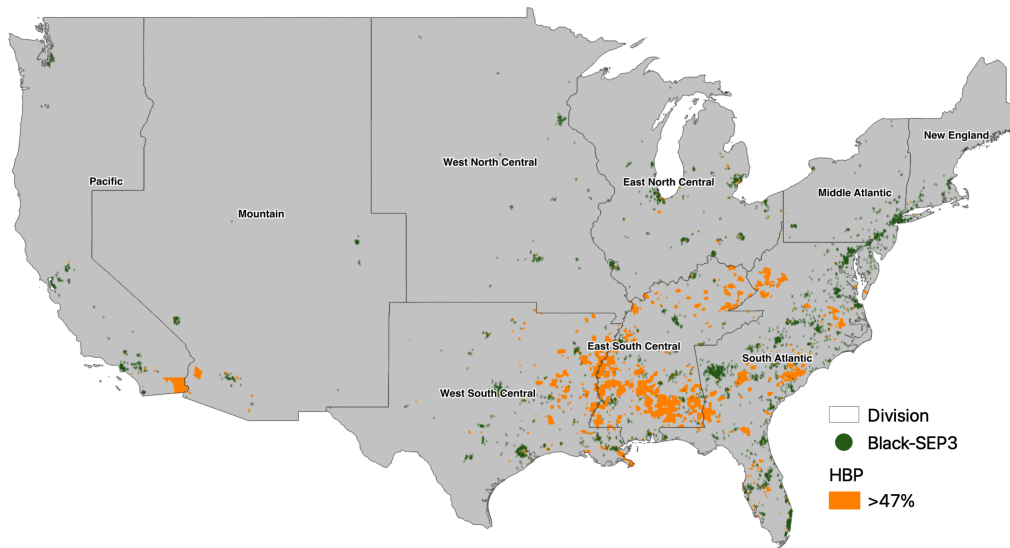
SEP 3 Non-Hispanic White Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 12

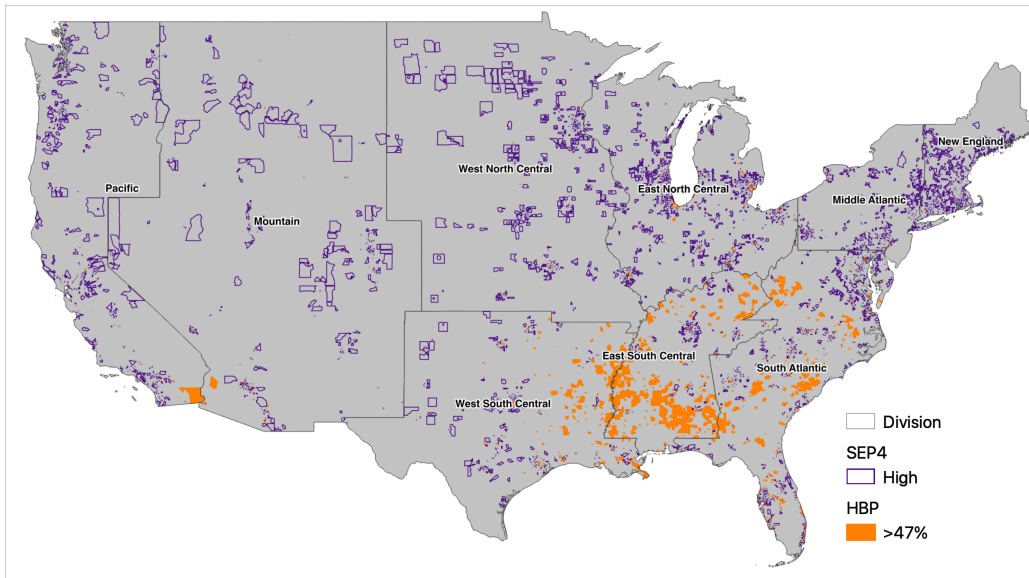
SEP 3 Non-Hispanic Black Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 13

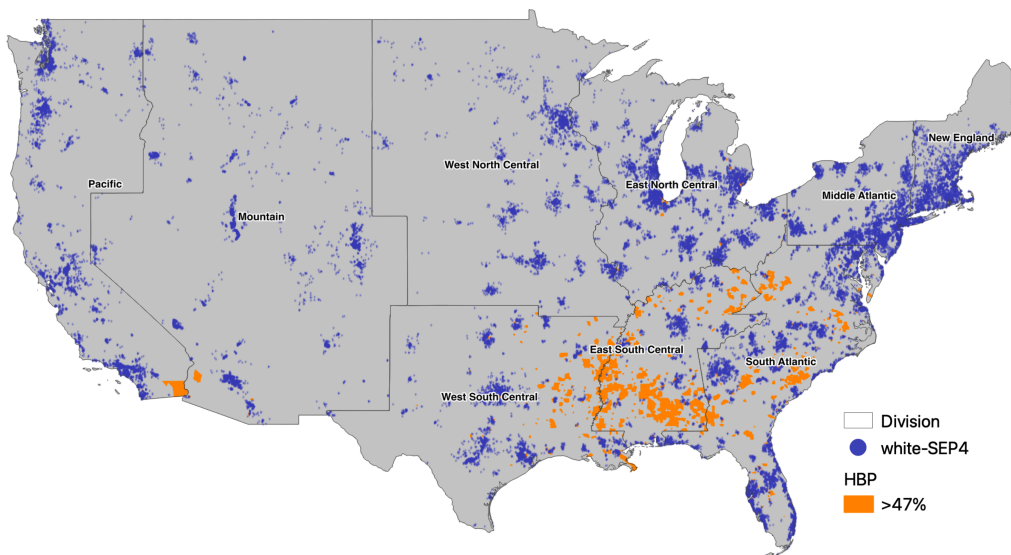
SEP 4 Neighborhoods and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 14

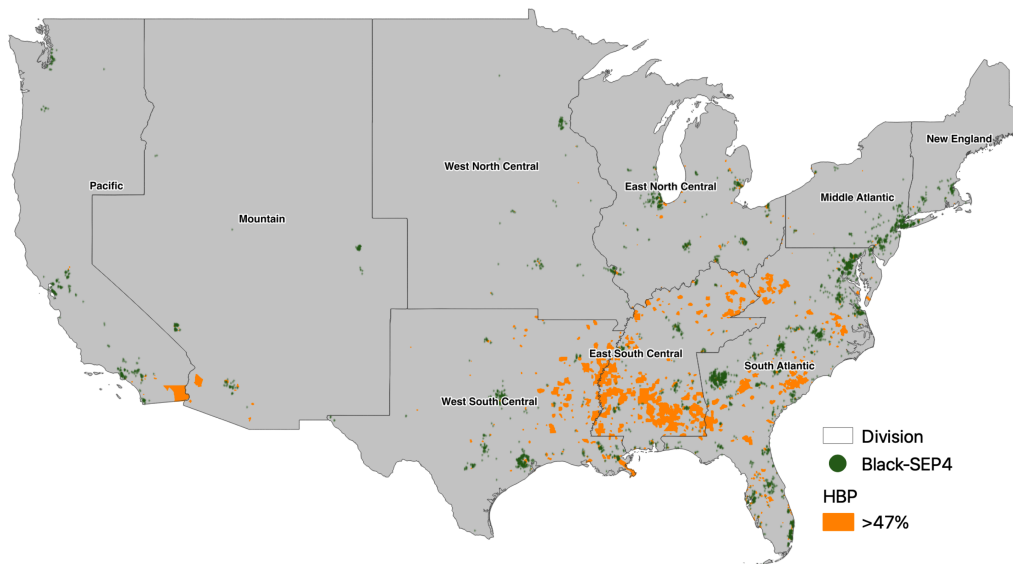
SEP4 Non-Hispanic White Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 15

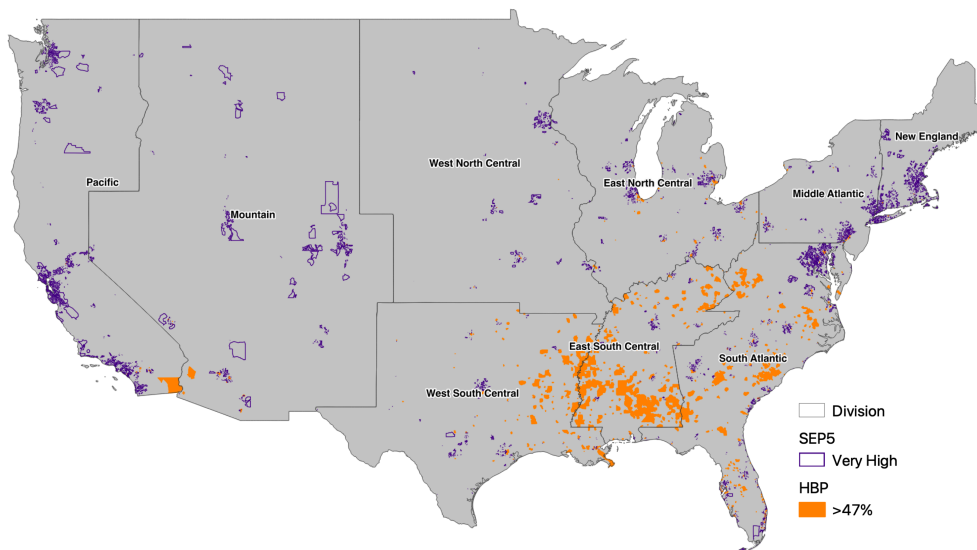
SEP4 Non-Hispanic Black Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 16

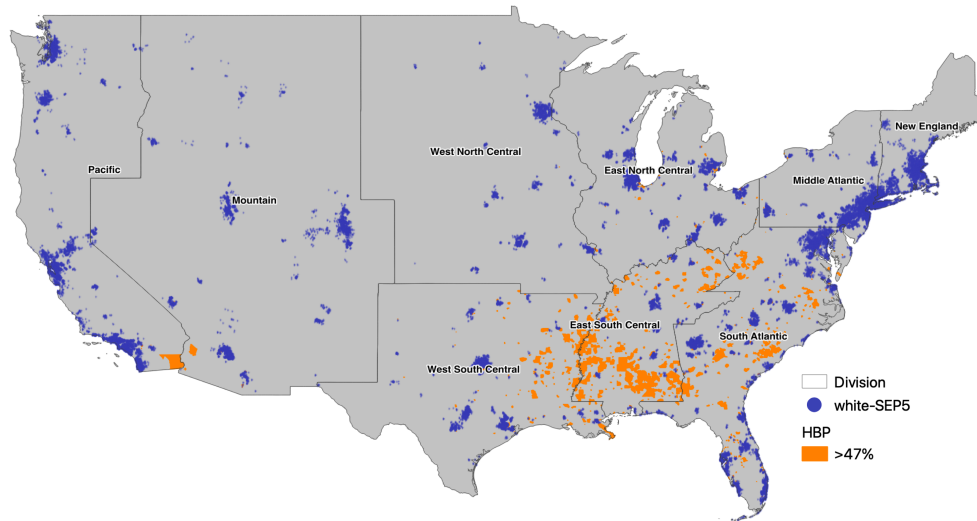
SEP 5 Neighborhoods and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 17

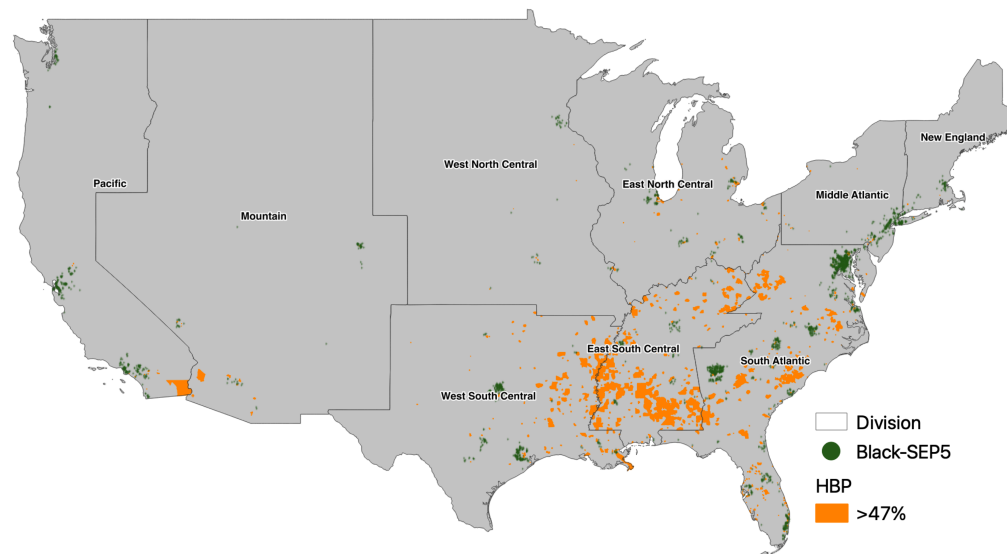
SEP 5 Non-Hispanic White Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Figure 18

SEP 5 Non-Hispanic Black Population Density and HBP Prevalence Greater Than 47%



Note. Map generated by Cordelia Martin-Ikpe using Q-GIS 3.26.1 – U.S. projection EPSG:3857

Neighborhoods with a HBP prevalence rate above 47% were most concentrated in the southern region of the country. Regional patterns of low and very low SEP were also concentrated in the South, but when looking at the population density of non-Hispanic Blacks and whites in SEP 1, there was a slight difference in how those populations were distributed across SEP 1. SEP 1 non-Hispanic white populations were concentrated near the northern border of the East South Central Census Division (Kentucky, Ohio, and Indiana), whereas SEP 1 non-Hispanic Blacks were concentrated in the South Atlantic Census Division of the country (North Carolina, South Carolina, Georgia, Alabama, and Mississippi). Despite these divisional population density patterns by race, both the Black and white SEP 1 populations overlapped with neighborhood HBP prevalence rates above 47%, but as previously stated, one must consider the percent of total population represented in each density map – Blacks and whites are unevenly distributed across neighborhood SEP.

Hypothesis 2: Mean HBP Prevalence Across SEP

Hypotheses 2 was: The mean neighborhood HBP prevalence rate at each level of SEP is significantly different across SEP, with the highest prevalence rates being within SEPs 4 and 5 and the lowest being in SEPs 1 and 2.

After establishing the relationship between neighborhood HBP prevalence and SEP, investigation of whether mean HBP prevalence across SEP differed significantly began. Figure 19 is a plot of mean HBP prevalence across SEP. As previously established, as SEP decreased, mean HBP prevalence increased. Figure 20 is a box plot of mean HBP prevalence across SEP. Though the means differed across SEP, there was overlap in the boxes; therefore, I performed a one-way ANOVA test to determine whether the HBP prevalence means were significantly different across SEP. ANOVA analysis revealed there was a statistically significant difference

between at least two pairs of mean HBP prevalence rates, $F(4,37) = [2.3721]$, $p = 2 \times 10^{-16}$ ($p < 0.0001$).

Figure 19

Mean HBP Prevalence by SEP: United States, 2019

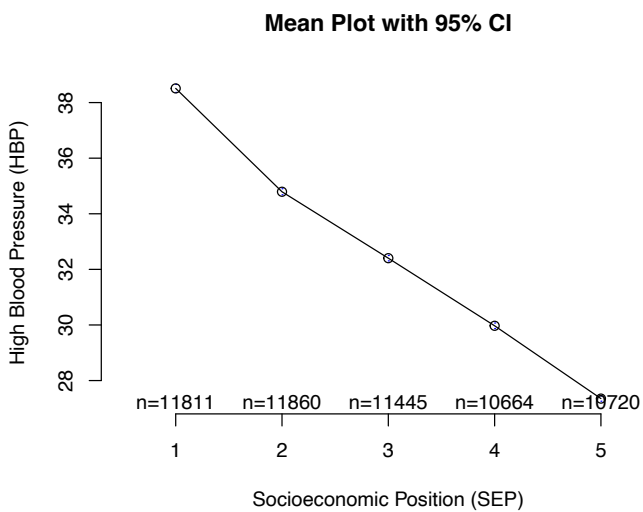
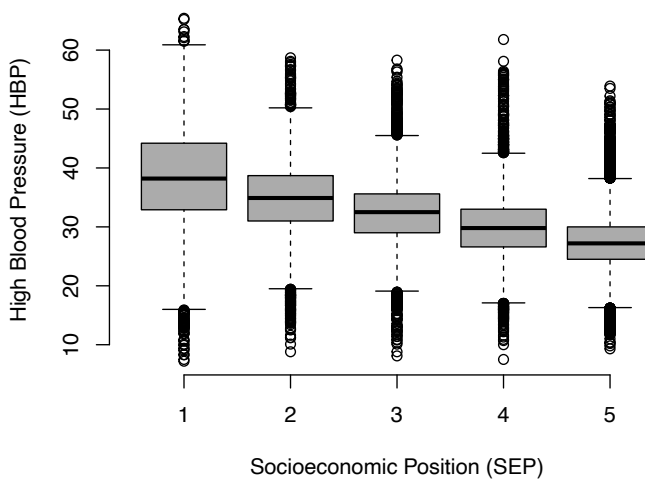


Figure 20

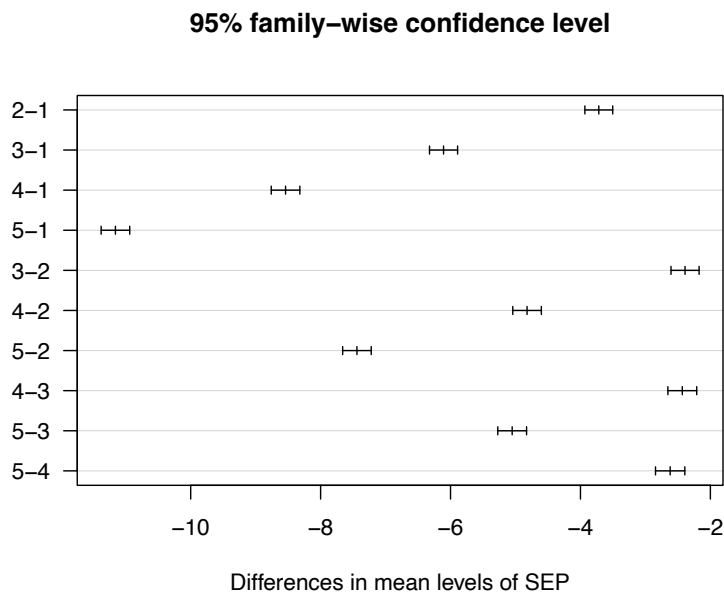
Box Plot Analysis of Mean HBP Prevalence by SEP: United States, 2019



Tukey's HSD (post hoc) test for multiple comparisons found the mean HBP prevalence between all levels of SEP was significantly different. Figure 21 details the level of difference between 10 pairs of means. The most significant mean differences were between SEPs 1 and 5, 4 and 1, and 5 and 2. The least significant mean HBP prevalence differences were between SEPs 3 and 2 and 4 and 3. SEP 2–1 ($p < 0.0001$, 95% CI[-3.93,-3.50]), SEP3–1 ($p < 0.0001$, 95% CI[-6.32, -5.89]), SEP 4–1 ($p < 0.0001$, 95% CI[-8.76, -8.32]), SEP 5–1 ($p < 0.0001$, 95% CI[-11.38, -10.94]), SEP 3–2 ($p < 0.0001$, 95% CI[-2.61, -2.17]), SEP 4–2 ($p < 0.001$, 95% CI[-5.04, -4.60]), SEP 5–2 ($p < 0.0001$, 95% CI[-7.66,-7.22]), SEP 4–3, 95% CI[-2.65, -2.21]), SEP 5–3 ($p < 0.0001$, 95% CI[-5.27, -4.83]), SEP 5–4 ($p < 0.001$, 95% CI[-2.84,-2.39]).

Figure 21

Tukey HSD (Post Hoc Test): Significance of Paired SEP Mean HBP Prevalence Difference



The results of the box plot analysis and Tukey HSD (post hoc) test supported Hypothesis 3. Because mean hypertension prevalence rates were significantly different across each level of

SEP, it further justified a need to control for neighborhood characteristic in the analysis of Black–white disparities in hypertension.

Hypothesis 3: Non-Hispanic Black and White Proportional Difference in SEPs 1 and 5

Hypothesis 3 was: The hypertension prevalence gap between non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1 will be similar to the prevalence gap between non-Hispanic whites in SEP 5 and non-Hispanic Blacks in SEP 1. With similar being defined as the two proportional difference 95% confidence intervals of each proportion difference will overlap.

According to the post hoc analysis results (see Figure 21), the most significant difference in neighborhood hypertension prevalence means were between SEPs 1 and 5. In looking at the distribution of non-Hispanic Black and white individuals across SEP (see Table 11), SEP decreased as the population of non-Hispanic Blacks increased. Over 50% of non-Hispanic Blacks live in SEPs 1 and 2, with exactly 41.8% living in SEP 1 as opposed to only 10.7% of whites living in SEP 1. When looking at SEP 5, the non-Hispanic Black population was 10.9% compared to the non-Hispanic white SEP 5 population of 24.3%. Despite these Black-white differences in Neighborhood SEP distribution, researchers have rarely controlled for neighborhood characteristics in the analysis of Black-white health disparities (Darden et al, 2010). This analysis approach resulted in a relatively large Black–white disparity gap compared to the disparity gaps among Blacks and whites living in similar SEPs. The assumption of Hypothesis 3 was when comparing the Black hypertension proportions of Blacks living in SEP 5 to those of whites living in SEP 1, the resulting proportional difference gap would be similar to that of the proportional difference gap among non-Hispanic whites in SEP 5 and Blacks in SEP 1. Due to the enduring legacies of racial residential segregation, an investigation of this sort would not be possible without the application of the Darden-Kamel Index methodology.

A proportional difference z test was performed to test the significance of the proportional hypertension difference between Blacks in SEP 5 and whites in SEP 1 and whites in SEP 5 and Blacks in SEP 1. Table 13 outlines the findings of this analysis. According to the reported results in Table 13, the two sets of proportional differences are statistically different; therefore, one can suggest that if non-Hispanic Blacks were primarily located in SEP 5 and non-Hispanic whites were located in SEP 1, the observed disparity gap would likely remain statistically significant, but in favor of the non-Hispanic Black population.

However, though both proportional difference pairs in Table 13 are statistically significant, in looking at their respective confidence intervals, there was no overlap among both sets of confidence intervals. The lack of overlap suggested the proportional differences are not similar (per the definition of similar outlined in footnote number 2). The proportional difference among non-Hispanic Blacks in SEP 5 compared to that of non-Hispanic whites in SEP 1 was actually greater than the proportional difference among non-Hispanic Whites in SEP 5 and non-Hispanic Blacks in SEP 1, but more importantly the 95% confidence intervals of each proportional difference did not overlap. Therefore, Hypothesis 3 was rejected.

Table 13

Black–White Proportional Hypertension Differences Across Different SEP

Hypertensive White SEP 1	Hypertensive Black SEP 5	% difference	p value	CI 95%
41.76	25.6	16.16	2.20E-16***	[16.11, 16.23]
Hypertensive Black SEP 1	Hypertensive White SEP 5	% difference	p value	CI 95%
42.62	27.66	14.96	2.20E-16***	[14.92, 14.99]

Note. p value $<.05$ =*, p value $<.01$ =**, p value $<.001$ =***

Hypothesis 4: Non-Hispanic Black and White Hypertension Proportion Difference

Hypothesis 4 was: The non-Hispanic Black–white hypertension prevalence gap narrows among non-Hispanic Blacks and whites living in similar neighborhood SEP. The proportional hypertension percentage difference at each level of SEP will be less than the total/across SEP proportional Black–white hypertension prevalence difference.

The uncontrolled/total SEP Black–white hypertension proportions represent how racial disparities in hypertension are reported at the national scale, without any account or control of neighborhood characteristics; therefore, the assumption was after controlling for neighborhood SEP, Blacks and whites will have similar hypertension prevalence rates, leading to a narrowing of the observed proportion difference gaps at each level of SEP relative to the uncontrolled/total SEP proportion difference. Proportional difference gaps are synonymous to disparity; when gaps are small (i.e., <5% point difference) the assumption is a disparity may not exist or be statistically significant. Conversely, when proportional difference gaps are greater than 5% points, the disparity may be significant (Moore et al., 2020). I compared the Black–white hypertension proportional difference gaps at each level of SEP to that of the uncontrolled/total SEP proportional difference gap. The uncontrolled/across SEP 1-5 proportion difference gap was greater than 5% points, while the proportional difference gaps at SEP levels 1, 2, 4, and 5 were less than 5% points. As previously stated, the uncontrolled/total SEP Black–white hypertension proportions represent how racial disparities in hypertension are reported at the national scale, without any account or control of neighborhood characteristics.

Table 14 outlines the non-Hispanic Black–white hypertension proportions and their differences at each level of SEP and across SEP. A two-proportion difference z test revealed the Black–white hypertension proportions are significantly different at each level of SEP, as all p

values were less than .05. Additionally, proportion differences at SEPs 1, 2, 4, and 5 were less than the uncontrolled/total SEP proportion difference. Based on these data, Blacks and whites in SEPs 1, 2, 4 and 5 have more similar hypertension prevalence rates. It is worth noting that in SEP 5, Blacks have a lower hypertension prevalence than whites. Considering that non-Hispanic Blacks only comprise 7.69% of the total SEP 5 population, the observed Black–white hypertension proportions may have been influenced by the small non-Hispanic Black sample size in SEP 5. Nonetheless, what is important is the Black–white hypertension prevalence gap in SEP 5 is less than the uncontrolled/total SEP prevalence gap.

Table 14

Black–White Hypertension Proportion Difference by SEP

SEP	% hypertensive non-Hispanic Black	% hypertensive non-Hispanic white	% difference	CI 95%	<i>p</i> value
1	42.62	41.76	0.86	[0.81, 0.89]	2.2e-16***
2	37.89	36.70	1.19	[1.13, 1.23]	2.2e-16***
3	39.77	33.42	6.35	[6.30, 6.41]	2.2e-16***
4	34.94	32.82	2.12	[2.06, 2.18]	2.2e-16***
5	25.60	27.66	-2.06	[-2.12, -2.01]	2.2e-16***
Uncontrolled (Total SEP)	38.41	33.34	5.07	[5.05, 5.09]	2.2e-16***

Note. *p* value <.05 =*, *p* value <.01=**, *p* value<.001=***

Unlike SEPs 1, 2, 4, and 5, SEP 3 did not have a Black–white hypertension proportion difference that was less than the uncontrolled/total SEP. In total, 39.77% of non-Hispanic Blacks were hypertensive compared to 33.34% of non-Hispanic whites, resulting in a proportional percentage difference gap of 6.35. When thinking about this result, it is important to highlight that SEP 3 represents neighborhoods of middle socioeconomic position (MSEP), and 22.2% of the weighted survey population of this study belongs to SEP 3. Of the total SEP 3 population, 10.19% are non-Hispanic Black and 89.81% are non-Hispanic white. The Black–white

proportional hypertension difference result at SEP 3 did not agree with the stated Hypothesis 3, unlike that of the proportional differences at SEPs 1, 2, 4, and 5. Middle SEP (i.e., SEP 3) is a threshold of sorts, representing the U.S. middle class. As outlined in Table 1, an estimated 67.56% of those residing in SEP 3 own their home, the median household income is \$62,209.02 per year, and only 4.69% are unemployed. In many respects, those who reside in SEP 3 have achieved a level of economic stability that presumably equates to better health care, education, and housing (American Psychological Association, 2022) .

The characteristics of SEP 3 are also worth mentioning because despite non-Hispanic Blacks being exposed to the same middle SEP neighborhood characteristics as non-Hispanic whites residing in SEP 3, there was a prominent disparity in hypertension between the two groups. The result may suggest the Black middle class encounter a set of unique experiences that lead to poorer hypertension outcomes than the white middle class. In addition to the relatively large Black–white hypertension proportion difference gap at SEP 3, non-Hispanic Blacks in SEP 3 have a greater prevalence of hypertension than non-Hispanic Blacks in SEP 2. Greater detail about SEP 3 is forthcoming in the section titled Regression Models A, B, and C.

Proportion difference gaps and odds ratios comprised the base level of hypertension disparities analysis of this study. Regression modeling, which is presented later in this chapter, explored the factors of age and sex in the observed Black–white hypertension diagnosis at each level of SEP among the study population. After calculating the Black–white hypertension proportional difference gaps (see Table 14), Black–white hypertension odds ratios and their respective 95% confidence intervals were calculated using R 4.2.1. Black–white hypertension odds ratios at each level of SEP are outlined in Table 15. The results of this analysis partially support Hypothesis 3. At SEPs 1, 2, 4, and 5, the non-Hispanic Black odds of being hypertensive

relative to non-Hispanic whites is not significant, whereas the uncontrolled/total SEP Black odds is significant. This result suggests at SEPs 1, 2, 4, and 5, no significant hypertension outcome disparity exists among non-Hispanic Blacks and whites who live in similar SEP. Conversely, the Black hypertension odds at SEP 3 and across SEP are significant, suggesting that being Black is associated with a greater odd of being diagnosed as hypertensive in both of those analysis categories. Once again, SEP 3 is an outlier. Blacks living in middle SEP neighborhoods do not experience comparable hypertension outcomes to that of whites living in middle SEP neighborhoods. The Black odds of hypertension at SEP 3 are greater than the uncontrolled/total SEP Black hypertension odds. This result does not support Hypothesis 3.

Table 15

Black–White Hypertension Diagnosis Odds Ratios: Race/Ethnicity as a Regression Predictor of High Blood Pressure Diagnosis

SEP	OR	CI 95%	<i>p</i> value
1	1.04	[0.81, 1.32]	0.78
2	1.05	[0.78, 1.43]	0.75
3	1.32	[1.01, 1.71]	0.04*
4	1.10	[0.77, 1.58]	0.61
5	0.90	[0.56, 1.43]	0.66
SEP 1–5	1.25	[1.08, 1.43]	0.00**

Note. *p* value <.05 =*, *p* value <.01=**, *p* value<.001=***

Analysis of non-Hispanic Black and white proportional hypertension differences and hypertension odds ratios revealed partial support of Hypothesis 3 because after controlling for neighborhood SEP, non-Hispanic Blacks and whites living in SEPs 1, 2, 4, and 5 have narrower proportional difference gaps relative to the uncontrolled/total SEP proportional difference gap among non-Hispanic Blacks and whites. Odds ratios analysis results were consistent with the proportional difference *z* test results. Without controlling for SEP, the Black odds of

hypertension is significant, unlike the Black hypertension odds at SEPs 1, 2, 4, and 5, which were not statistically significant.

Regression Models A, B, and C

At this stage in the study, Hypothesis 3 was not rejected because regression analysis allows for investigation of the key biological factors of age and sex, which past studies have found to be significant confounders of hypertension outcomes and racial disparities (Foti et al., 2019). Binomial regression analysis was performed using R Studio 4.2.1. MEPS survey data were subset by SEP, and regression analysis of each level of SEP along with the combined SEP 1–5 subset was performed. I ran each of those models in the following sequence: (a) race/ethnicity alone as a predictor of hypertension; (b) race/ethnicity, age, and sex as predictors of hypertension but with no predictor interaction terms; and (c) race/ethnicity, age, and sex as predictors of hypertension but with predictor interaction terms.

Before running the models, the study design was set for each of the six models, which set the observation person weights and standard error estimates. Before sub setting the 2019 MEPS HC dataset, the survey design of the data was set in the model to reflect adjustments for survey nonresponse and adjustments to population control totals which allowed for the calculation of the standard errors associated with weighted estimates. The models were subset to only include adults who were identified as male or female, non-Hispanic Black or white, and who answered *yes* or *no* to being diagnosed with hypertension unrelated to pregnancy.

Figure 22 is a plot of regression coefficients and their 95% confidence intervals. The displayed coefficient plot reflects estimates that were calculated from a regression model fit with race/ethnicity (RACETHX) as the only predictor of hypertension. Each model listed in the key on the right side of Figure 22 directly corresponds to SEP ranking (e.g., SEP 1 equates to model

1, SEP 2 equates to Model 2). However, Model 6 represents the uncontrolled/total SEP category, which incorporates values across all five levels of SEP. In looking at Figure 22, the confidence interval whiskers straddle zero in Models 1, 2, 4, and 5, which means after controlling for neighborhood characteristics, race/ethnicity alone did not predict a hypertension diagnosis in SEPs 1, 2, 4, and 5. This finding is consistent with the analysis findings presented in Tables 14 and 15. The findings presented in Figure 22 partially support Hypothesis 3, as the coefficients for SEPs 1, 2, 4, and 5 (Models 1, 2, 4, and 5) estimate that being Black is not a predictor of hypertension. In contrast, Model 6, which represents SEP 1–5 values, estimates that race/ethnicity is a predictor of hypertension. Once again, analysis results suggest the control of neighborhood characteristic diminishes the nationally observed Black–white disparity in hypertension prevalence; however, SEP 3 remains the exception. At SEP 3, race/ethnicity is a predictor of hypertension. When comparing Models 6 (SEP 1–5) and 3, there is an overlap in confidence intervals, however, Model 3’s lower bound is closer to zero than Model 6, indicating that race/ethnicity is not as strong of a predictor of hypertension in Model 3 as that of Model 6. The plotting of model coefficients highlights the relationships between the models and levels of SEP and determine the possible extent to which race/ethnicity is a predictor of hypertension in Models 1, 2, 4, and 5 compared to that of Model 6.

Figure 22

Regression Coefficients: Race/Ethnicity as a Predictor of High Blood Pressure Diagnosis

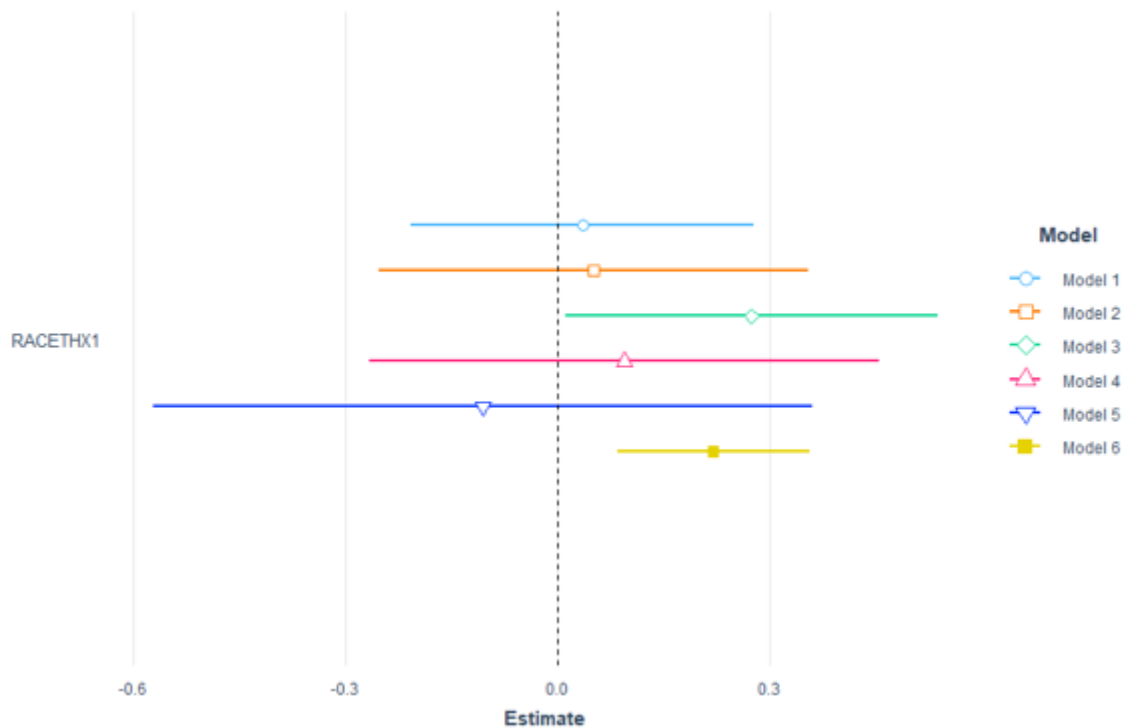


Figure 23 is a plot of regression coefficients with race/ethnicity, age, and sex set as predictors without interaction between predictors. Not setting an interaction between predictors allowed me to run a model that estimated the strength of the individual predictor irrespective of other hypertension predictors. For analysis purposes, age was split into two categories: above and below 60 years of age. Adults aged 18–59 were coded as 0, whereas seniors aged 60 and older were coded as 1. The plotted age regression coefficients represent senior age status as a predictor of hypertension. With regard to sex as a predictor of hypertension, the variables of male and female were already coded as 0 and 1 respectively; therefore, the plotted sex coefficients represent female status as a predictor of hypertension. After setting race/ethnicity, age, and sex as predictors of hypertension, it became evident that senior age status was the

strongest independent predictor of hypertension across all models, whereas sex was not a significant independent predictor across all models. Race/ethnicity, however, was a significant predictor of hypertension at SEP levels 3 and 4 and in Model 6 (uncontrolled/across SEP). The results of analysis with race/ethnicity, age, and sex set as predictors without interactions indicate some level of effect with regard to age and sex on race/ethnicity as a predictor; yet, because no interaction terms were applied for this analysis, the dynamics of the effect could not be conclusively determined at this stage.

Figure 23

Binomial Regression Coefficients: Race/Ethnicity, Age, and Sex as Predictors of High Blood Pressure Diagnosis

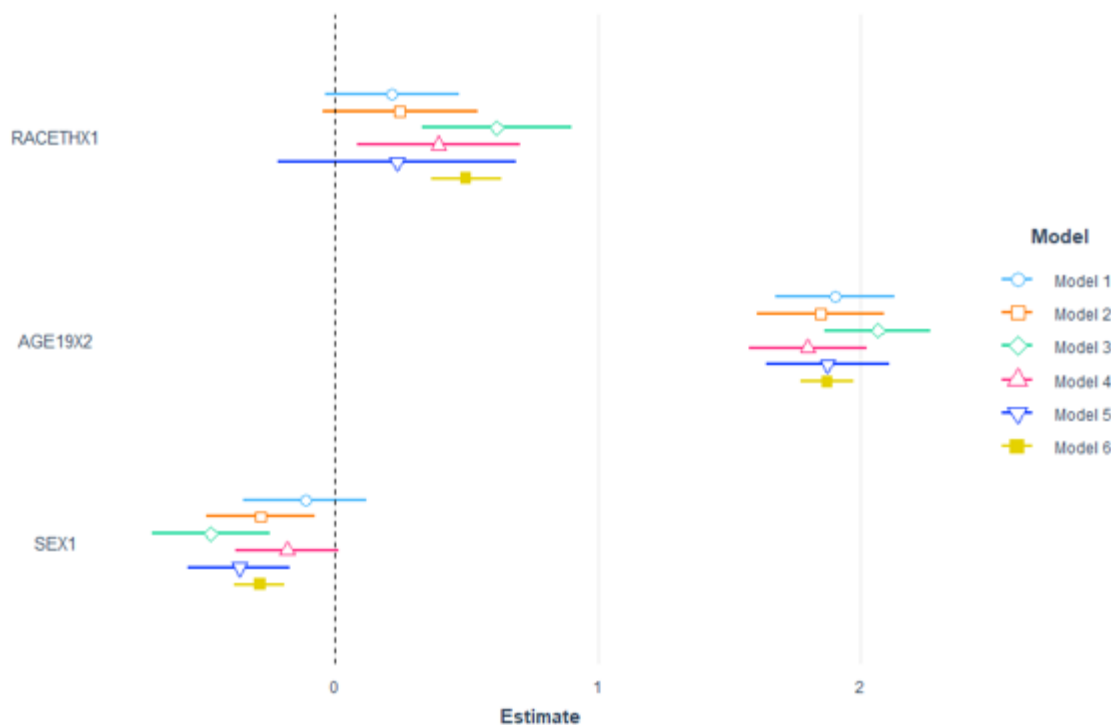
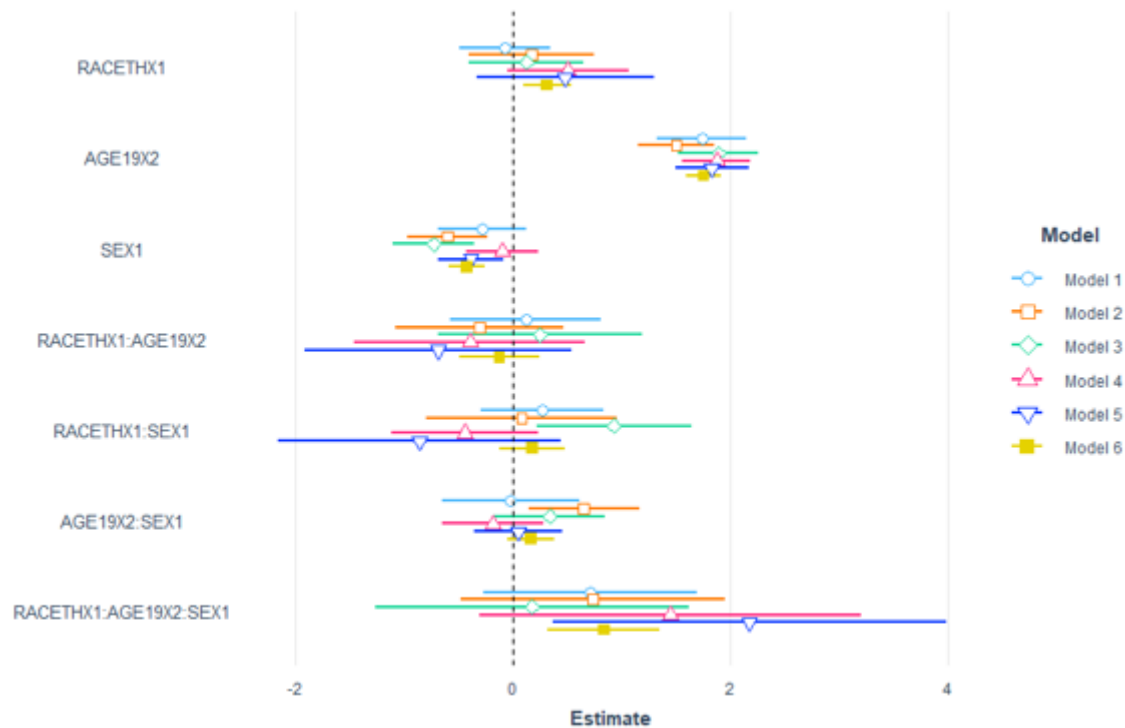


Figure 24 is a plot of regression coefficients with race/ethnicity, age, and sex set as predictors with interaction between the predictors. Setting interactions between predictors resulted in running the model to account for the combined effect of predictors. Setting predictor

interactions resulted in race/ethnicity being an insignificant predictor of hypertension for Models 1–5 relative to the uncontrolled Model 6. This result fully supports the stated Hypothesis 3. In looking at the predictor interactions, it is possible that the race/ethnicity and sex interaction has the most effect on the observed significance of race/ethnicity as a predictor of hypertension in Model 3 (i.e., SEP 3) because the race/ethnicity predictor coefficient results of Figures 22 and 23 are consistent with the race/ethnicity and sex interaction coefficient results of figure 24. This consistency suggests that after adjusting for the interaction between race/ethnicity and sex, race/ethnicity as a predictor of hypertension diagnosis is insignificant across all levels of SEP. Their similarity indicated the combined effect of race/ethnicity and sex at SEP 3 has a bearing on the significance of race/ethnicity as a predictor of hypertension. Setting model predictor interactions across all models allowed for observation of the significance of race/ethnicity as a predictor of hypertension when interactions between race/ethnicity, age, and sex are controlled for. Statistically, this model was the strongest because it accounts for the combined effects of key biological confounding variables, which is a more robust model type (Norton et al., 2019).

Figure 24

Binomial Regression Coefficients: Interaction Between Race/Ethnicity, Age, and Sex Predictors of High Blood Pressure Diagnosis



Model type *a* of Table 16 lists the same odds ratios that were reported in Table 15. In looking at Figure 22 in conjunction with Tables 14 and 15, it became evident that Hypothesis 3 was only partially supported when race/ethnicity alone is set as the only predictor of hypertension. When looking at model type *b*, it was clear that age and sex have some effect on race/ethnicity as a predictor of hypertension, but the details of that connection are not conclusive. Only after fitting the regression model with race/ethnicity, age, and sex as predictors with interactions, as represented by model type *c*, did regression coefficient estimates support Hypothesis 3. After fitting the model with race/ethnicity, age, and sex as predictors with interactions, race/ethnicity was an insignificant predictor of hypertension across all SEP levels. According to Table 16, the Black odds of being hypertensive was insignificant at each level of

SEP relative to the Black odds across SEP (SEP 1–5) only after controlling for the interactions of race/ethnicity, age, and sex. Comparing Figures 22, 23 and 24 revealed the interaction of race/ethnicity and sex were especially significant at SEP 3 because only after controlling for race/ethnicity did sex interaction with race/ethnicity become an insignificant predictor of hypertension relative to the uncontrolled (SEP 1–5) category of analysis. The results of model type *c* supported Hypothesis 3, therefore, Hypothesis 3 was accepted.

Table 16*Race as a Predictor of Hypertension by Model Type and SEP*

Model/SEP	Predictor (Race/Ethnicity)	Model type by Linear model (svyglm) predictor formula					
		a: Race alone as a predictor		b: Race, age, and sex as predictors without interaction		c: Race, age, and sex as predictors with interaction	
		OR [CI 95%]	<i>p</i> value	OR [CI 95%]	<i>p</i> value	OR [CI 95%]	<i>p</i> value
Model 1 (SEP 1)	Non-Hispanic	1.04 [0.81,1.32]	0.78	1.24 [0.96,1.61]	0.09	0.93 [0.62,1.41]	0.75
Model 2 (SEP 2)	Black	1.05 [0.78,1.43]	0.75	1.28 [0.95,1.71]	0.11	1.19 [0.67,2.13]	0.56
Model 3 (SEP 3)	Non-Hispanic	1.32 [1.01, 1.71]	0.04*	1.85 [1.39,2.46]	4.479e-05***	1.14 [0.67, 1.93]	0.63
Model 4 (SEP 4)	Black	1.10 [0.77, 1.58]	0.61	1.48 [1.09,2.02]	0.01*	1.67 [0.96, 2.90]	0.07
Model 5 (SEP 5)	Non-Hispanic	0.90 [0.56, 1.43]	0.66	1.27 [0.80,1.99]	0.31	1.62 [0.72, 3.65]	0.25
Model 6 (SEP 1-5)	Black	1.25 [1.08, 1.43]	0.00**	1.65 [1.44,1.88]	9.052e-12***	1.37 [1.10, 1.71]	0.01**

Note. *p* value <.05 =*, *p* value <.01=**, *p* value<.001=***

CHAPTER 7: SUMMARY AND CONCLUSIONS

The objectives of this study were twofold: first, I conducted a comprehensive spatial analysis of hypertension prevalence across U.S. neighborhoods; second, I investigated the significance of the relationship between neighborhood socioeconomic position (SEP) and Black–white hypertension disparities. Pursuit of these objectives emphasized that non-Hispanic Blacks and whites are exposed to very different neighborhood characteristics, which highlights the legacies of racial residential segregation and neighborhood disinvestment. Racial residential segregation and neighborhood disinvestment are key systemic injustices that have led to the perpetually inequitable distribution of Blacks and whites across neighborhood SEP – Blacks are disproportionately exposed to neighborhoods of very low neighborhood SEP while whites are primarily exposed to neighborhoods of high and very high SEP.

Based upon the neighborhood effects theoretical framework and the findings of this study, it is reasonable to suggest that the disproportionate exposure of Blacks to very low SEP neighborhoods maintains racial disparities in hypertension and other diseases. The applied methodology (the Modified Darden-Kamel Composite Index) of this study presents an opportunity to consistently center the role of neighborhood characteristics in perpetual racial disparities in hypertension and health overall. The absence of the spatial perspective in racial health disparities analysis is arguably one of many reasons why disparities in health are increasing (Arcaya, 2017; Metcalf, 2018). Perhaps, where people live is not being considered enough. The simultaneous capturing of the racial, spatial and socioeconomic structure of the U.S. reveals a very uncomfortable truth, where Black and white Americans live and what they are exposed to is largely by design. If the approach of this study to disparities analysis becomes standard practice, the uncomfortable truth of America’s oppressive and unjust systems will be

consistently brought to the forefront. Hopefully, as a result, politicians and public health experts will formulate and implement policy and interventions with a level of spatial consciousness.

Despite longstanding emphasis on the significance of neighborhood quality as a determinant of health outcomes, there exists a significant methodological gap in the account and control of neighborhood characteristics in health disparities analysis (Krieger et al., 2003; Darden et al, 2010). This dissertation study addressed this methodological gap and was the first to do so through its application of the Darden-Kamel Index methodology across the United States using a large national health survey. Use of a large national health survey allows for reliable population level estimates that can subsequently inform evidence-based policy. Additionally, this dissertation holds the potential to serve as a template for the standardization of spatially conscious health disparities analysis.

The comprehensive robustness of the applied Darden-Kamel Index methodology simultaneously captured the racial, spatial, and socioeconomic structure of most U.S. neighborhoods (approximately 73%) in the analysis of Black-white disparities in hypertension. This high level of comprehensive analysis also adds to the reliability of the presented population estimates, and further enhances its appeal as a reliable and widely adoptable means of disparities analysis. Investigation of the following hypotheses are an example of a comprehensive and spatially centered approach to the analysis of the relationship between neighborhood SEP and racial disparities in hypertension.

Hypothesis 1 was: There is an inverse relationship between HBP prevalence and neighborhood SEP. The highest HBP prevalence rates will be in SEPs 1 and 2 (i.e., very low and low neighborhood characteristic) and the lowest HBP prevalence rates will be in SEPs 4 and 5 (i.e., high and very high neighborhood characteristic). Hypothesis 1 was accepted using chi-

square testing and geographic information system (GIS) analysis software. Neighborhood HBP prevalence rates were split into four categories, < 16%, 16–31%, 32–47%, and > 47%. A count of neighborhoods falling within those four defined ranges across SEP were calculated. Table 12 outlines a clear pattern: SEPs 4 and 5 had the least number of neighborhoods falling into the highest HBP prevalence ranges, whereas SEPs 1 and 2 had the greatest number of neighborhoods falling into the highest HBP prevalence ranges. Chi-square analysis revealed a statistically significant relationship between neighborhood HBP prevalence and SEP, $X^2(12, n = 56500) = 16299, P = 2.2e16 (p < 0.0001)$. Map analysis using GIS software revealed prominent overlap between neighborhoods of very low SEP and neighborhoods with a HBP prevalence above the 47% national average.

Hypothesis 2 (i.e., the mean neighborhood HBP prevalence rate at each level of SEP is significantly different across SEP, with the lowest prevalence rates being within SEPs 4 and 5 and the highest being in SEPs 1 and 2) was tested using analysis of variance (ANOVA) testing and Tukey's HSD (post hoc) testing. ANOVA testing revealed that mean hypertension prevalence at each level of SEP was significantly different. Because there were more than three pairs of means, a Tukey's post hoc test was performed to determine which pairs of means were statistically significant. Analysis revealed all ten paired means were statistically different, but the most significant mean differences were between SEPs 1 and 5. Hypothesis 2 was accepted because not only were mean hypertension prevalence rates statistically different at each level of SEP, but each pair of mean differences were also statistically significant.

Hypothesis 3 (i.e., the hypertension prevalence gap between non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1 will be similar to the prevalence gap between non-Hispanic whites in SEP 5 and non-Hispanic Blacks in SEP 1) was rejected. Though a two-proportion

difference z test revealed that the proportional hypertension difference between non-Hispanic Blacks in SEP 5 and non-Hispanic whites in SEP 1 and the proportional difference between non-Hispanic whites in SEP 5 and non-Hispanic Blacks in SEP 1 were statistically significant, their proportional difference 95% confidence intervals did not overlap. Lack of overlap between the proportional difference 95% confidence intervals revealed that both sets of proportional differences were not similar.

Finally, Hypothesis 4 (i.e., the non-Hispanic Black–white hypertension prevalence gap narrows among non-Hispanic Blacks and whites living in similar neighborhood SEP. The proportional hypertension percent difference at each level of SEP will be less than the total/across SEP proportional Black–white hypertension prevalence difference). Hypothesis 4 was accepted through binomial regression analysis. After fitting a model where interactions between race/ethnicity, age, and sex were set as predictors of hypertension, race/ethnicity was found to be a statistically insignificant predictor of hypertension at each level of SEP relative to the uncontrolled/across SEP analysis category. It is important to emphasize that this result does not suggest that disparities do not exist. Regression analysis revealed that disparities between Blacks and whites living in similar neighborhood characteristics are not as prominent compared to that of the uncontrolled/across SEP disparity gap . However, due to the enduring legacies of residential segregation and past and present neighborhood disinvestment Blacks and whites do not live in neighborhoods of equal quality. The disproportionate distribution of Blacks and whites across SEP disproportionately exposes each group to health deteriorating neighborhood characteristics.

Significance and Contribution to the Field

At the time of this study, a comprehensive spatial analysis of Black–white hypertension disparities across the entire United States had not been performed. The defining feature of a spatially comprehensive approach is an ability to incorporate most, if not all, of the tract level geographies of a designated area (e.g., city, county, metro, nation) while simultaneously capturing the racial, spatial, and social structures of that area. Additionally, as thoroughly outlined in preceding chapters of this dissertation, this study’s applied methodology filled a significant analysis gap by analyzing the hypertension prevalence gaps between Blacks and whites living in similar and different SEP. This approach is ideal, because according to the analysis results of Hypothesis 2 testing, mean neighborhood prevalence rates are significantly different at each level of SEP. This finding emphasizes the need to control for neighborhood SEP in disparities analysis.

Neighborhood SEP index scores were calculated by computing a composite z score that incorporated nine American Community Survey (ACS) derived neighborhood-level socioeconomic variables. The nine variables are routinely collected by the U.S. Census for all census tracts across the United States; therefore, in theory, every neighborhood in the United States can be included in analysis. Neighborhood level variables such as racial integration and equal Black–white income are exclusive to only a select few of neighborhoods across the United States. Segregated neighborhoods and neighborhoods with unequal Black-white income cannot be included in a health disparity study that is dependent upon those neighborhood features.

Morenoff et al. (2007) used factor analysis to control for neighborhood characteristics across an entire geographic area in disparities analysis. Factor analysis, which is often used in the analysis of survey data, is a methodology that simplifies a set of correlated variables into distinct

dimensions/factor categories (Tavakol et al., 2020). Morenoff et al. used 20 variables to generate four separate dimensions of neighborhood quality and control for neighborhood context (based upon those dimensions) across the city of Chicago. However, the composite effect of those dimensions is not captured in the Morenoff et al. study. The applied Darden-Kamel Index methodology of this dissertation study differs in its ability to consider the composite effect of nine variables in order to generate a single and easily interpreted neighborhood SEP score. Ease of application and interpretation makes the Darden-Kamel Index methodology an ideal approach to the standardization of neighborhood SEP indexing of hospital and government health data.

In addition to the methodological contributions of this study, my ability to access and analyze individual health data with race and ethnicity variables intact at census tract level is rare. Such access allows for the investigation of questions that are seldom explored. Additionally, given that the utilized health data of this study (2019 Medical Expenditure Panel Survey, Household Component data) allowed for the generating of national population estimates, the findings of this study highlight very timely and urgent national concerns around injustice and can be seriously considered in population level intervention strategies.

Continuation of Research

There were two primary limitations of this study: (a) MEPS data access and (b) the MEPS data SEP match rate. Gaining access to a publicly restricted MEPS dataset required numerous resources. The application process was a huge undertaking in itself, as a number of letters of support and other documentation were needed to apply. Processing and approval of the application can take anywhere from 6–8 weeks. In my case, delays in the release of 2020 Census data due to the COVID-19 global pandemic postponed my ability to start the application as early as planned. Though I submitted my application in December 2021, processing of my initial

application did not begin until April 2022. MEPS data access was granted in June 2022 and my first trip to the Agency for Healthcare Research Quality (AHRQ) data center occurred in July 2022. Between July and October 2022, I traveled to Rockville, Maryland three times for a combined total of 3 weeks to analyze the 2019 MEPS dataset used for this study. Notably, internet access is not allowed in the AHRQ datacenter; therefore, all of the R studio codes used to analyze the data had to be tediously planned before arriving to the data center. The ability to troubleshoot in real time when a particular R Studio code returned in error was nearly impossible. The internet restriction policy prolonged the time it took to run the models of this study.

Ultimately, had it not been for the support of my advisor, Professor Joe Darden, and the American Association of Geographers (AAG), my fully funded trips to Maryland would have not been possible. Though I eventually accessed and analyzed MEPS data, most graduate students are not in the position to do so. This accomplishment sets my work apart in that it allowed me to produce national population estimates that were derived from the use of individual tract level health survey data. I also owe a huge thanks to AHRQ for its practice of waiving the \$300 application fee for students needing to use the data for thesis and dissertations. Nonetheless, those planning to access MEPS data must take its restrictions into account.

Finally, nearly 73% of the MEPS observations were successfully matched to an SEP score. The matching of 2019 MEPS observation IDs (DUPERSID) to a neighborhood SEP was performed by the data center as a security measure. After AHRQ matched the SEP scores with a DUPERSID, I was able to match the SEP scores to the 2019 MEPS survey dataset by DUPERSID. As a result, the details of the initial match on the part of the AHRQ data center are unknown to me. I sent the data center a file containing all U.S. Census tracts with an assigned

SEP score; about 10% of the census tracts in the file did not have an assigned SEP score due to gaps in ACS data for those tracts. Of the 15,294 MEPS observations that were eligible for analysis, 11,123 were assigned an SEP score. To my knowledge, those 4,171 observations that were not assigned an SEP were the tracts in the original match file that did not have an assigned SEP score due to ACS data gaps.

In the future, I will reconsider the criteria a census tract must meet to be assigned an SEP score. Investigating ways to compute a composite index score (CSI) and assign an SEP score despite gaps in ACS data will ensure that the neighborhood characteristics of the study population are optimally captured in analysis. Though a match rate closer to 90% would have been ideal, the ability to simultaneously capture the racial, spatial, and socioeconomic profile of nearly three fourths of the eligible 2019 MEPS survey sample is significant.

In addition to taking time to highlight the key limitations of this dissertation research it is important to highlight opportunities to expand the scope of this study. When looking at hypertension specifically, the contribution of psychosocial factors (i.e. stress) is worthy of consideration. Broadly speaking, psychosocial stress occurs when one is unable to adapt to environmental demands because of a lack of resources – resources being authority, money, social support, knowledge, etc. (Spruill, 2010). Analysis results of this study revealed that after controlling for neighborhood SEP, the Black-white disparity gap narrows relative to the uncontrolled/across SEP Black-white prevalence gap. Though this finding underscores the significance of neighborhood SEP in measured hypertension disparities along race, there are other factors to consider. The discrimination related stress that is encountered by Blacks who reside in neighborhoods of high and very high SEP neighborhoods is worth investigating.

The underlying mechanisms of the stress-hypertension relationship are believed to involve a sympathetic nervous system response. A sympathetic nervous system response is an immediate response to a stress event. Typical sympathetic responses include increased heart rate, cardiac output, and elevated blood pressure (Spruill, 2010). The contribution of stress to sustained/chronic high blood pressure overtime is less understood compared to the well documented sympathetic response to acute stresses (Spruill, 2010). In thinking about the contribution of stress overtime, the various day-to-day social encounters that occur in one's neighborhood are important to consider. Frequented spaces such as school, the local pharmacy, and neighborhood parks, etc. involve some level of social engagement with fellow residents of the community. Blacks who live in SEP 4 and 5 neighborhoods are very few relative to white SEP 4 and 5 residents, as displayed in Tables 2 and 8-11. Therefore, given the rarity of the Black presence in SEP 4 and 5 neighborhoods, one can suspect that the chances of experiencing a racial discrimination event are high.

Measuring discrimination incidence over time among Blacks in SEP 4 and 5 neighborhoods would offer a more insightful analysis of neighborhood characteristics and their health disparity effects. Despite the assumed advantages of residing in a SEP 4 or 5 neighborhood those advantages may come at a cost, especially over-time. There are a number of available methods (Broman, 1996; Brondolo et al., 2003; Taylor et al., 2004; Williams, et al., 2009) that could be employed to measure the psychosocial burden of discrimination among Blacks living in SEP 4 and 5 neighborhoods. A study that accounts for the increased risk of neighborhood based psychosocial stress events among Blacks who reside in SEP's 4 and 5 would offer a more thorough perspective on the relationship between hypertension disparities, neighborhoods characteristics, and psychosocial pathways.

Policy Implications

Based upon the results of this study, I propose the following: (a) census tracts should be added to all aggregate health population data and neighborhood SEP index scores should be applied to all individual health data (e.g., hospital intake and discharge records, health surveys, and health insurance claims data); and (b) policy officials should prioritize enhanced spatial mobility policy in order to reduce the disproportionate distribution of Blacks and other marginalized people in low and very low SEP neighborhoods.

Standardizing the inclusion of neighborhood SEP as a health data variable and prioritizing spatial mobility policy would facilitate sustainable health disparity prevention strategies and agendas by centering the connection between spatial injustice and measured racial health disparities. Spatial mobility policies that disrupt the disproportionate distribution of Blacks and other marginalized people in low and very low SEP neighborhoods would serve as an acknowledgement of the enduring legacies of racial residential segregation and recognition of the intersectionality of health, wealth, and housing (American Public Health Association (APHA), n.d.).

Where one lives has a profound impact on their life chances and health profile across their lifespan. Those who are currently subjected to the characteristics of low and very low socioeconomic position neighborhoods deserve an opportunity to access higher SEP neighborhoods as to avoid the perpetual cycles of wealth, health, and quality neighborhood and housing disparities. A key to reducing health disparities is to improve access to high SEP neighborhoods, which are commonly considered neighborhoods of opportunity (Acevedo-Garcia et al., 2004; Darden et al., 2010).

Multiple examples illustrate the effectiveness of spatial mobility interventions and policies geared toward improving access to neighborhoods of opportunity (Chetty et al., 2016). Key examples include the 1985 Yonkers Housing Intervention, which was a citywide deconcentration of public housing. As a part of this initiative, half of public housing residents were selected via a lottery to move to better housing. Two years later, those who moved reported better health (i.e., overall health and lower levels of substance abuse); higher neighborhood quality (i.e., lower neighborhood disorder and violence and higher levels of satisfaction with public transportation, recreation facilities and medical care); and during subsequent follow-ups – improved economic outcomes (i.e., higher rates of employment and lower rates of welfare use) (Williams & Cooper, 2019).

During the Clinton Administration in the 1990s, the Department of Housing and Urban Development (HUD) sought to improve the economic opportunity and the quality of life in disadvantaged communities (Turner et al., 2005). Among those efforts was the creation of the Moving to Opportunity (MTO) intervention, which focused on residential relocation. The goal of MTO was to help poor families move from high-poverty public housing to neighborhoods with lower levels of poverty.

Though initial (short-term) MTO results were mixed regarding neighborhood effects on employment, earnings, and educational attainment, researchers found large and statistically significant positive effects on the mental health of adults and young women who changed neighborhoods (Acevedo-Garcia et al., 2004; Darden et al., 2010). The cases of Yonkers and HUD's MTO initiative underscore the potential of spatial mobility policies. However, despite the potential of MTO inspired policies, it is met with a number of criticisms. Among the listed criticisms are: (a) access barriers to opportunity neighborhoods and, (b) MTO's mixed results.

With regards to access barriers, Bergman's et al.(2020) findings offer a solution. Bergman et al. (2020) found that barriers in the housing search process are key impediments to moving to high-upward mobility neighborhoods. However, the experimental group who received customized search assistance, landlord engagement, and short-term financial assistance were 53% more likely to move to high-upward-mobility areas compared to only 15% of the control group. Also, once settled into a high-upward mobility neighborhood, the families that did not have to compromise in other areas of neighborhood quality tended to stay in their new neighborhoods when their leases were up for renewal, and they reported higher levels of neighborhood satisfaction after moving.

Regarding the mixed results of the MTO study, one must consider age differences in short and long-term effects (Chetty et al., 2016; Chyn et al., 2021). In the short-term, adults and young girls experienced improved mental health outcomes (Acevedo-Garcia et al., 2004; Chyn et al., 2021; Darden et al., 2010) whereas improved life chances and social mobility were observed among study participants who were young children (not yet teenagers) when they moved to high upward mobility neighborhoods (Chetty et al., 2016;Chyn et al., 2021). Study participants who relocated to neighborhoods with low levels of concentrated neighborhood poverty as young children experienced better education attainment, employment, and income outcomes as adolescents and adults relative to peers who remained in high concentrated poverty neighborhoods (Chetty et al., 2016; Chyn et al., 2021).

Therefore, MTO inspired policies should target families with young children because according to the findings of the MTO study, short term health effects are most likely to be observed in adults and children (especially young girls), and in the long-term the social mobility benefits of moving to a high opportunity neighborhood are likely to be observed among

individuals who move as small children. The Yonkers and MTO interventions yielded statistically significant health improvement results; therefore, intervention strategies that have led to better health outcomes should form the bases of evidence-based health intervention policy. Furthermore, based upon the findings of Bergman et al., (2020) the effectiveness of health equity and fair housing policies should include provisions that supply customized search assistance, landlord engagement, and short-term financial assistance to low-income housing voucher recipients. Such provisions will likely reduce barriers to high opportunity neighborhoods and contribute to the mitigation and reduction of racial health disparities.

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