Dismantling The System: Unpacking Racism's Impact On Inequities In Behavioral Health, Healthcare Utilization, And Access To Care

Nana Akosua Adjeiwaa-Manu

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Abstract
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DISMANTLING THE SYSTEM: UNPACKING RACISM'S IMPACT ON INEQUITIES IN
BEHAVIORAL HEALTH, HEALTHCARE UTILIZATION, AND ACCESS TO CARE

Nana Akosua Adjeiwaa-Manu

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Nana Akosua Adjeiwa-Manu
The visual symbol above is one of many adinkra symbols, which the Akan people of Ghana created to communicate concepts and meanings. This symbol is called ɔdɔ nyera fie kwan, which translates as “love never loses its way home.”

I dedicate this work to my parents, Dr. Charles Manu and Dr. Vera Kuffour-Manu: you have always been my constant, my solid foundation, and my biggest cheerleaders. I am because you are. Thank you for always being yourselves and for being the most amazing examples of perseverance against all odds. Thank you for loving me and sacrificing for me so that I could follow my purpose. I am so grateful for you. To my ancestors and elders: thank you for paving the way.

Nyame nnhyira mo.
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This Adinkra symbol is called *nkonsonkonson*, which translates as “in unity lies strength.” It is a reminder to always contribute to the community. In the spirit of this symbol, I give thanks to the many people who have supported me in the process of writing this dissertation.

Throughout my time in graduate school, I have learned that the purpose of a doctoral degree is to contribute to the broader community around me in some small way. And, I have found that a dissertation, although written independently, results from consistent dialogue, feedback, and support from other people. I could not have completed this process without the many people who supported me throughout my journey. I thank all of them for seeing me through this process.

It is only because of God and my community that I am here. To my Lord and Savior Jesus Christ, thank you for never failing me. All the glory belongs to You.

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The dissertation process has been a humbling experience, and it is my hope that this small offering contributes in some way to the full thriving and wellness of Black and Brown communities. May we all work towards finding justice and wholeness throughout life's journey.
ABSTRACT

DISMANTLING THE SYSTEM: UNPACKING RACISM’S IMPACT ON INEQUITIES IN BEHAVIORAL HEALTH, HEALTHCARE UTILIZATION, AND ACCESS TO CARE

Nana Akosua Adjeiwaa-Manu
Chenoa A. Flippen

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CHAPTER 1: INTRODUCTION

This dissertation examines the role of structural racism in shaping inequities in behavioral health, healthcare use, and healthcare access. Developing quantitative work that employs structural theories of racism to mirror the social realities of racial stratification more closely in the United States can contribute to insights into the sources of inequities in health outcomes and healthcare access (Zuberi 2011). A small but growing body of work links structural racism to population health outcomes (see, for example, Williams et al. 2019). These studies have primarily examined the association between markers of structural racism and physical and mental health. Such features include racial residential segregation and, more recently, socioeconomic status (Bell and Owens-Young 2020; Williams and Collins 2001). Although this literature has provided important insights on the relationship between structural racism and health, there is less information that unpacks how the many components of structural racism work together to shape not only systemic inequities in health outcomes but also in healthcare use and access.

The dissertation argues that the complex features of structural racism that pervade the domains of healthcare, criminal justice, politics, education, housing, and the economy produce health inequities among racially and ethnically classified groups. These inequities demonstrate structural racism's function as an anti-Black system that permeates society. The dissertation investigates health inequities as a model of how structural racism may function in other areas. In particular, this dissertation works to operationalize critical perspectives on racism that clarify how this system operates. By unpacking the
features of the system of structural racism, research in this area can contribute to dismantling it.

The dissertation first explores the relationship between self-reported racial and ethnic classification, which I conceptualize as placement in the racial hierarchy relative to whiteness, and inequities in behavioral health outcomes. In addition, I view each racially and ethnically classified group’s place in the racial hierarchy as a measure of how vulnerable they are to racism (Ford and Airhihenbuwa 2010). Next, I consider inequities in behavioral healthcare use by racial and ethnic classification. Finally, the dissertation builds on the results from these two lines of inquiry by considering whether the level of racial-gender equity in an area is related to access to mental healthcare. I conceptualize racial-gender equity as whether groups in U.S. counties classified by race, ethnicity, and sex have the same level of access to socioeconomic resources. Overall, each chapter parses out the dynamics of structural racism to better understand the production of inequities in health outcomes, healthcare utilization, and healthcare access.

The second chapter of the dissertation evaluates how racial and ethnic classification intersects with socioeconomic inequality and race-based stressors to shape inequities in mental health outcomes. Given that the United States is so strongly organized around race, people's life experiences and mental health may be affected based on their placement in the racial hierarchy. The study's results demonstrate that, despite tending to have a lower socioeconomic status and greater exposure to race-based stress, communities racially and ethnically classified as Black and Hispanic retain an advantage in their lifetime and current mental health compared to whites. Further, the study finds
that even the threat of contact with the criminal justice system is associated with increased odds of lifetime and current mental health challenges. Thus, if exposure to these mechanisms of inequality were even across groups with different racial and ethnic classifications, people of color's advantage in mental health would be even larger. These findings suggest that the benefits of being at the top of the racial hierarchy for groups racialized as white may not necessarily extend to mental health, while racial inequities in treatment and diagnosis of mental illness may help explain nonwhite communities’ lower prevalence of mental illness despite exposure to higher levels of overall and race-based stress. This chapter indicates that quantifying mechanisms of racial inequality in a way that is connected to social realities helps explain what shapes the advantage in mental health among communities racially classified as Black and non-Black people of color.

The third chapter examines the processes that shape inequities in access to smoking cessation treatments. Although cigarette use has declined in recent years, inequities in successful smoking cessation among racially and ethnically classified groups persist. This paper contributes to the literature on smoking cessation by identifying when inequities in health care seeking occur and contextualizing its findings through critical theories of race. Results indicate that viewing the nicotine in Nicotine Replacement Therapy (NRT) as very or extremely harmful, not being aware of NRT, and exposure to secondhand smoke resulted in decreased odds of using a smoking cessation therapy. Further, the study's results indicate that communities racially classified as White, Indigenous American, Asian, and Pacific Islander had greater access to smoking cessation therapies than communities racially classified as Black. In turn, if
socioeconomic resources and exposure to tobacco were equal across social groups, communities racially classified as White, Indigenous American, Asian, and Pacific Islander's greater access to smoking cessation therapies would be even larger. In contrast, the difference in access between groups racially and ethnically classified as Hispanic and Black would be smaller.

The final chapter of the dissertation examines the relationship between county-level racial-gender equity and access to mental healthcare, conceptualized as the supply of mental health professionals. This chapter suggests that mesolevel (county and state) political dynamics mirror structural patterns at the macrolevel that systematically sustain inequities in access to healthcare. Results demonstrate that areas with lower equity are more likely to lack an adequate supply of mental health professionals. However, the association was mediated through the county’s socio-political landscape, including the state governor’s political orientation, a county’s urban or rural designation, and home internet access. Having a Democratic governor was the key macrolevel factor that explained the association between racial-gender equity and the availability of mental healthcare. Counties with Democratic governors had lower odds of being located in a mental health professional shortage area than counties with Republican governors. On the other hand, home internet access was the primary microlevel factor that explained the association. Areas with average or higher levels of internet access compared to the national average had lower odds of being in a mental health professional shortage area than those with low internet access.
By examining multiple dimensions of health outcomes and the healthcare system, this dissertation sheds light on how the dynamics of structural racism manifest in inequities in treatment that codify inequality in the healthcare system and policies at the local level. These inequities help explain divergent behavioral health, healthcare use, and healthcare access outcomes among racially and ethnically classified groups. The dissertation’s results suggest that understanding how vulnerability to racism and an area’s level of racial-gender equity is associated with health outcomes, healthcare use, and healthcare access can help clarify the components of structural racism at work in producing inequities. Thus, this dissertation underscores structural racism’s role as a pervasive system that is at the foundation of inequities in healthcare access and, as a result, healthcare use and health outcomes.
References


CHAPTER 2: AN EXAMINATION OF STRUCTURAL RACISM'S RELATIONSHIP TO BEHAVIORAL HEALTH INEQUITIES

Abstract

Structural racism has been identified as a fundamental cause of differences in health outcomes among racially and ethnically classified groups. The purpose of this study is to evaluate how racial and ethnic classification, conceptualized as vulnerability to racism – a measure of placement in the racial hierarchy – intersects with multiple dimensions of inequality to shape mental health outcomes. This study uses data from a sample of 35,732 adults from the third wave of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC-III), collected from 2012 to 2013. The study examines how racial and ethnic classification, socio-demographic background, and two mechanisms of racial inequality: socioeconomic status and race-based stressors, shape lifetime and past year anxiety or mood disorders. The study’s results demonstrate that, despite tending to have a lower socioeconomic status and greater exposure to race-based stress, communities racially and ethnically classified as Black and Hispanic retained an advantage in their lifetime and current mental health as compared to communities classified as white. An analysis of the results shows that living in poverty, experiencing unemployment, and regional location in the United States are associated with higher odds of lifetime and current anxiety or mood disorders. Further, the study finds that even the threat of contact with the criminal justice system is associated with higher odds of lifetime and current anxiety and mood disorders. Respondents who self-identified as Black, Indigenous American, and Latino had higher odds of living in poverty and being unemployed.
Further, they also tended to have experienced more potential or actual contact with the criminal justice system. In addition, they had higher odds of experiencing the loss of a loved one, healthcare discrimination, racial slurs, mocking, and threats. Thus, if exposure to these mechanisms of inequality were even across groups with various racial and ethnic classifications, the advantage in mental health among people classified as Black and Latino would be even larger. This study demonstrates that the benefits groups at the top of the racial hierarchy typically receive do not necessarily extend to mental health outcomes. Further, the study shows that the many components of structural racism may mask the stressors that result from placement at the bottom of the racial hierarchy. Future studies on racism and mental health can more explicitly acknowledge how racism patterns social factors and better quantify this process in their analysis. These studies can provide more context on how racism intersects with myriad factors to shape lifetime and past-year mental health outcomes.

**Introduction**

The United States presents a unique social environment within which to study racial and ethnic inequities in mental health. It is a society with a strong racial hierarchy (Bashi and McDaniel 1997), where people’s life chances are directly impacted by the racial or ethnic identity they have been assigned. Given that the United States is so strongly organized around race, people’s life experiences and consequently their mental health may be affected based on their racial and ethnic classification, among other factors. Further, a growing body of literature has recognized that racism is a fundamental
cause of racial and ethnic differences in health (Link and Phelan 1995; Mays et al. 2007; Williams and Jackson 2005).

Prior work on race, ethnicity, and mental health has provided valuable insights on how the onset of mental illness and lifetime mental illness differs among people with different racial and ethnic classifications (see Goldstein et al. 2016). These studies have found that groups classified as nonwhite have an advantage in mental health (Asnaani et al. 2010; Blazer et al. 1994; Budhwani et al. 2015; Earl et al. 2011; Hoffman and Hinton 2014; Robins and Regier 1991; Sohail et al. 2014) despite being exposed to more stress across the life course (Boen 2020).

Only a handful of studies have made strides towards understanding the advantage in mental health among people who self-identify as Black or as a member of another community of color (for example, see Brown et al. 2020). In addition, there remain areas of the multiple ways that racism is related to mental health that are understudied. First, there is limited work that describes how advantages or disadvantages in mental health function as an outcome of the process of racialization. To that end, more studies are needed that examine how racial classification intersects with ethnic classification and socioeconomic status to shape health (Williams and Earl 2007:759). Further, while prior literature has explored how various forms of contact with the criminal justice system shapes mental health, the way that potential contact with the criminal justice system shapes mental health is limited. In addition, the mechanisms of inequality that accumulate over time across the life course and affect both current and lifetime mental health are also understudied (Alvarez et al. 2019; Goldstein et al. 2016; Lehavot et al. 2018; Smith et al.
Finally, quantitative research on race tends not to treat race as a macro-level factor that shapes other variables within analyses (Zuberi 2001b), which can affect researcher’s understandings of how racial stratification operates (Bashi and McDaniel 1997; Zuberi 2001a).

To contribute to these gaps in the literature, the purpose of this study is to determine how racial and ethnic classification, conceptualized as vulnerability to racism – an indicator of placement within the racial hierarchy – intersects with multiple dimensions of inequality to shape mental health outcomes. The study’s results demonstrate that, despite tending to have a lower socioeconomic status and greater exposure to race-based stress, communities who self-identify as Black and Hispanic retain an advantage in their lifetime and current mental health as compared to communities who self-identify as white. An analysis of the results indicates that living in poverty, experiencing unemployment, and regional location in the United States are associated with higher odds of lifetime and current anxiety or mood disorders. Further, the study finds that even the threat of contact with the criminal justice system is associated with higher odds of lifetime and current anxiety and mood disorders.

Respondents who self-identified as Black and Latino had higher odds of living in poverty and being unemployed. Further, they also tended to have experienced more potential or actual contact with the criminal justice system, the loss of a loved one, and discrimination. Thus, if exposure to these mechanisms of inequality were even across entities of people with various racial and ethnic classifications, groups classified as nonwhite would have an even larger advantage in mental health.
These findings suggest that the benefits groups at the top of the racial hierarchy typically receive do not necessarily extend to mental health outcomes. Further, the study shows that the many components of structural racism may mask the stressors that result from placement at the bottom of the racial hierarchy. In addition, the results demonstrate the importance of understanding racial classification as a measure of vulnerability to racism, defined as groups’ placement in the racial hierarchy, and quantifying mechanisms of racial inequality that better reflect people’s social realities. This conceptualization helps to better explain how racism intersects with multiple measures of inequality to shape the advantage in mental health among people who self-identify as Black or as non-Black people of color.

**Theoretical Framework**

**Background**

Mood disorders are “a mental health problem that affects a person’s emotional state” (Cleveland Clinic 2018). People who experience mood disorders may experience long periods of sadness, happiness, or both emotions. Major depression and dysthymia are two of the most common mood disorders. Major depression is a leading cause of disability worldwide (World Health Organization 2018), while dysthymia, also known as persistent depressive disorder, is a common form of chronic depression that can last for two years or more. Although depression is characterized as a form of grief or sadness that occurs even after a stressful event has passed and appears to be an individual problem, prior research shows that structural inequality plays a role in short-term and long-term health outcomes (Williams and Jackson 2005; Williams et al. 2019). This research
suggests that in a world of global white supremacy, structural racism plays a role in life chances (Bashi and McDaniel 1997; Bonilla-Silva 1997; Williams et al. 2019; Zuberi 2000; Zuberi 2001b; Zuberi and Bonilla-Silva 2008).

In addition, prior research indicates that communities classified as Black have a lower prevalence of mood disorders compared to communities classified as white (Blazer et al. 1994; Earl et al. 2011; Robins and Regier 1991; Sohail et al. 2014). However, communities classified as Black tend to experience misdiagnosis of mental illness and stigma around reporting mental health issues. Further, their mental illnesses are usually more prolonged and “debilitating” (Earl et al. 2011:489). Taken together, most groups who identify as people of color tend to have a lower prevalence of mood disorders compared to groups who identify as white (Breslau et al. 2006; Ghafoori et al. 2012; Sohail et al. 2014; Williams and Earl 2007). However, people who self-identify as Indigenous Americans tend to have higher psychological distress than other racially and ethnically classified groups. Historical trauma and colonialism may partially explain this group’s mental health outcomes (Walters et al. 2011; Williams and Mohammed 2009).

Prior research notes that historical trauma refers to highly stressful external events intended to upend and terminate communities that have a particular identity in common, such as tribal affiliation, racial or ethnic classification, or religion (Walters et al. 2011:179, 181). This work suggests that histories of harm can continue to impact the health of communities in the present.

In contrast to mood disorders, anxiety occurs when an individual has feelings of restlessness and fear. These feelings occur when a person is in an unfamiliar, threatening,
or particularly stressful situation. Anxiety can be protective and important for survival when an individual is in a threatening situation (Agorastos et al. 2012:68). However, it can also become debilitating and affect a person’s ability to carry out their daily life (Agorastos et al. 2012:69). Anxiety disorders include panic disorder, agoraphobia, social anxiety, Generalized Anxiety Disorder, and specific phobia. Panic disorder involves unanticipated episodes of fear, including physical symptoms such as shortness of breath. In addition, agoraphobia refers to anxiety about situations that might result in embarrassment or panic. Finally, Generalized Anxiety Disorder involves persistent worry about multiple issues.

Studies show that communities racially classified as white are most likely to meet the criteria for having anxiety disorders such as Generalized Anxiety Disorder, panic disorders, and social anxiety compared to people of color (Asnaani et al. 2010; Budhwani et al. 2015; Hoffman and Hinton 2014). Communities racially classified as Asian American were less likely to meet the criteria for having generalized anxiety disorder, social anxiety disorder, and panic disorder as compared to people who identified as white (Asnaani et al. 2010). Adjusting for sociodemographic characteristics such as age, gender, and socioeconomic status still leave much of the racial differences in anxiety disorders unexplained.

However, other studies suggest that the relative mental health advantage of people of color relative to whites could reflect measurement issues, as reporting and diagnosis differs across groups. Schnittker and McLeod (2005:79) note that there are many inconsistencies in how groups classified as nonwhite report mental health disorders. This
inconsistency may arise from several factors, including the fact that groups classified as nonwhite tend to report what is actually a mental health issue as pain in the body (Agorastos et al. 2012; Vega and Rumbaut 1991:357; Venters and Gany 2011:358). Thus, there may be a particular presentation of mental health challenges that racial stratification creates. Further, people of color are less likely to receive a diagnosis for a health problem (Williams and Jackson 2005, qtd. in Boen 2020). Scholars have also described the “ambiguity of mental illness” (Schnittker 2017:4). This ambiguity demonstrates that even with the most “scientifically credible diagnostic criteria,” psychiatric disorders are challenging to assess because of differences in patient backgrounds and in reporting symptoms of mental illness (Schnittker 2017:4). Further, stigma may shape how widely mental health issues are reported (Pescosolido and Martin 2015:95).

**Conceptualizing & Operationalizing the Impact of Racism on Health**

Whether groups classified as nonwhite experience a mental health advantage or if disadvantage is masked by differential access to mental health care, diagnosis, and reporting, a better understanding of how racism shapes health and health inequities is needed. Racism is a system that affords differential economic, political, social, and psychological benefits to groups structured around racial classifications (Bonilla-Silva 1997; Brown 2003). This system is at the foundation of the process of assigning racial meaning to social groups (Bonilla-Silva 1997:467; Crenshaw et al. 1995; Mills 1998; Zuberi 2000; Zuberi 2001b; Zuberi 2011). In other words, race is a by-product of racism (Gilroy 2004, qtd. in Roberts 2011). Further, racism and race are both socially defined
and constructed. Racism provides an orienting structure for guiding rational actors in the
differential benefits groups structured around racial and ethnic classification receive.

Most social science scholarship acknowledges that race and racism are socially
constructed. However, quantitative work on race and racism tends to justify – rather than
explain – “the process of racial stratification” (Zuberi 2011:101; Zuberi 2001b; Zuberi
and Bonilla-Silva 2008). Scholars have argued that Critical Race Theory (CRT) can
provide a guide for properly conceptualizing race and racism in quantitative work (Brown
2003; Brown 2008; Crenshaw 1995; Ford and Airhihenbuwa 2010; Mills 1998; Zuberi
2000; Zuberi 2001b; Zuberi 2011). CRT acknowledges and documents how racism
manifests throughout society.

CRT recognizes race as how vulnerable a group is to experiencing racism
(Bonilla-Silva 2004:932; Ford et al. 2009, qtd. in Ford and Airhihenbuwa 2010). In
practice, vulnerability to racism functions as placement within the racial hierarchy.
Several studies have proposed theories on the dynamics of the racial hierarchy in the
United States (for example, see Bashi and McDaniel 1997 and Bonilla-Silva 2004). One
such theory is the tri-racial order perspective (Bonilla-Silva 2004), which suggests that
the United States is moving from a bi-racial order that organizes social groups as white or
nonwhite into a tri-racial order.

There are three “loosely organized racial strata” in this new hierarchy: people
classified as (1) White, (2) honorary white, and (3) collective Black (Bonilla-Silva 2004:
932). The white stratum includes people who self-identify as white American, white
immigrants, and, in the future, white Latinos who have fully assimilated into an assumed
white identity, some light-skinned multiracial people, Indigenous Americans who do not live on a reservation, and some Asian Americans. Next, the honorary white stratum includes light-skinned Latinos, East Asians (Japanese, Korean, Asian Indian, and Chinese Americans), Middle Eastern Americans, most multiracial people, and Filipino Americans. Finally, the collective Black stratum includes all other people classified as nonwhite and who have limited access to the benefits of whiteness (Roediger 1991, qtd. in Bonilla-Silva 2004: 932). This group includes Southeast Asians (Vietnamese, Laotian, and Hmong Americans), dark-skinned Latinos, Black Americans, African and Afro-Caribbean immigrants, and Indigenous Americans who live on reservations. The tri-racial order reflects a “pigmentocratic logic,” in which people are assigned differential statuses based on their skin color (Bonilla-Silva 2004: 931). This perspective suggests that mental health advantages and disadvantages are outcomes of the process of racial stratification.

Based on these perspectives, CRT views race as a “macrolevel variable” (Bashi and McDaniel 1997:678) that shapes each aspect of a person’s life outcomes (Bashi and McDaniel 1997; Stewart 2008). Further, the theory recognizes racism as a set of mechanisms that engender racial inequality (Crenshaw et al. 1995; Ford and Airhihenbuwa 2010; Mills 1998). As a result, CRT demonstrates that attempting to quantify racism – rather than race – can better reflect the outcomes of the process of racial stratification. Taken together, CRT can help researchers to understand how mechanisms of racial inequality shape differences in health outcomes based on racial and ethnic classification.
Several studies have demonstrated that racism is a stressor that shapes health outcomes (Boen 2020; LaVeist 1989; Williams and Collins 2001; Williams and Jackson 2005; Williams and Sternthal 2010). It has also identified several pathways through which racism is related to health, showing that racial inequality patterns the ways that people are “exposed to risks and resources in society” (Williams and Jackson 2005:325). For instance, previous studies found that discrimination negatively impacts health (Chou et al. 2012; Gee et al. 2007; Williams and Mohammed 2009, qtd. in Williams and Sternthal 2010; Williams et al. 2019). In addition, socioeconomic inequality and medical care are key drivers of racial inequities in health (LaVeist 1989; Krieger 1999, qtd. in Walters et al. 2011; Massey and Denton 1993; Mezuk et al. 2013; Williams and Collins 2001; Williams and Jackson 2005; Williams and Sternthal 2010).

Further, the literature finds that people of color have more overall stress than white people. They also face everyday and major life discrimination, financial strain, lifetime trauma, among other stressors (Campbell et al. 1976, qtd. in Boen 2020; Krause et al. 2004; Williams et al. 1997). Prior work has also demonstrated how racial trauma is a key stressor for people of color. Racial trauma is a form of race-based stress. Race-based stress is a reaction to dangerous events and real or perceived experiences of racial discrimination (Comás-Diaz et al. 2019:1). Examples of racial trauma include seeing racial discrimination happen to other people of color and being threatened with harm or injury because of one’s racial classification. Race-based stress is related to traumatic reactions such as dissociation, anxiety, and depression, especially when a person finds
negative race-based experiences stressful (Carter et al. 2020). In addition, race-based stress also includes contact with the criminal justice system and the loss of a loved one. These stressors also shape mental health (Massoglia and Pridemore 2015; Turney et al. 2012; Sugie and Turney 2017), and prior work demonstrates that they disproportionately affect people of color (Alexander 2012; Umberson et al. 2017).

Yet, even though people of color tend to report more exposure to stress than people who self-identify as white, they do not show the predicted “increase in psychological distress” (Brown et al. 2020:651). Some studies argue that perceived discrimination may help explain why black people have lower rates of mood and anxiety disorders, which are “stress sensitive” (Mays et al. 2007:213). They argue that if one is chronically exposed to racism, they are constantly in a state of psychological distress. Thus, rather than a particular situation triggering the onset of a mood or anxiety disorder, groups that are more vulnerable to racism are constantly in a state of stress.

Other work has demonstrated how coping with racial discrimination may shape mental health, adding to the importance of understanding how racism contributes to the burden of disease. Scholars of color have long described the “mask” that people who self-identify as Black and as non-Black people of color have used to navigate racism and manage stereotype threat (Bobo 2000; Du Bois [1899] 1995; Du Bois [1903] 2015; Du Bois [1935] 2007; Fanon 1967; Kelley 1996; Steele 1997). Even amidst forms of isolation and historical trauma such as enslavement, colonialism, Jim Crow, and mass incarceration, people who self-identify as Black and as non-Black people of color have found ways to handle racial discrimination (Alexander 2012; Du Bois [1903] 2015; Du
Coping mechanisms can either be subversive or ones of deference (Fanon 1967; Kelley 1996; Welsing 2017; Wilson 1994:101). These coping mechanisms may impact how people of color report symptoms of poor mental health.

Despite people of color’s higher exposure to stressors, some scholars also argue that people of color may have more psychosocial resources, such as a strong connection to one’s ethnic identity, that may help them navigate the stress of racism (Alvarez et al. 2019; Brown et al. 2020; Townsend et al. 2020). Further, Black Advantage Vision (Pattillo, forthcoming) may also help explain the advantage in mental health among people who self-identify as Black and as non-Black people of color. This perspective argues for no longer seeing Black people as a group that only has deficits and problems (Du Bois 1898). Instead, Black Advantage Vision argues for examining domains in which Black people perform better than whites. Mental health may be one such domain.

A handful of studies have addressed people of color’s advantage in mental health by exploring communities racialized as white’s disadvantage in this domain. Though people who self-identify as white benefit from the system of racism, scholars have argued that they may experience conflicting feelings and enact “dysfunctional behaviors” that negatively impact their mental health (Brown 2003:293). In turn, these behaviors reflect the “public and psychological wages of whiteness (Du Bois [1935] 2007; Roediger 1991), again illustrating the ways that racial stratification is related to particular presentations of mental health problems. Other scholars have examined how the racial classification of whiteness shapes health (Metzl 2019). This body of work argues that
whiteness involves “narratives of imagined victimhood and domination” and “white resentment” towards other racial groups (Metzl 2019:7, 9). In addition, this work indicates that whiteness is a reactionary identity created to facilitate white dominance and racial inequality. The expression of this identity may help explain this community’s negative mental health outcomes.

While white supremacy is designed to benefit communities racially classified as white, they simultaneously experience greater social advantages while tending to have poorer health outcomes compared to other entities of people who self-identify with non-white racial and ethnic classifications (Malat et al. 2017, qtd. in Metzl 2019). These outcomes may stem from voting against policies that would expand access to healthcare (Metzl 2019). Other scholars argue that communities racially classified as white, particularly those who have less education, are also more vulnerable to “deaths of despair” such as suicide and drug overdoses (Ho 2017; Kochanek et al. 2016, qtd. in Elo et al. 2019). Communities racially classified as white with less education tend to find that they are less financially secure than their parents. In turn, this loss of social standing may explain the group’s higher poor health outcomes (Case and Deaton 2015).

The Life Course Perspective and Health Outcomes

Finally, the life course perspective indicates the importance of examining whether an individual has ever been exposed to a mental disorder in their lifetime. The life course perspective states that the conditions an individual is exposed to earlier or later in life impact their health outcomes (Lynch and Davey Smith 2005:2; Lynch 2003). This perspective emphasizes the importance of time and the accumulation of risk as an
individual passes through different age trajectories (Lynch and Davey Smith 2005; Thorpe and Kelley-Moore 2012). The concept of linked lives (Elder Jr. 1998; Gee et al. 2012; Serbin & Karp 2004, qtd. in Torres and Young 2016:144) suggests that the conditions of other people’s lives affect each other, which in turn shapes their long-term health. This literature suggests that disadvantage begins earlier in life for people of color. Further, the life course perspective highlights the effect of contextual factors, such as racism, that shape an individual’s health outcomes across the lifespan.

**Gaps in the Literature**

Prior literature finds that people of color have an advantage of mental health and that racism is a stressor that increases psychological distress. However, the mechanisms through which racism is related to mental health are understudied, and scholars emphasize the importance of understanding how multiple dimensions of social disadvantage interact to shape mental health. For instance, prior work has explored how various forms of contact with the criminal justice system shapes physical health. Yet, there is little work that explores how potential contact with the criminal justice system shapes mental health.

In addition, there are few studies that highlight how advantages or disadvantages in mental health function as an outcome of the process of racialization. As a result, more work is needed that investigates how racial classification, ethnic classification, and socioeconomic status work together to impact mental health (Williams and Earl 2007:759). Further, the literature suggests that racial trauma, racial oppression, race-based stress, and discrimination can be better integrated into discussions of the mechanisms that drive mental health outcomes (Comás-Diaz et al. 2019; Gee et al. 2007;
Shellae Versey et al. 2019; Skewes and Blume 2019; Williams et al. 2019). Finally, quantitative research on race does not always treat race as a factor that globally affects life chances – which would more closely align with the process of racialization. In turn, interpretations of race contribute to racial stratification rather than trying to understand and dismantle it (Zuberi 2001b).

To contribute to these gaps in the literature, the purpose of this study is to determine how vulnerability to racism – conceptualized as placement within the racial hierarchy of the tri-racial order – intersects with multiple dimensions of inequality to shape mental health outcomes. Empirically, the study aims to answer the following question: how does placement in the racial hierarchy shape mental health outcomes? As illustrated in Figure 2.1, my conceptual framework views self-reported racial and ethnic classification, the key independent variable, as a group’s level of vulnerability to racism and representation of their placement in the racial hierarchy. I illustrate each group’s placement in the racial hierarchy in Figure 2.2. As a racial ideology, group placement in the racial hierarchy relative to whiteness affects all of the variables within the analysis (Bashi and McDaniel 1997; Stewart 2008). To better quantify racism, the study identifies two mechanisms of racial inequality that play a role in lifetime and current mental health: socioeconomic status and race-based stressors.

The study identifies lifetime and current anxiety or mood disorders as the outcome variables. There are also feedback loops included between the key independent and outcome variables. In addition, there are feedback loops between the key independent and the mediator variables. These feedback loops acknowledge theoretical perspectives
that groups’ life chances are a result of the process of placement in the racial hierarchy, and that placement in the racial hierarchy also shapes outcomes (Bashi and McDaniel 1997). While I expect that people of color will have an advantage in mental health as compared to whites, either due to more effective coping strategies or reporting difference, I also expect that people of color will disproportionately report more discrimination and stress in all domains than groups classified as white. An analysis of the results demonstrates how exposure to stress undermines the mental health and well-being of groups racially and ethnically classified as Black and Latino, despite their advantage in mental health.

There are also feedback loops included between self-reported racial and ethnic classification and the outcome variables. In addition, there are feedback loops between self-reported racial and ethnic classification and the mediator variables. These feedback loops acknowledge theoretical perspectives that groups’ life chances are a result of the process of placement in the racial hierarchy, and that placement in the racial hierarchy also shapes outcomes (Bashi and McDaniel 1997). While I expect that people of color will have an advantage in mental health as compared to whites, either due to more effective coping strategies or reporting difference, I also expect that people of color will disproportionately report more discrimination and stress in all domains than groups classified as white. An analysis of the results demonstrates how exposure to stress undermines the mental health and well-being of groups racially and ethnically classified as Black and Latino, despite their advantage in mental health.
Data, Measures, and Methods

Analytic Sample

This study’s analytic sample comes from the National Epidemiologic Survey on Alcohol and Related Conditions, Wave III (NESARC-III). The NESARC-III is a nationally representative, longitudinal study of randomly sampled noninstitutionalized adults in the United States. The National Institutes on Alcohol Abuse and Alcoholism (NIAAA) were the principal investigators of this survey. The data were collected in person between 2012 and 2013. This wave’s full sample size was 36,309. The survey response rate for this wave was 61 percent, representing roughly a 16 percent loss of respondents from the first wave of data (Office of the Assistant Secretary for Planning and Evaluation 2006). The study investigators oversampled communities ethnically and racially classified as Hispanic, Black, and Asian. Further, they took additional measures, including contacting national Indigenous American organizations, tribal leaders, and tribal health officials, to oversample communities racially classified as Indigenous American who lived on reservations. This sampling strategy resulted in a sample racially classified as Indigenous American that represented ten of the nearly 600 Indigenous American tribes in the United States. This comprehensive, limited-access dataset includes multiple indicators of physical and mental health. It also provides information on past experiences that shape physical and mental health, such as trauma and contact with the criminal justice system.

1 This manuscript was prepared using a limited access dataset obtained from the National Institute on Alcohol Abuse and Alcoholism (NIAAA) and does not reflect the opinions or views of NIAAA or the U.S. Government.
The final analytic sample includes adults from all racial and ethnic groups. Respondents with missing data on the explanatory, mediator, and outcome measures were excluded. In turn, the final analytic sample consisted of 35,732 adults.

**Measures**

*Key Explanatory Measure: Self-Reported Racial and Ethnic Classification*

The key explanatory measure is self-reported racial and ethnic classification, which this study conceptualizes as level of exposure and vulnerability to racism and corresponds to people’s placement in the racial hierarchy. Respondents self-identified from the five major Census racial and ethnic categories:\(^2\): (1) Non-Hispanic white; (2) Non-Hispanic Black; (3) Indigenous American; (4) Asian\(^4\); and (5) Hispanic. Based on the tri-racial hierarchy framework, my discussion of the results for each racially and ethnically classified group centers around whether they are located in the white, honorary white, or collective Black stratum. The first stratum includes respondents racialized as white, while the second stratum includes those racially and ethnically classified as Asian or Hispanic. Finally, the third stratum includes groups racialized as Non-Hispanic Black and Indigenous American.

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\(^2\) Respondents were also asked to identify their country of heritage or ancestry.

\(^3\) The NESARC investigators followed the Census Bureau’s analytic strategy of coding multiracial respondents as a single racial or ethnic classification based on the order in which they reported their identities. As a result, this study does not provide a full picture of multiracial respondents’ experiences.

\(^4\) People who reported their heritage or ancestry as East Asian, according to the countries outlined in Bonilla-Silva’s tri-racial hierarchy, formed about 40 percent of the sample classified as Asian. On the other hand, people who reported their heritage or ancestry as Southeast Asian, according to the countries outlined in Bonilla-Silva’s tri-racial hierarchy, formed about 17 percent of the sample classified as Asian.
**Key Outcome Measures**

The key outcome measures are lifetime anxiety or mood disorders and current anxiety or mood disorders.\(^5\) NESARC investigators coded all mental health problems according to DSM-V guidelines.

Lifetime mood disorder was measured by combining the variables that examine whether the respondent ever met the criteria for major depressive disorder or dysthymia, which is also known as persistent depression. Current mood disorder is measured by combining the variables that examine whether the respondent meets the criteria for past year major depressive disorder or past year dysthymia.

Lifetime anxiety disorder was measured by combining the variables that examine whether the respondent met the criteria for specific phobia, panic disorder, social phobia, agoraphobia, or generalized anxiety disorder. Current anxiety disorder was measured by combining the variables that examine whether the respondent met the criteria for past year specific phobia, panic disorder, social phobia, agoraphobia, or generalized anxiety disorder.\(^6\)

To better understand total exposure to mental illness in the sample, lifetime anxiety or mood disorders were measured by combining the lifetime anxiety and mood disorder variables. Current anxiety or mood disorders were measured by combining the current anxiety and mood disorder variables.

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\(^5\) I also examined each type of disorder separately and obtained the same substantive findings.

\(^6\) As demonstrated in the theoretical context section, panic disorder involves unanticipated episodes of fear, including physical symptoms such as shortness of breath. In addition, agoraphobia refers to anxiety about situations that might result in embarrassment or panic. Finally, Generalized Anxiety Disorder involves persistent worry about multiple issues.
Mediator Measures

The mediating measures are two mechanisms of racial inequality: socioeconomic factors and race-based stressors.

Socioeconomic factors that prior research has determined as fundamental avenues through which racial inequality persists (Williams and Jackson 2005) include educational attainment, region, poverty, and employment status. For educational attainment, I distinguish between those with less than a high school education; a high school education or GED; some college; and a four-year college degree and above. Next, the control for region distinguishes between the South and non-South to account for locational inequality (Baker 2020), using Census-defined regions. Poverty status was determined using the 2013 poverty guidelines updated periodically in the Federal Register by the U.S. Department of Health and Human Services under the authority of 42 U.S.C. 9902(2). The control for poverty status distinguishes between those whose income was less than 100 percent of the Federal Poverty Line (FPL); 100 to 200 percent of the FPL; and greater than 200 percent of the FPL. Those with incomes that were less than 100 percent of the federal poverty line are below the poverty line. Finally, the control for employment status distinguishes between those who were employed and unemployed.

Race-based stressors measure “events of danger related to real or perceived experience of racial discrimination” (Comas-Díaz et al. 2019:1). Thus, race-based stressors are the byproducts of experiencing the effects of global white supremacy. Race-

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7 I use the incomes presented in the descriptive statistics only to calculate the poverty status for each racially and ethnically classified group. As such, I do not include the income variable in the analysis, given that the poverty status variable provides a better indicator of the level of resources each group has.
based stressors were comprised of the death of a close family member or friend, potential or actual trouble with the law, and experiences with discrimination.

The loss of a close friend or family member is a binary variable. This study uses the loss of a close friend or family member as a proxy for the disproportionate number of people of color who are murdered in the United States due to police brutality and mass incarceration and higher health-related mortality among people classified as African Americans (Alexander 2012; Umberson et al. 2017). Further, recent work suggests that people classified as Black are more likely than people classified as white to have experienced the death of a parent between childhood and midlife (Umberson et al. 2017). This work suggests that earlier and more frequent exposure to family member deaths may vary by racial and ethnic classification.

The potential or actual trouble with the law or police measure is a categorical measure. I created this measure by combining two binary variables: (1) potential trouble with the law or police, a variable which measured whether the respondent had done something for which they could have been arrested, regardless of whether they were caught or not; and (2) actual trouble with the law or police, a variable that was measured by asking the respondent whether they had serious trouble with the law or police. The resulting three-category variable was coded in the following way: (1) No potential or actual trouble with the law or police, the omitted reference category; (2) Potential, but not actual, trouble with the law or police; and (3) Actual trouble with the law or police.

I created healthcare discrimination and racial slurs measures based on an exploratory factor analysis of the dataset’s discrimination measure. This factor analysis
examined the six variables that measure experiences of racial discrimination and those that measure experiences of discrimination due to Hispanic ethnicity. For details on how I conducted the exploratory factor analysis and the analysis results, see Appendices 2.A and 2.B.

The healthcare discrimination measure combined the variables that measured discrimination in the ability to obtain healthcare and in how the individual was treated when receiving healthcare due to their racial and ethnic classification. Next, the racial slurs measure combined the items that measured being called a racial or ethnic slur and being made fun of, picked on, or threatened because of one’s racial and ethnic classification. Each of the two variables included the following categories: (1) no discrimination or did not experience discrimination in either domain; (2) low discrimination (experienced discrimination in one domain); and (3) high discrimination (experienced discrimination in both domains). No discrimination was the omitted reference category.

Age, sex, and marital status are included as standard demographic covariates in the model. Age was included as a categorical variable with the following categories: (1) 18 to 34; (2) 35 to 54; (3) 55 to 64; and (4) 65 and above. Respondents who were ages 35 to 54 were the omitted reference category, given that lifetime anxiety peaks at this age group (Hasin and Grant 2015). Sex is a binary variable, and males were the omitted reference category. Marital status was coded as a three-category variable that includes individuals who are (1) single, (2) married or cohabiting, or (3) previously married (widowed, divorced, or separated). Single people were the omitted reference category.
Analytic Strategy

I first report descriptive statistics by racial and ethnic classification on the study’s dependent variables. Next, I show how exposure to race-based stressors vary based on racial and ethnic classification, and how these stressors relate to mental health outcomes. Finally, given that socioeconomic and demographic risk factors also vary by racial and ethnic classification, I model mental health outcomes using binary logistic regression.

Descriptive Results

Table 2.1 suggests that lifetime and current mood and anxiety disorders vary by racial and ethnic classification. The results demonstrate that people racially classified as Non-Hispanic White and Indigenous American have the highest proportion of any current anxiety or mood disorder at 32 and 22 percent, respectively. People racially classified as Asian have the lowest prevalence, 13 percent, while people racially and ethnically classified as Black and Hispanic fall in between, at 18 percent. Communities racialized as white – located at the top of the racial hierarchy – and Indigenous Americans living in reservations, placed in the collective Black stratum, had a disadvantage in mental health. In both cases, being at either extreme of the racial hierarchy resulted in a disadvantage in mental health. On the other hand, being in the honorary white buffer group and the beginnings of the collective Black stratum resulted in an advantage in mental health.

In addition, this table shows a higher prevalence of lifetime mental disorders than current, which suggests that a larger proportion of people had experienced a mental health condition at some point in their lives rather than in the past year. Further, the
pattern for lifetime mental disorders by racial and ethnic classification mirrored current mental disorders.

Table 2.2 presents descriptive statistics for the explanatory variables. Overall, respondents tended to be middle-aged, female, live in non-Southern regions, and have average incomes below the poverty level. These factors varied considerably, however, across groups. The samples racially classified as honorary white or collective Black were younger, on average, than the sample classified as white, with a higher share of young adults and a far lower share over 65. In addition, communities racially classified as Black were overrepresented among female respondents in the sample. In contrast, communities ethnically and racially classified as Hispanic and Non-Hispanic white were underrepresented among female respondents.

A larger proportion of communities racially classified as Black resided in the South, while a smaller proportion of communities racially classified as Asian lived in the South relative to other groups. Apart from samples racially classified as Asian, samples racially classified as honorary white and collective Black were more likely than those racially classified as white to live in poverty and have an income below $25,000.

Overall, the sample was primarily employed and tended to have at least a high school education. In addition, respondents were more likely to be married. Further, the sample ethnically classified as Hispanic was overrepresented among employed people. On the other hand, the sample racially classified as Indigenous American was underrepresented. Respondents racially classified as Asian were more highly educated than any other racially and ethnically classified group. Finally, respondents racially
classified as Asian formed the highest share of the married sample, while people racially
classified as Black were overrepresented among single respondents.

The overall sample had not experienced healthcare discrimination, racial slurs,
mocking, or threats. They tended not to have lost a loved one and had not experienced
potential or actual trouble with the law or police. On the other hand, a larger share of the
groups racially classified as collective Black, including those ethnically and racially
classified as Hispanic, non-Hispanic Black, and Indigenous American, experienced both
low and high amounts of healthcare discrimination compared to those classified as
honorary white or white. The samples racially classified as non-Hispanic Black and
Indigenous American had a higher share of people who had experienced the death of a
loved one than those racially classified as white. In addition, the sample racially
classified as collective Black was overrepresented among people who had experienced
being called racial slurs or had experienced mocking or threats because of their racial and
ethnic classification.

Finally, groups racially classified as white and Indigenous American were the
most likely to have experienced potential or actual trouble with the law or police. Yet
overall, communities racially classified as collective Black were more likely to have been
exposed to more race-based stress in most domains than those racially classified as
whites.

**Multivariate Results**

Table 2.3 suggests that the odds of lifetime anxiety or mood disorders vary by
racial and ethnic classification. The baseline model regresses lifetime or current mood or
anxiety disorders on racial and ethnic classification. Model 2 includes racial and ethnic classification along with the socio-demographic covariates (age, sex, and marital status). Model 3 includes socio-demographic covariates and the first mechanism of racial inequality: socioeconomic factors (educational attainment, employment status, poverty status, and region). Model 4 includes socio-demographic covariates, socioeconomic factors, and race-based stressors. I compared all models using likelihood ratio tests. I do not include communities racially classified as Indigenous American and Asian in the models, given that these groups had small sample sizes in the race-based stress and lifetime or current anxiety disorder crosstabulations.

As found in previous studies, an analysis of the results show that communities of color have lower odds of meeting the criteria for lifetime anxiety or mood disorders as compared to communities racially classified as Non-Hispanic white. The substantive findings are the same for lifetime and current anxiety or mood disorders. Thus, I include the models for current anxiety and mood disorders in appendix 2.C. This similarity in findings suggests that even exposure to mechanisms of racial inequality at a single point in time shapes mental health across the life course.

Adding demographic background characteristics in model 2 improves the mental health of groups racially classified as honorary white and collective Black relative to those racially classified as white across the board. Further, the advantage shown among respondents racially and ethnically classified as Black and Hispanic relative to those racially classified as white widens. After accounting for compositional differences across groups, and the greater tendency for middle aged, women, and unmarried respondents to
have worse mental health, the relative position of people of color improves relative to people classified as white.

Next, after adding socioeconomic status variables in model 3, the size of the advantage in mental health among respondents racially and ethnically classified as Black and Hispanic relative to those racially classified as whites increases. This model illustrates that those who lived in poverty and were unemployed tended to have worse mental health. However, higher educational attainment was positively associated with higher odds of lifetime anxiety or mood disorders. Those who had completed some college or a college degree and above had higher odds of experiencing lifetime anxiety or mood disorders. After considering the differential composition of groups classified according to their racial and ethnic classification and the higher tendency for those living in poverty, experiencing unemployment, or having a higher education level to have worse mental health, communities of color had better mental health outcomes than those racially classified as white.

Finally, adding race-based stressor variables in model 4 further increased the effect size of the advantage in mental health groups among groups racially and ethnically classified as non-Hispanic Black and Hispanic. Even after considering the greater tendency for those who have experienced the loss of a loved one, potential or actual trouble with the law or police, high healthcare discrimination, and a high frequency of racial slurs, mocking, or threats to have worse mental health, the advantage in mental health remains among communities of color. Most strikingly, those who experienced potential trouble with the law or police had 2.5 times (OR = 2.533) the odds of meeting
the criteria for lifetime anxiety or mood disorders compared to those who have not experienced any trouble with the law or police. This large effect was apparent even when accounting for experiences with healthcare discrimination and racial slurs, mocking, and threats. Further, the coefficient for those who had experienced potential trouble with the law was slightly larger than for those who had experienced actual trouble with the law (OR = 2.388). This finding suggests that even the threat of legal trouble is associated with lifetime mental disorders, and that potential stressors play an important role in shaping whether an individual ever meets the criteria for poor mental health. Taken together, after accounting for people of color’s greater exposure to race-based stressors, the advantage in lifetime mental health widens considerably among groups racially and ethnically classified as Black and Hispanic. Thus, if all groups had equal exposure to these stressors, people of color’s mental health would substantially improve.

Discussion

This study has explored how racism intersects with multiple forms of inequality to shape lifetime and current mood or anxiety disorders. Mood disorders impact daily life activities (National Institute of Mental Health 2018) and are one of the leading causes of disability worldwide (World Health Organization 2018). Anxiety disorders are some of the most prevalent mental illnesses worldwide (Institute for Health Metrics and Evaluation 2017, qtd. in Ritchie and Roser 2018). Understanding how structural racism plays a role in the high prevalence of mental disorders is therefore useful for both health care delivery and health care policy. Given that racism is embedded into the way that society is organized and essential for its functioning, research that accounts for how
exposure to racism shapes life chances is relevant for further understanding how health outcomes differ among racial and ethnic groups.

Previous research suggests that while nonwhite people report more exposure to stress, they have lower levels of overall psychological distress (Brown et al. 2020). This advantage in mental health may result from the vastly different environments in which racially and ethnically classified groups live (Mezuk et al. 2013), the higher psychosocial resources people of color may have to manage the stress of racism (Brown et al. 2020), and underdiagnosis (Williams and Jackson 2005). Given this finding, some scholars have argued that using disease as an outcome may underestimate racial and ethnic health inequalities (Boen 2020). The results of this study focus on mechanisms of racial inequality to address what may be missing from current understandings of these health inequities. Overall, while prior literature has made strides towards understanding Black people and people of color’s advantage in mental health, there is limited work that studies how racism intersects with multiple dimensions of inequality to shape mental health outcomes. The results of this study focus on mechanisms of racial inequality to address what may be missing from current understandings of these health inequities.

The study’s results, which align with prior research (Asnaani et al. 2010; Breslau et al. 2006; Budhwani et al. 2015; Ghafoori et al. 2012; Hoffman and Hinton 2014; Sohail et al. 2014; Williams and Earl 2007) indicate that people of color have an advantage in lifetime and current mental health as compared to whites. After accounting for sociodemographic background, socioeconomic inequality, and race-based stressors, communities racially and ethnically classified as Black and Hispanic had lower odds of
experiencing lifetime and current anxiety or mood disorders. The study found that living in poverty and experiencing unemployment – factors that were more common among the sample’s communities of color – were associated with higher odds of lifetime and current anxiety or mood disorders. In contrast, having a higher education level – which was more common in the sample racially classified as white – did not protect against poor lifetime and current mental health. Thus, taking the differences across racially and ethnically classified groups in socioeconomic status and race-based stress into account only widened people of color’s advantage in mental health.

The study’s finding that people of color retain an advantage in mental health despite their mostly higher levels of race-based stress compared to whites is consistent with prior literature (Boen 2020). This study also aligns with prior research that argues that people of color’s psychosocial resources may help them cope with stress (Brown et al. 2020). However, I argue that these psychosocial resources may take the form of resisting or accepting racial discrimination (Kelley 1996; Bennett et al. 2012).

The prevalence of mental illness among communities racially and ethnically classified as Non-Hispanic Black and Hispanic may result from being located at or near the bottom of the racial hierarchy. These communities tend to be underdiagnosed for mental health conditions, particularly given that they are constantly exposed to race-based stressors. Race-based stressors, which often compound and overlap (Mays et al. 2007), highlight the ubiquity of trauma and stress among communities racialized as collective Black that come from interacting with a world organized around white supremacy. In addition, since the stressors that shape exposure to racism remain among
racially and ethnically classified groups even after accounting for other factors, the results show that the presence of advantage does not indicate the absence of racism’s effects on people’s health. The persistent advantage in mental health among communities racially classified as Black thus describes how racial stratification affects health outcomes (Du Bois [1935] 2007; Metzl 2019; Roediger 1991).

In addition, exposure to racism affects every variable within the analysis. As such, this study also finds that race-based stressors, including healthcare discrimination, experiencing racial slurs, along with undergoing the loss of a loved one and potential or actual contact with the criminal justice system, are associated with higher odds of lifetime and current anxiety and mood disorders. Prior research has established that contact with the criminal justice system is related to poor mental health (Massoglia and Pridemore 2015; Sugie and Turney 2017; Turney et al. 2012). This study shows that those who experienced even potential trouble with the law or police had higher odds of meeting the criteria for lifetime anxiety or mood disorders compared to those who had not experienced any trouble with the law or police.

Potential contact with the criminal justice system is a structural problem that affected groups racialized as collective Black (Indigenous American and Black) and white in the sample. For groups racialized as collective Black, these findings illustrate that systems of inequality are interconnected and that the groups most vulnerable to racism experience its effects in multiple domains. Prior research has indicated that contact with the police can affect both physical and emotional health (Thoits 2010, qtd. in Sewell et al. 2021). Further, those who witness police violence in an area near them tend
to change their behavior because of what they have seen (Desmond, Papachristos, and Kirk 2016, qtd. in Sewell et al. 2021). In addition, police surveillance in neighborhoods often functions as a mode of social control, particularly in communities racialized as nonwhite (Alexander 2012; Browne 2015, qtd. in Sewell et al. 2021). As a result, the threat of surveillance and violence affects the mental health of communities racialized as nonwhite, especially given that these groups are more likely to be racially profiled. Further, these findings demonstrate the severe psychological manifestation of racism among those most vulnerable to it, even when they have not yet encountered an institution steeped in anti-Blackness. At the same time, the findings illustrate that although communities that are the least vulnerable to racism may not end up facing arrest, the threat of encountering the criminal justice system dampens the potential benefits of being at the top of the racial hierarchy.

This study's finding that communities racialized as Black had a higher rate of losing a loved one than other racially and ethnically classified groups also aligns with prior research. Prior studies suggest that communities racialized as Black tend to experience the loss of a loved one earlier in life and more frequently than other groups (Umberson 2017). In addition, the disproportionate number of black people killed by the police, mass incarceration, and higher health-related mortality due to underdiagnosis of illnesses. Further, the higher rates of healthcare discrimination and racial slurs, mocking, and threats among communities racially classified as Black may come from the anti-Blackness inherent in the racialized social system.
In contrast, communities classified as white’s placement at the top of the racial hierarchy, experience of perceived discrimination, and perceived threats to their racial classification may partially explain their higher prevalence of mood and anxiety disorders. Recent work notes that groups racially classified as white tend to take more drugs for illnesses that may have suicide or depression listed as a side effect (Do and Schnittker 2020:4). This finding demonstrates that the benefits of being at the top of the hierarchy may be associated with poor mental health given that mental illness and treatment are more often identified for communities racialized as white.

As a whole, these findings provide more context on the mechanisms of racial inequality that add to people of color's burden of disease despite their advantage in lifetime and current mental health. Further, they illustrate that discrimination in healthcare and interpersonal racially coded language and threats – a marker of ongoing systemic racism - are associated with mental disorders. In addition, the results help unpack the domains of discrimination that are most critical for understanding differences in mental health disorders.

The lens of Black Advantage Vision may also provide insight into the ways that people of color may thrive despite higher vulnerability to racial inequality (Pattillo, forthcoming). Prior work has theorized that people of color experience double consciousness, which involves constantly being considered an Other. They may wear a mask of deference (Fanon 1967; Welsing 2017; Wilson 1994:101) or subversiveness (Kelley 1996) in the face of potential stereotype threat that would paint them in a negative light (Steele 1997). While prior work has shown that the presence of stereotype
threat may lead to worse outcomes (Aronson et al. 2013; Burgess et al. 2010; Steele 1997), this study suggests that the presence of stereotype threat is associated with people of color’s *advantage* in mental health. Taken together, whether communities classified as nonwhite have an actual mental health advantage due to greater resilience or whether they are merely under-diagnosed, racism adds to the burden of disease among these populations.

Further, consistent with Critical Race Theory (Brown 2003; Brown 2008; Crenshaw et al. 1995; Ford and Airhihenbuwa 2010; Mills 1998; Zuberi 2000; Zuberi 2001a; Zuberi 2001b; Zuberi 2011), this study also demonstrates the utility of reinterpreting racial classification in a way that is consistent with the process of racial stratification (Zuberi 2001b). Thus, the study has implications for how researchers can interpret health outcomes and outcomes in other domains.

*Limitations*

This study is not without limitations. First, the ethnic classification term Non-Hispanic functions as an excluder. In turn, this study cannot speak to the process of racial stratification for people ethnically classified as Hispanic. Additionally, given that the study data are cross-sectional, this research cannot make inferences about changes in mental health over time. In addition, the racial classification of Indigenous Americans has limitations. Given that the study investigators only sampled about two percent of tribes in the United States, the study findings for this group may not be representative of all tribes. Second, while the study includes criteria about physical pain based on the DSM-V for diagnosing anxiety disorders, such as whether respondents had tense or aching muscles, it
does not include these indicators in the criteria for diagnosing mood disorders. The DSM-V's inclusion of only mental and emotional symptoms in its mood disorder criteria could potentially mask communities classified as nonwhite's physical symptoms of these disorders. Further, the study does not include a measure of skin color (Monk 2015), which could provide further insight into how proximity to whiteness might affect how racially and ethnically classified groups experience their mental health.

**Implications**

This study's results do not align with research arguing that the racial ability to withstand mental health challenges explains inequities in mood and anxiety disorders by racial and ethnic classification (Pearson et al. 2014; Lilienfeld 2017). First, the study finds that the benefits of whiteness do not necessarily translate to an advantage in mental health. In addition, this work illustrates that structural factors embedded into the fabric of society, such as potential and actual contact with the law or police – rather than individual-level factors such as temperament – shape mental health outcomes.

In addition, the study found that there were no significant differences in lifetime and current anxiety or mood disorders between those who actively responded to instances of discrimination and those who kept these experiences to themselves. Further, communities racialized as white had the most social support of all groups, yet they still reported poorer mental health than other racially and ethnically classified groups.

These findings indicate that future research can continue to identify other mechanisms of racial inequality to contribute to understandings of how racism intersects with myriad factors to shape health inequities. Other mechanisms of racial inequality
include insurance status, how providers assess for mental disorders, and the level of racial and ethnic diversity in an area. Identifying additional indicators of racial inequality can contribute to better understanding how these factors shape people of color’s advantage – and disadvantages among people classified as white – in mental health. Additionally, using longitudinal or observational data, future studies can employ causal mediation analysis to decompose how much mechanisms of racial inequality may explain the variation in inequities in mental health by racial and ethnic classification (Jackson and VanderWeele 2019; Nguyen et al. 2015).

This research also suggests that future studies can more concretely operationalize race in quantitative work and contribute to understanding the impact of race-based stress on health. Scholars of color have long theorized that race has been incorrectly interpreted in quantitative research (Zuberi 2000; Zuberi 2001b; Zuberi and Bonilla-Silva 2008). Using Critical Race Theory, the present study takes steps towards reinterpreting race and racism quantitatively to better represent people’s social realities. Finally, to contribute to understandings of how race-based stress shapes health, future research can continue to explore other potential stressors that have already been identified in the stress literature, including work and financial stress (Boen 2020). These studies can shed light on continuing to identify the many ways that racism is embedded and institutionalized within society, and in turn how its ubiquity shapes health.

The present study has demonstrated the importance of understanding race as a measure of vulnerability to racism and quantifying mechanisms of racial inequality in a way that is connected to people’s social realities. Further, this study shows how structural
racism continues to contribute to the burden of disease among communities of color. In turn, this work underscores the importance of examining the mechanisms of racism to contribute towards dismantling this system of inequality.

Acknowledgement

I thank the National Institute on Alcohol Abuse and Alcoholism’s (NIAAA) Data Access Committee, particularly Dr. Pamela Wernett, Dr. Patricia Chou, and Veronica Wilson, for their assistance with obtaining access to the dataset.
References


Mezuk, Briana, Cleopatra M. Abdou, Darrell Hudson, Kiarri N. Kershaw, Jane A. Rafferty, Hedwig Lee, and James S. Jackson. 2013. “‘White Box’ Epidemiology and the Social Neuroscience of Health Behaviors: The Environmental Affordances Model.” *Society and Mental Health* 3(2).


**Tables and Figures**

**Figure 2.1: Conceptual Model**
Figure 2.2: Racial Hierarchy - The Tri-Racial Order

<table>
<thead>
<tr>
<th>RACIAL HIERARCHY: THE EMERGING TRI-Racial ORDER&lt;sup&gt;3&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>STRATUM 1: White</td>
</tr>
<tr>
<td>Whites</td>
</tr>
<tr>
<td>White immigrants</td>
</tr>
<tr>
<td>In the future: Fully assimilated White Latinos</td>
</tr>
<tr>
<td>In the future: Light skinned multiracial people</td>
</tr>
<tr>
<td>In the future: Urban Native Americans</td>
</tr>
<tr>
<td>In the future: Some Asians</td>
</tr>
<tr>
<td>STRATUM 2 (Intermediate/Buffer Group): Honorary White</td>
</tr>
<tr>
<td>Light-skinned Latinos</td>
</tr>
<tr>
<td>East Asian Americans (Japanese Americans, Korean Americans, Asian Indian Americans, Chinese Americans)</td>
</tr>
<tr>
<td>Middle Eastern Americans</td>
</tr>
<tr>
<td>Most multiracial people</td>
</tr>
<tr>
<td>Filipino Americans</td>
</tr>
<tr>
<td>STRATUM 3: Collective Black</td>
</tr>
<tr>
<td>Southeast Asian Americans (Vietnamese Americans, Hmong Americans, Laotian Americans)</td>
</tr>
<tr>
<td>Dark-skinned Latinos</td>
</tr>
<tr>
<td>Black Americans</td>
</tr>
<tr>
<td>African and Afro-Caribbean immigrants</td>
</tr>
<tr>
<td>Native Americans living on reservations</td>
</tr>
</tbody>
</table>

Table 2.1: Descriptive Statistics of Dependent Variables

<table>
<thead>
<tr>
<th></th>
<th>Self-Reported Racial and Ethnic Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NH White</td>
</tr>
<tr>
<td>Current† Mental Disorder</td>
<td>Any Current Anxiety² or Mood³ Disorder (%)</td>
</tr>
<tr>
<td>Lifetime Mental Disorder</td>
<td>Any Lifetime Anxiety or Mood Disorder (%)</td>
</tr>
<tr>
<td>Observations</td>
<td>18,947</td>
</tr>
</tbody>
</table>

SOURCE: National Epidemiologic Survey on Alcohol and Related Conditions, Wave 3 (NESARC III), 2012-2013. All statistics are weighted. The sample is restricted to respondents with no missing information on the explanatory, mediating, and dependent variables.

†Denotes non-Hispanic.

²Current mental disorders are defined as mental disorders diagnosed in the past year.

³Anxiety disorders are comprised of: (1) Panic Disorder; (2) Agoraphobia (Specific Anxiety); (3) Social Anxiety; (4) Generalized Anxiety Disorder; and (5) Specific Phobia.

⁴Mood disorders are comprised of major depressive disorder and dysthymia (persistent depression).
Table 2.2: Descriptive Statistics of Explanatory Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Self-Reported Racial and Ethnic Classification</th>
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</thead>
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<tr>
<td></td>
<td>Non-Hispanic White</td>
</tr>
<tr>
<td>Age</td>
<td></td>
</tr>
<tr>
<td>Younger Adults, 18-34 (%)</td>
<td>26</td>
</tr>
<tr>
<td>Middle-Aged Adults, 35-54 (%)</td>
<td>35</td>
</tr>
<tr>
<td>Older Adults, 55-64 (%)</td>
<td>18</td>
</tr>
<tr>
<td>Elderly Adults, 65 and above (%)</td>
<td>21</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
</tr>
<tr>
<td>Male (%)</td>
<td>48</td>
</tr>
<tr>
<td>Female (%)</td>
<td>51</td>
</tr>
<tr>
<td>Region</td>
<td></td>
</tr>
<tr>
<td>Non-South (%)</td>
<td>65</td>
</tr>
<tr>
<td>South (%)</td>
<td>35</td>
</tr>
<tr>
<td>Income</td>
<td></td>
</tr>
<tr>
<td>Less than $25,000 (%)</td>
<td>48</td>
</tr>
<tr>
<td>$25,000-$49,999 (%)</td>
<td>26</td>
</tr>
<tr>
<td>$50,000-$79,999 (%)</td>
<td>15</td>
</tr>
<tr>
<td>$80,000 or more (%)</td>
<td>11</td>
</tr>
<tr>
<td>Poverty Level</td>
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</tr>
<tr>
<td>Less than 100% of FPL (%)</td>
<td>40</td>
</tr>
<tr>
<td>100%-200% of FPL (%)</td>
<td>34</td>
</tr>
<tr>
<td>Greater than 200% of FPL (%)</td>
<td>26</td>
</tr>
<tr>
<td>Employment Status</td>
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</tr>
<tr>
<td>Employed (%)</td>
<td>70</td>
</tr>
<tr>
<td>Unemployed (%)</td>
<td>30</td>
</tr>
<tr>
<td>Education</td>
<td>Less than High School (%)</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td></td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>32</td>
</tr>
<tr>
<td>Marital Status</td>
<td>Single (%)</td>
</tr>
<tr>
<td></td>
<td>Married (%)</td>
</tr>
<tr>
<td></td>
<td>Previously Marriedb (%)</td>
</tr>
<tr>
<td></td>
<td>Healthcare Discrimination</td>
</tr>
<tr>
<td></td>
<td>Low (%)</td>
</tr>
<tr>
<td></td>
<td>None (%)</td>
</tr>
<tr>
<td>Racial Slurs, Mocking, or Threats</td>
<td>High (%)</td>
</tr>
<tr>
<td></td>
<td>Low (%)</td>
</tr>
<tr>
<td></td>
<td>Did Not Experience (%)</td>
</tr>
<tr>
<td>Death of a Loved One</td>
<td>Yes (%)</td>
</tr>
<tr>
<td></td>
<td>No (%)</td>
</tr>
<tr>
<td>Potential or Actual Trouble with</td>
<td>Actual Trouble with the</td>
</tr>
<tr>
<td>the Law or Police</td>
<td>Law or Police (%)</td>
</tr>
<tr>
<td></td>
<td>Potential Trouble with</td>
</tr>
<tr>
<td></td>
<td>the Law or Police (%)</td>
</tr>
<tr>
<td></td>
<td>None (%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>18,947</th>
<th>7,594</th>
<th>500</th>
<th>1,774</th>
</tr>
</thead>
</table>

Notes: *FPL - Federal Poverty Line, 2013 estimates. Incomes less than 100% of the FPL are defined as below the poverty level.
bPreviously Married respondents include those who are widowed, divorced, or separated.
Table 2.3: Multivariate Results for Lifetime Anxiety or Mood Disorders

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Anxiety or Mood Disorders</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic Black (Ref: Non-Hispanic White)</td>
<td>0.597***</td>
<td>0.518***</td>
<td>0.522***</td>
<td>0.435***</td>
</tr>
<tr>
<td></td>
<td>(-17.01)</td>
<td>(-20.68)</td>
<td>(-19.74)</td>
<td>(-23.64)</td>
</tr>
<tr>
<td>Hispanic (Ref: Non-Hispanic White)</td>
<td>0.639***</td>
<td>0.595***</td>
<td>0.583***</td>
<td>0.574***</td>
</tr>
<tr>
<td></td>
<td>(-14.41)</td>
<td>(-16.24)</td>
<td>(-16.12)</td>
<td>(-15.96)</td>
</tr>
<tr>
<td>Younger Adults, 18-34 years old (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>0.927*</td>
<td>0.894***</td>
<td>0.889***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.51)</td>
<td>(-3.65)</td>
<td>(-3.72)</td>
<td></td>
</tr>
<tr>
<td>Older Adults, 55-64 years old (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>0.987</td>
<td>0.953</td>
<td>0.999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.37)</td>
<td>(-1.35)</td>
<td>(-0.03)</td>
<td></td>
</tr>
<tr>
<td>Elderly Adults, 65 years old and Above (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>0.502***</td>
<td>0.454***</td>
<td>0.525***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-18.07)</td>
<td>(-18.92)</td>
<td>(-15.07)</td>
<td></td>
</tr>
<tr>
<td>Sex (Ref: Male)</td>
<td>1.895***</td>
<td>1.796***</td>
<td>2.174***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(26.21)</td>
<td>(23.44)</td>
<td>(29.23)</td>
<td></td>
</tr>
<tr>
<td>Married/Cohabiting (Ref: Single)</td>
<td>0.848***</td>
<td>0.880***</td>
<td>0.898***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.28)</td>
<td>(-4.06)</td>
<td>(-3.33)</td>
<td></td>
</tr>
<tr>
<td>Previously Married (Ref: Single)</td>
<td>1.327***</td>
<td>1.378***</td>
<td>1.343***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.83)</td>
<td>(8.77)</td>
<td>(7.87)</td>
<td></td>
</tr>
<tr>
<td>High School (Ref: Less than High School)</td>
<td>0.956</td>
<td>0.967</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.14)</td>
<td>(-0.81)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Some College (Ref: Less than High School)</td>
<td>1.136**</td>
<td>1.133**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.26)</td>
<td>(3.12)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 1: OLS Results for Perceived Discrimination and Self-Rated Health

<table>
<thead>
<tr>
<th>Category</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>College Degree and Above (Ref: Less than High School)</td>
<td>1.080</td>
<td>1.133**</td>
</tr>
<tr>
<td>Unemployed (Ref: Employed)</td>
<td>1.135***</td>
<td>(4.11)</td>
</tr>
<tr>
<td>Less than 100% of FPL (Ref: 100-200% of FPL)</td>
<td>1.203***</td>
<td>(6.37)</td>
</tr>
<tr>
<td>Greater than 200% of FPL (Ref: 100-200% of FPL)</td>
<td>0.908**</td>
<td>(-2.65)</td>
</tr>
<tr>
<td>South (Ref: Non-South)</td>
<td>0.904***</td>
<td>(-4.09)</td>
</tr>
<tr>
<td>Death of a Loved One (Ref: No Death of a Loved One)</td>
<td>1.452***</td>
<td>(14.42)</td>
</tr>
<tr>
<td>Low Healthcare Discrimination (Ref: No Discrimination)</td>
<td>1.459***</td>
<td>(6.03)</td>
</tr>
<tr>
<td>High Healthcare Discrimination (Ref: No Discrimination)</td>
<td>1.448***</td>
<td>(4.96)</td>
</tr>
<tr>
<td>Low Frequency of Racial Slurs, Mocking or Threats (Ref: Did Not Experience Racial Slurs, Mocking, or Threats)</td>
<td>1.659***</td>
<td>(9.26)</td>
</tr>
<tr>
<td>High Frequency of Racial Slurs, Mocking or Threats (Ref: Did Not Experience Racial Slurs, Mocking, or Threats)</td>
<td>1.786***</td>
<td>(5.71)</td>
</tr>
<tr>
<td>Potential Trouble with the Law or Police (Ref: No Potential or Actual Trouble with the Law or Police)</td>
<td>2.533***</td>
<td>(28.07)</td>
</tr>
<tr>
<td>Actual Trouble with the Law or Police (Ref: No Potential or Actual Trouble with the Law or Police)</td>
<td>2.388***</td>
<td>(10.20)</td>
</tr>
</tbody>
</table>

**Observations**


**Source:** National Epidemiologic Survey on Alcohol and Related Conditions, Wave 3 (NESSARC-III), 2012-2013. The sample is restricted to respondents with no missing information on the explanatory, mediating, and dependent variables. Given that there were small sample sizes in the study’s initial cross-tabulation for the trouble with the law or police and discrimination indicators, groups classified as Indigenous American and Asian are excluded from the regression analysis.

T statistics are in parentheses. Models were compared using likelihood ratio tests.

* p < .05; ** p < .01; *** p <.001 (two-tailed tests).

FPL - Federal Poverty Line, 2013 estimates. Incomes less than 100% of the FPL are defined as below the poverty level.

This variable measures individuals who engaged in activities that could have resulted in an arrest.
Appendices

Appendix 2.A: Exploratory Factor Analysis for Discrimination Measure

Since the discrimination scale items qualitatively differ, I conducted an exploratory factor analysis to determine whether there were any meaningful combinations of the measure. This dataset includes six variables that measure experiences of racial discrimination. It also contains six variables that measure experiences of discrimination due to being ethnically classified as Hispanic. Each variable measures whether respondents experienced discrimination due to their racial or ethnic classification in the following domains: (1) the ability to obtain healthcare; (2) how the individual was treated when getting healthcare; (3) in public; (4) in any other situation; (5) being called a racial or ethnic slur; and (6) being made fun of, picked on, or threatened.

For each domain of discrimination, respondents could choose from the following answers: (1) Never; (2) Almost never; (3) Sometimes; (4) Fairly often; and (5) Very often. To better categorize experiences of discrimination, I combined the respondent answer choices in the following way for each variable: one category combined the “Never” and “Almost never” answer choices, and a second category combined the “Sometimes,” “Fairly often,” and “Very often” answer choices. The combined never or almost never category was the omitted reference group.

As shown in Appendix 2.B, the healthcare discrimination and racial slurs and threats factors explained 61 percent of the total variance observed. Discrimination in the ability to obtain healthcare and while receiving healthcare primarily defined the healthcare discrimination factor. This factor had an eigenvalue of 1.89 and explained 31 percent of the total variance observed. The racial slurs, mocking, and threats factor had
an eigenvalue of 1.80 and explained 30 percent of the total variance observed. Based on the exploratory factor analysis results, healthcare discrimination and racial slurs were most relevant for understanding the discrimination measure.
## Appendix 2.B: Exploratory Factor Analysis Results for Discrimination Measure

### Rotated Factor Loadings

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor 1: Healthcare Discrimination</th>
<th>Factor 2: Racial Slurs</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent experienced discrimination due to their racial or ethnic classification when trying to obtain healthcare</td>
<td>0.852</td>
<td>0.071</td>
<td>0.269</td>
</tr>
<tr>
<td>Respondent experienced discrimination due to their racial or ethnic classification in treatment when receiving healthcare</td>
<td>0.846</td>
<td>0.148</td>
<td>0.263</td>
</tr>
<tr>
<td>Respondent experienced discrimination due to their racial or ethnic classification in public</td>
<td>0.420</td>
<td>0.582</td>
<td>0.485</td>
</tr>
<tr>
<td>Respondent experienced discrimination due to their racial or ethnic classification in any other situation</td>
<td>0.502</td>
<td>0.516</td>
<td>0.481</td>
</tr>
<tr>
<td>Respondent experienced being called a racial or ethnic slur due to their racial or ethnic classification</td>
<td>0.127</td>
<td>0.778</td>
<td>0.378</td>
</tr>
<tr>
<td>Respondent experienced being made fun of, picked on, or threatened due to their racial or ethnic classification</td>
<td>0.039</td>
<td>0.750</td>
<td>0.436</td>
</tr>
</tbody>
</table>

**Variance Explained (%)**

- Factor 1: Healthcare Discrimination: 31%
- Factor 2: Racial Slurs: 30%
- Cumulative Variance Explained (%): 61%

**SOURCE**: National Epidemiologic Survey on Alcohol and Related Conditions, Wave 3 (NESARC-III), 2012-2013.

**Note**: Factor loadings were rotated using the orthogonal varimax (Kaiser off) technique for ease of interpretation.
### Appendix 2.C: Multivariate Results for Current Anxiety or Mood Disorders

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current Anxiety or Mood Disorders</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic Black (Ref: Non-Hispanic White)</td>
<td>0.723***</td>
<td>0.612***</td>
<td>0.584***</td>
</tr>
<tr>
<td></td>
<td>(-9.48)</td>
<td>(-13.78)</td>
<td>(-14.56)</td>
</tr>
<tr>
<td>Hispanic (Ref: Non-Hispanic White)</td>
<td>0.789***</td>
<td>0.725***</td>
<td>0.657***</td>
</tr>
<tr>
<td></td>
<td>(-6.81)</td>
<td>(-9.04)</td>
<td>(-11.25)</td>
</tr>
<tr>
<td>Younger Adults, 18-34 years old (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>1.050</td>
<td>0.995</td>
<td>0.998</td>
</tr>
<tr>
<td></td>
<td>(1.44)</td>
<td>(-0.15)</td>
<td>(-0.06)</td>
</tr>
<tr>
<td>Older Adults, 55-64 (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>0.930</td>
<td>0.872***</td>
<td>0.913*</td>
</tr>
<tr>
<td></td>
<td>(-1.83)</td>
<td>(-3.39)</td>
<td>(-2.21)</td>
</tr>
<tr>
<td>Elderly Adults, 65 and Above (Ref: Middle-aged Adults, 35-54 years old)</td>
<td>0.510***</td>
<td>0.417***</td>
<td>0.488***</td>
</tr>
<tr>
<td></td>
<td>(-15.09)</td>
<td>(-18.09)</td>
<td>(-14.52)</td>
</tr>
<tr>
<td>Sex (Ref: Male)</td>
<td>1.848***</td>
<td>1.721***</td>
<td>2.063***</td>
</tr>
<tr>
<td></td>
<td>(22.06)</td>
<td>(19.03)</td>
<td>(24.03)</td>
</tr>
<tr>
<td>Married/Cohabiting (Ref: Single)</td>
<td>0.744***</td>
<td>0.787***</td>
<td>0.801***</td>
</tr>
<tr>
<td></td>
<td>(-8.49)</td>
<td>(-6.80)</td>
<td>(-6.19)</td>
</tr>
<tr>
<td>Previously Married (Ref: Single)</td>
<td>1.234***</td>
<td>1.286***</td>
<td>1.244***</td>
</tr>
<tr>
<td></td>
<td>(5.27)</td>
<td>(6.22)</td>
<td>(5.29)</td>
</tr>
<tr>
<td>High School (Ref: Less than High School)</td>
<td>0.908*</td>
<td>0.924</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.24)</td>
<td>(-1.78)</td>
<td></td>
</tr>
<tr>
<td>Some College (Ref: Less than High School)</td>
<td>0.974</td>
<td>0.976</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.61)</td>
<td>(-0.56)</td>
<td></td>
</tr>
<tr>
<td>College Degree and Above (Ref: Less than High School)</td>
<td>0.849***</td>
<td>0.894*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.32)</td>
<td>(-2.23)</td>
<td></td>
</tr>
<tr>
<td>Unemployed (Ref: Employed)</td>
<td>1.249***</td>
<td>1.278***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.56)</td>
<td>(7.09)</td>
<td></td>
</tr>
<tr>
<td>Variable</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>Less than 100% of FPL&lt;sup&gt;b&lt;/sup&gt; (Ref: 100-200% of FPL)</td>
<td>1.297***</td>
<td>1.257***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.00)</td>
<td>(6.90)</td>
<td></td>
</tr>
<tr>
<td>Greater than 200% of FPL (Ref: 100-200% of FPL)</td>
<td>0.849***</td>
<td>0.872**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.76)</td>
<td>(-3.08)</td>
<td></td>
</tr>
<tr>
<td>South (Ref: Non-South)</td>
<td>0.907***</td>
<td>0.931*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.49)</td>
<td>(-2.51)</td>
<td></td>
</tr>
<tr>
<td>Death of a Loved One (Ref: No Death of a Loved One)</td>
<td>1.491***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.96)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Healthcare Discrimination</td>
<td>1.543***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Ref: No Discrimination)</td>
<td>(6.55)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Healthcare Discrimination</td>
<td>1.736***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Ref: No Discrimination)</td>
<td>(7.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Frequency of Racist Slurs, Mocking or Threats (Ref: Did Not Experience Racist Slurs, Mocking, or Threats)</td>
<td>1.612***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Frequency of Racist Slurs, Mocking or Threats (Ref: Did Not Experience Racist Slurs, Mocking, or Threats)</td>
<td>1.804***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.60)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Potential Trouble with the Law or Police&lt;sup&gt;c&lt;/sup&gt;</td>
<td>2.294***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Ref: No Potential or Actual Trouble with the Law or Police)</td>
<td>(23.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual Trouble with the Law or Police (Ref: No Potential or Actual Trouble with the Law or Police)</td>
<td>2.456***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.26)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Observations**: 35,732

**Source**: National Epidemiologic Survey on Alcohol and Related Conditions, Wave 3 (NESARC-III), 2012-2013. The sample is restricted to respondents with no missing information on the explanatory, mediating, and dependent variables. Given that there were small sample sizes in the crosstabulation for the trouble with the law or police and discrimination indicators, groups classified as Indigenous American and Asian are excluded from the regression analysis.

T statistics are in parentheses. Models were compared using likelihood ratio tests.

* p < .05; ** p < .01; *** p < .001 (two-tailed tests).

<sup>b</sup> Current anxiety or mood disorders are defined as any anxiety or mood disorder that was diagnosed in the past year.

<sup>c</sup> FPL - Federal Poverty Line, 2013 estimates. Incomes less than 100% of the FPL are defined as below the poverty level.

<sup>c</sup> This variable measures individuals who engaged in activities that could have resulted in an arrest.
Abstract

Although cigarette use has declined in recent years, inequities by racial and ethnic classification in successful smoking cessation persist. The purpose of this study is to determine how racism intersects with multiple dimensions of inequality to shape the use of smoking cessation therapies. This study uses data from a sample of 10,838 adults from the fifth wave of the Population Assessment of Tobacco and Health (PATH) Study, collected from 2018 to 2019. Empirically, the study examines how self-reported racial and ethnic classification, socioeconomic resources, tobacco use history, experience, and exposure shape the use of Nicotine Replacement Therapy (NRT) or non-nicotine prescription medications. The study conceptualizes self-reported racial and ethnic classification as group placement in the racial hierarchy relative to whiteness and, in turn, their level of vulnerability to racism. Communities racially classified as white, Indigenous American, Asian, and Pacific Islander tended to use smoking cessation therapies more than communities racially classified as Black. On the other hand, communities ethnically classified as Hispanic had lower odds of using a smoking cessation therapy than communities racially classified as Black. Socioeconomic resources, tobacco use history, experience, and exposure largely widened, rather than explaining away, inequities in the use of smoking cessation therapies among racially and ethnically classified groups. First, people who were uninsured tended to have lower odds of currently using smoking cessation therapies. In contrast, those who were unemployed, had completed some college or above, and who received government assistance had
higher odds of currently using a smoking cessation therapy. On the other hand, viewing the nicotine in NRT as very or extremely harmful, not being aware of NRT, and exposure to secondhand smoke resulted in lower odds of using a smoking cessation therapy. In turn, if socioeconomic resources and exposure to tobacco smoke were even across racially and ethnically classified groups, communities classified as white, Indigenous American, Asian, and Pacific Islanders’ use of smoking cessation therapies would be even larger. In contrast, the difference in use between communities ethnically and racially classified as Hispanic and Black would be smaller. Identifying when inequities in health outcomes occur and situating analyses in the context of racial inequality can provide an expanded understanding of how systems of inequality intersect to shape access to and utilization of healthcare. Whether inequities in smoking cessation by racial and ethnic classification stem from fewer recovery options, socioeconomic inequality, or differences in tobacco experiences, a better understanding of how racism shapes the use of and adherence to care is needed. Future studies on racism and adherence to care can center the effects of racial inequality in their analyses. Such studies can further explain how racism intersects with multiple axes of oppression to impact the use of behavioral healthcare.
Introduction

Examining the sources of inequities in smoking cessation among racially and ethnically classified groups provides critical insights on improving overall access to and utilization of health care. While smoking has declined in recent years (Nguyen-Grozavu et al. 2020), prior research has found that differences persist by racial and ethnic classification in the prevalence of cigarette use, quit attempts, and successfully quitting (Centers for Disease Control and Prevention 2011; Leventhal et al. 2021; Mills et al. 2021). These findings demonstrate that use of and access to smoking cessation therapies may be related to exposure to racial inequality in different communities. To that end, a growing number of studies in the health disparities literature point to naming racism as a determinant of these differences (Pearson et al. 2021; Williams and Mohammed 2009; Williams and Sternthal 2010).

Prior research and recent news media on smoking cessation has found that inequities in socioeconomic resources (Honjo et al. 2006; Leventhal et al. 2021; Zhuang et al. 2015) contribute to inequities in smoking cessation outcomes. However, in the studies that examine the social factors that shape differences in quitting and quit attempts,

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8 Scholars often disagree about the meaning of the term ‘health disparities,’ and as a result there are several meanings of this concept in the literature (Carter-Pokras and Bacquet 2002:428). Throughout this chapter—and in the dissertation as a whole—I use the terms health inequalities and health inequities to highlight that many of the differences in health outcomes and access to care are avoidable. Further, these differences result from a structural cause: the unequal distribution of resources and privilege in multiple domains of society (Carter-Pokras and Bacquet 2002:428). The categories that divide humans are socially, politically, and systematically constructed and maintained on the basis of anti-Blackness. Working from an approach that centers the equality of humanity, there is no disparity by racial classification, ethnic classification, class, or gender identity categories. Instead, there are structural inequities that affect people based on the categories in which they have been placed. In turn, I only use the word disparity if it is explicitly stated in the literature I am citing.
there is little to no mention of how structural racism, access to, and use of quality care to support recovery from tobacco use are interrelated (Pearson et al. 2021).

Despite the literature’s acknowledgment of inequities in the use of and access to recovery from smoking cigarettes, there is limited information on two additional dimensions of tobacco use history and experience that may shape cessation: the cessation experiences of non-daily smokers, the majority of whom come from communities racialized as Black (Nollen et al. 2018), and how widespread tobacco cessation advertisements are within a community (for examples; see Emery et al. 2012; Langley et al. 2012; Tauras et al. 2005). Finally, more quantitative work on health inequities that situates its analysis within the context of the racial ideology of the society being studied is needed to examine race in a way that reflects the social realities of racial stratification.

To address these gaps in the literature, the purpose of this study is to determine how racism intersects with multiple dimensions of inequality to shape the use of behavioral health care. Empirically, the study aims to answer the following question: how does placement in the racial hierarchy shape the use of smoking cessation therapies? The cessation therapies of interest in this study are Nicotine Replacement Therapy (NRT) and non-nicotine prescription medications. The study’s results indicate that communities racially classified as white, Indigenous American, Asian, and Pacific Islander tended to use smoking cessation therapies at higher levels than communities racially classified as Black. On the other hand, communities ethnically classified as Hispanic had lower odds of using a smoking cessation therapy than communities racially classified as Black. Further, socioeconomic resources, tobacco use history, experience, and exposure largely
widened, rather than explaining away, inequities in the use of smoking cessation therapies among racially and ethnically classified groups. People who were uninsured tended to have lower odds of currently using smoking cessation therapies. In contrast, those who were unemployed, had completed some college or above, and who received government assistance had higher odds of currently using a smoking cessation therapy.

On the other hand, viewing the nicotine in Nicotine Replacement Therapy (NRT) as very or extremely harmful, not being aware of NRT, and exposure to secondhand smoke resulted in lower odds of using a smoking cessation therapy. In turn, if exposure to socioeconomic resources and tobacco were even across racially and ethnically classified groups, communities racially classified as white, Indigenous American, Asian, and Pacific Islanders’ greater use of smoking cessation therapies would be even larger. In contrast, the difference in use between communities racially and ethnically classified as Hispanic and Black would be smaller.

Overall, these findings suggest that identifying when inequities in health outcomes occur and situating analyses in the context of racial inequality can provide an expanded understanding of how systems of inequality intersect to shape access to and the utilization of healthcare.

**Theoretical Context**

**Background**

Using tobacco is the main cause of preventable illness, disability, and death in the United States (Centers for Disease Control and Prevention 2021). Fourteen percent of all adults in the nation smoke cigarettes (Centers for Disease Control and Prevention 2021),
and nearly 21 percent of nonsmokers are exposed to secondhand smoke from tobacco products (Brody et al. 2021). National averages of cigarette use differ between racially and ethnically classified groups. Groups racially classified as Indigenous American and Alaska Native have the highest cigarette use rate of nearly 21 percent, while groups racially classified as Non-Hispanic white and non-Hispanic Black have cigarette use rates of 16 percent and 15 percent, respectively (Cornelius et al. 2020). Other studies have found that communities racially classified as Black tend to use menthol cigarettes at higher levels (Giovino et al. 2013), which are more addictive than non-menthol cigarettes (Neptune, Leone, and Kathuria 2020; Willis et al. 2011). Finally, communities ethnically and racially classified as Hispanic and Asian have the lowest smoking rates – at nearly 9 percent and 7 percent – respectively.

Studies have also shown that cigarette use varies by insurance status, income, and education. In particular, those who are uninsured or using Medicaid, those with a lower income, and those with less education are more likely to use cigarettes than other groups (Cornelius et al. 2020; Marbin et al. 2021).

While quitting smoking can be challenging, typically requiring multiple attempts (Kruger et al. 2016; Rigotti 2011), recent studies demonstrate that nearly 70 percent of people who use cigarettes in the United States are interested in quitting (Babb et al. 2017). In addition, just over half of smokers had attempted to quit cigarettes in the past year (Creamer et al. 2019). Although many people attempt to quit smoking, a recent study found that only about eight percent were successful in their attempts (Creamer et al. 2019). A few factors may explain this finding. First, over 40 percent of people who
currently use cigarettes do not receive advice from a doctor to quit (U.S. Department of Health and Human Services 2020). Further, only about 30 percent of smokers use evidence-based smoking cessation therapies (Babb et al. 2017), which may affect their ability to quit smoking successfully.

The two main pharmacotherapies that support smoking cessation are Nicotine Replacement Therapy (NRT) and non-nicotine prescription medications. NRT is a form of medication that includes small amounts of nicotine. This therapy, which comes in several forms, including gums, nasal sprays, patches, inhalers, and tablets, helps to facilitate the transition from using tobacco by lowering cravings and symptoms of withdrawal. Studies have shown that NRT can increase quitting rates from 50 to 70 percent (Douglas and Ahmed 2021). NRT gums, patches, and tablets are available over the counter, while NRT nasal sprays and inhalers require a prescription (Neptune, Leone, and Kathuria 2020).

Varenicline (also known as Chantix) and Bupropion (also known as Wellbutrin and Zyban) are the two non-nicotine prescription medications that the Food and Drug Administration has approved for smoking cessation (Fagerström and Hughes 2008). These medications have effectively assisted people in quitting and continuing to abstain from smoking compared to not using a cessation medication (Ebbert et al. 2015; Koegelenberg et al. 2014; Rose and Behm 2017). Beginning in 2014, the Affordable Care Act began requiring state Medicaid programs to offer tobacco cessation medications (McAfee et al. 2014; Kaiser Family Foundation 2019).
NRT and prescription medications can be used separately, together, or in combination with phone counseling to support tobacco cessation (Coenraad et al. 2014; Douglas and Ahmed 2021; Soulakova and Crockett 2017; Tzelepis et al. 2015). As of 2018, 33 states offer phone counseling and options for accessing Nicotine Replacement Therapy (Kaiser Family Foundation 2019).

**Explaining Inequities in Smoking Cessation among Racially and Ethnically Classified Groups**

Prior studies have shown that communities racially and ethnically classified as Black and Hispanic are less likely than other groups to successfully quit smoking. This finding persists even though these communities tend not to smoke heavily and typically intend to and attempt to quit more often than other racially and ethnically classified groups. (Centers for Disease Control and Prevention 2011; Kohn et al. 2022). Several studies have hypothesized reasons for inequities in successfully quitting cigarette use by racial and ethnic classification. These include differences in workplace and other social environments’ smoke-free policies, in race-based and other forms of stress, and in tobacco advertising within communities classified as Black and in low-income communities (Hicks and Kogan 2018; Johansson, Johnson, and Hall 1991; Landsbergis et al. 1998, qtd. in Ho and Fenelon 2015; Lee et al. 2015; Levy et al. 2019; Slopen et al. 2012; Twyman et al. 2014). In turn, less access to recovery, secondhand smoke exposure, normalization of tobacco use, and exposure to tobacco advertisements can affect the process of quitting smoking.

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9 Phone counseling typically occurs through a free quitline. Quitlines are programs that provide tobacco treatment services to state residents to support tobacco recovery (Kaiser Family Foundation 2019).
In addition, other studies find that having more socioeconomic resources and being exposed to tobacco cessation advertisements can support access to and use of smoking cessation resources. Socioeconomic resources, including a higher income, education, being employed, and having insurance, are associated with increased access to and use of resources to support smoking cessation (Barbeau et al. 2004; Honjo et al. 2006; Niederdeppe et al. 2011, qtd. in Ho and Fenelon 2015; Leventhal et al. 2021; Liu 2010; Zhuang et al. 2015). Other work has shown that tobacco cessation advertising is related to higher use of Nicotine Replacement Therapy (Tauras et al. 2005).

Further, some studies have shown that although NRT and non-nicotine prescription medications are highly effective, most people who use tobacco attempt to quit without using a medication to support their recovery (Chapman and MacKenzie 2010; Edwards et al. 2014; Soulakova and Crockett 2017).\textsuperscript{10} Other studies have suggested that unassisted quit attempts may stem from, among other factors, communities’ concerns about how safe the medication was and about whether they might accidentally misuse the medication (Bansal et al. 2004, qtd. in Liu 2010). In addition, prior studies have also shown that quitting unassisted can be less effective than quitting with medications (Croghan et al. 2010; Kim et al. 2019; Kotz et al. 2013; Smith et al. 2017), and in turn that more people are beginning to use medications to assist in quitting (Edwards et al. 2014). Another study found that those who quit with no assistance are typically less

\textsuperscript{10} With the rise of electronic cigarettes, (Etter and Bullen 2014, Hartmann-Boyce et al. 2020), some observational studies and clinical trials have suggested that they can be an effective cessation tool (Bullen et al. 2013, Caponnetto et al. 2013). However, the United States Surgeon General’s 2020 Annual Report notes that there is inconclusive evidence on whether electronic cigarettes are effective in supporting smoking cessation (U.S. Department of Health and Human Services 2020).
dependent on nicotine and had not seen their physician in the past year (Soulakova and Crockett 2017).

The interactive model of racial inequality (Stewart 2008), critical perspectives on substance dependence (Hansen and Roberts 2012; Netherland 2012), the clinical cascade model (Cranmer et al. 2018; Kay et al. 2016; Morgan et al. 2018), and policy perspectives on nicotine dependence (Neptune, Leone, and Kathuria 2020) provide helpful avenues for understanding the production of inequality as a process. These conceptual frameworks can therefore help pinpoint the sources of health inequities.

First, the interactive model of racial inequality suggests that racial inequality results from several social interactions in which people are afforded certain benefits based on their phenotype (Stewart 2008). Quantitatively modeling racial inequities can involve placing the social interactions that the researcher identifies in the broader context of the society's racial ideology. Additionally, the researcher can analyze the relationship between past reactions and treatment of the groups in the analysis. In this way, researchers can better demonstrate how social interactions in multiple domains work together to result in a particular inequality by racial and ethnic classification (Stewart 2008).

Critical perspectives on substance dependence build on the interactive model of racial inequality by highlighting how policies centered on treating addiction are linked with racial oppression (Hansen and Roberts 2012; Netherland 2012:xvi). These perspectives argue that drug policies focus on social control through punitive measures such as arresting people racially or ethnically classified as Black or Latino for drug
offenses. For example, drug policies often place people from these communities seeking methadone treatment for opioid addiction under the authority of doctors at clinics that the Drug Enforcement Agency (DEA) regulates (Hansen and Roberts 2012; Netherland 2012). In contrast, the development of buprenorphine, a medication to support opioid addiction, was mainly marketed to people racialized as white who were middle class, living in the suburbs or rural areas. Further, the federal government passed special legislation to ensure that doctors in private practices, a less heavily surveilled and more mainstream environment, could prescribe these medications. These racialized differences in approaches to medications for substance dependence may add to the stigma that people navigating treatment for substance and nicotine dependence already face.

In addition, the clinical cascade model offers an analytical window into the particular processes that may lead to inequities in health outcomes. Though the model comes from the literature on HIV, additional studies have applied it to other areas of sexual and reproductive health, substance misuse, mental health, and chronic diseases (Kay et al. 2016). The clinical cascade model for HIV describes the process of treating and caring for individuals with the disease. The steps in the process are (1) diagnosis; (2) connecting the patient with an HIV healthcare provider (known as linkage to care); (3) how much the patient continues to attend treatment appointments (known as retention in care); (4) continuing to use antiretroviral therapies as directed (known as adherence to antiretroviral therapy), and, finally, (4) "viral suppression," a reduction in the amount of HIV in the body, which allows the individual's immune system to better function and prevent illness (Centers for Disease Control and Prevention 2021; Kay et al. 2016:1).
Applying the clinical cascade to smoking cessation would result in the following process: (1) who looks for assistance with quitting smoking; (2) who receives assistance if they seek it; (3) who receives or is prescribed a smoking cessation therapy; (4) who fills their prescription; (5) who uses the prescription as intended; and (6) who can successfully quit using cigarettes as a result of using a smoking cessation therapy.\textsuperscript{11}

Building on the clinical cascade model, policy perspectives on nicotine dependence note that people seeking treatment may be concerned about whether they are safe or contain addictive ingredients although the treatments are FDA-approved. Until 2013, NRT packaging labels stated that smokers should not combine NRT products and should stop smoking while using NRT, which could have resulted in safety concerns among consumers (Neptune, Leone, and Kathuria 2020). These concerns may affect who receives assistance if they seek it and who ends up using NRT.

Taken together, the studies show that integrating these four conceptual frameworks can help researchers further unpack the points at which inequities in successful smoking cessation occur among racially and ethnically classified groups.

\textit{Conceptualizing \& Operationalizing the Impact of Racism on Behavioral Health}

Whether inequities in racially and ethnically classified groups' access to and use of smoking cessation therapies arise from differences in socioeconomic status or other factors, a better understanding of how racism shapes behavioral healthcare use is needed. Racism is a political system that affords differential economic, political, social, and psychological benefits to groups structured around racial classifications (Bonilla-Silva

\textsuperscript{11} Dr. Jason Schnittker, email correspondence, September 2, 2021.
1997; Brown 2003; Roberts 2011). This system is at the foundation of the process of assigning racial meaning to social groups (Bonilla-Silva 1997:467; Crenshaw et al. 1995; Mills 1998; Zuberi 2000; Zuberi 2001a; Zuberi 2001b; Zuberi 2011). In other words, race is a by-product of racism (Gilroy 2004, qtd. in Roberts 2011). Further, racism and race are both socially defined and constructed. Racism provides an orienting structure for guiding rational actors in the differential benefits groups structured around race receive.

Most social science scholarship acknowledges that race and racism are socially constructed. However, quantitative work on race and racism tends to justify – rather than explain – “the process of racial stratification” (Zuberi 2011:101; Zuberi and Bonilla-Silva 2008; Zuberi 2001b). Scholars have argued that Critical Race Theory (CRT) can provide a guide for properly conceptualizing race and racism in quantitative work (Brown 2003; Brown 2008; Crenshaw 1995; Ford and Airhihenbuwa 2010; Mills 1998; Zuberi 2000; Zuberi 2001b; Zuberi 2011).

CRT acknowledges and documents how racism manifests throughout society. This framework recognizes race as how vulnerable a group is to experiencing racism (Bonilla-Silva 2004:932; Ford et al. 2009, qtd. in Ford and Airhihenbuwa 2010). The theory also recognizes racism as a set of mechanisms that engender racial inequality (Crenshaw et al. 1995; Ford and Airhihenbuwa 2010; Mills 1998). In turn, CRT demonstrates that attempting to quantify racism – rather than race – can better reflect experiences of the process of racialization.

In practice, CRT’s conceptualization of vulnerability to racism functions as placement within the racial hierarchy. Several studies have proposed theories on the
dynamics of the racial hierarchy in the United States (for example, see Bashi and McDaniel 1997; Bonilla-Silva 2004). One such theory is the theory of racial and immigrant stratification, which suggests that the United States has a dichotomous racial hierarchy where people racialized as white are at the top and people racialized as non-white are at the bottom (Bashi and McDaniel 1997). This theory argues that Blackness was created as a byproduct of white supremacy, and it is not designed to be assimilable into whiteness. The theory also argues that immigrants use ethnic options – a means of distinguishing themselves from people racialized as Black – to find their place in the racial hierarchy. However, committing to a place in the racial hierarchy also involves committing to white supremacy, which in turn structures their social experiences. Finally, the theory suggests that race is a “macrolevel variable” that shapes each aspect of a person’s life outcomes and accounts for variation among groups (Bashi and McDaniel 1997). Taken together, critical perspectives on race and racism provide a foundation for understanding variation in the use of healthcare among racially and ethnically classified groups.

Gaps in the Literature

The clinical and epidemiological literature has made important strides towards understanding the prevalence of smoking cessation, attempts to quit smoking, and elucidating several perceived barriers to smoking cessation. However, in studies that examine the social factors that shape differences in quitting and quit attempts, there is little to no mention of the connection between structural racism, access to, and use of quality care to support recovery from tobacco use (Pearson et al. 2021). For example,
prior work shows that structural racism can shape neighborhood conditions, which may affect the level of stress people experience (Williams et al. 2019) and, in turn, affect their use of cigarettes and ability to quit smoking successfully.

Next, while prior scholarship has acknowledged inequities in the use of and access to recovery from smoking cigarettes, more information is needed on additional dimensions of tobacco use history and experience. For example, few studies provide information on the cessation experiences of non-daily smokers, among whom communities classified as Black are overrepresented (Nollen et al. 2018). In addition, while prior studies have shown that tobacco product advertising in neighborhoods is associated with difficulty quitting smoking (Lee et al. 2015), few studies examine how advertising for tobacco cessation affects access to and use of smoking cessation therapies (see, for example, Emery et al. 2012; Langley et al. 2012; and Tauras et al. 2005).

Finally, more quantitative work on health inequities that situates its analysis within the context of the racial ideology of the society being studied is needed. Doing so can help researchers pinpoint when inequalities begin in the clinical cascade to better determine the sources of observed inequalities (Stewart 2008). As a result, researchers can better understand how mechanisms of inequality are racially patterned and how they intersect with one another. Quantitative research on race does not always treat race as a factor that globally affects life chances – which would more closely align with the outcomes of the process of being racialized. In turn, interpretations of race tend to contribute to racial stratification rather than attempting to explain and dismantle this system (Zuberi 2001b).
To contribute to these gaps in the literature, the purpose of this study is to determine how racism intersects with multiple dimensions of inequality to shape the use of behavioral health care. Empirically, this study seeks to answer the question: how does placement in the racial hierarchy shape the use of smoking cessation therapies?

As illustrated in Figure 3.1, the study's conceptual model views the key independent variable, self-reported racial and ethnic classification, as a group’s placement within the racial hierarchy. Placement in the racial hierarchy indicates each racially and ethnically classified group’s level of vulnerability to racism based on whether or not they are racially classified as white or nonwhite. As shown in Figure 3.2, this study identifies the system of racial stratification as the proposed racial hierarchy, where people racialized as white are organized into the top of the hierarchy and people racialized as nonwhite are othered into the bottom of the hierarchy. The racial and ethnic classifications in the nonwhite category intentionally do not include ancestry categories to underscore the theory’s argument that ethnic identities are subsumed into simplistic racial identities in the U.S.’s system of racial stratification (Bashi and McDaniel 1997:672-673). This study also emphasizes that whiteness results in advantages in life chances based on the process of racial stratification. It also illustrates that racial and ethnic classification is a product of the process of being racialized (Gilroy 2004:39, qtd. in Roberts 2011:25). In addition, white supremacy maintains the racial hierarchy by ensuring that people commit to their particular places in the hierarchy (Bashi and McDaniel 1997:676).
The conceptual model defines inequities in the current use of a smoking cessation therapy (either Nicotine Replacement Therapy or non-nicotine prescription cessation medications) as the outcome variable. Prior literature demonstrates that racism affects people's well-being. This study identifies the ways that racism shapes the utilization of care through its impact on two sets of mediator variables: socioeconomic inequality and experiences with tobacco use. There are also feedback loops included between the key independent and outcome variables. In addition, there are feedback loops between the independent and mediator variables. These feedback loops acknowledge theoretical perspectives that groups’ life chances are a result of the process of placement in the racial hierarchy, and that placement in the racial hierarchy also shapes outcomes (Bashi and McDaniel 1997). Further, the conceptual model builds on the interactive model of racial inequality and the clinical cascade model by illustrating how multiple actors work together to produce inequities in the usage of care.

This study’s conceptual model also situates all of the variables in the analysis within the racial ideology of the United States - a system of racial stratification wherein people have varying life chances based on where they are placed in the racial hierarchy relative to whiteness (Zuberi 2011, Bonilla-Silva 2004). As a result, this model provides the basis for an analysis that can better investigate how racism is related to both racial and ethnic classifications and inequities in health outcomes.
Data, Measures, and Methods

Analytic Sample

This study’s analytic sample comes from the fifth wave of the Population Assessment of Tobacco and Health (PATH) Study, a nationally representative, longitudinal study that examines tobacco use and health among adults and youth in the United States. Study investigators collected comprehensive respondent demographic, tobacco use history, tobacco cessation aid use, and biomarker data that examines exposure to and harm from tobacco use. The fifth wave of survey data, which were collected from 2018 to 2019 and had a weighted response rate of 69.4 percent, includes adults and youth from both the wave 1 cohort and new respondents who were sampled at wave 4 to account for sample attrition.

The PATH study includes respondents ages 9 and older randomly sampled from the civilian, noninstitutionalized population from households across the United States and Washington, D.C. who used and did not use tobacco. In addition, the study investigators oversampled communities racially classified as Black, given that prior studies have found that groups with this racial classification tend to use menthol cigarettes more than other racially and ethnically classified groups (Giovino et al. 2013; U.S. Department of Health and Human Services 2018). The study also oversampled young adults and people who used tobacco.

The PATH Study wave 5 dataset’s full sample size is 34,309. Eliminating those who had never used cigarettes or electronic nicotine products results in an analytical sample of 26,007. Next, former experimental electronic nicotine product users (defined as...
those who never used these products fairly regularly, in the past year, or at all at the time of the survey) and experimental cigarette users (who had not smoked 100 cigarettes in their lifetime and reported no use during the past year or at the time of the survey) were excluded because they were not asked about using smoking cessation therapies, reducing the analytical sample to 12,586. Lastly, respondents with missing observations in the explanatory, mediator, and outcome measures were also excluded, resulting in a final analytic sample of 10,838 adults who currently use or have used cigarettes or e-nicotine products in the past year.

Measures

Key Explanatory Measure: Self-Reported Racial and Ethnic Classification

The key explanatory measure is self-reported racial and ethnic classification. Respondents self-identified from the following racial and ethnic classifications: (1) Non-Hispanic white; (2) Non-Hispanic Black or African American; (3) Hispanic Alone; (4) Asian; (5) Pacific Islander; and (6) Native American.\textsuperscript{12,13} I follow the PATH study investigators in combining respondents who identify as Native American, Asian, and

\textsuperscript{12} For conciseness, the rest of this manuscript refers to respondents racially classified as Non-Hispanic Black or African American and Non-Hispanic white as Black and white.

\textsuperscript{13} Theoretical perspectives on racial stratification highlight that immigrant ethnic identities typically become subsumed in racial identities as they are incorporated into the racial hierarchy of the United States (Bashi and McDaniel 1997). The present study tested this theory by combining an immigrant status variable with the racial and ethnic classification variables (see Appendix 3.A). Due to small sample sizes for immigrants racialized as Black and "other" (including Asians and Pacific Islanders), the study excluded these groups from the logistic regression analyses. I therefore opted not to add an immigrant status variable in this study because immigrant groups racialized as non-white would be excluded from the results. Despite these groups' exclusion from the regression analyses, the model including tobacco use, history, and experiences was still the best fit for the data, and cessation use differences remained statistically significant only for native-born people in groups racially classified as "other" (including Indigenous Americans, Asians, and Pacific Islanders) and white. As in the present study's results, these groups still had higher odds of using a cessation therapy than native-born people racially classified as Black. Thus, this study suggests that only racial and ethnic classification played a role in cessation therapy use.
Pacific Islander into one racially and ethnically classified group coded as ‘Other.’ Respondents racially classified as Non-Hispanic Black were specified as the omitted reference category to avoid using whiteness as a standard for analytic comparison and to uphold the perspective that there could be advantage or disadvantage among communities classified as Non-Hispanic Black (Pattillo, forthcoming).

**Key Outcome Measure**

Current use of a smoking cessation therapy, a binary variable, is the key outcome measure. To create this measure, I combined the variables that measured the use of Nicotine Replacement Therapy (NRT) and non-nicotine prescription cessation medications. To measure NRT use, respondents were asked if they had used a nicotine patch, gum, inhaler, nasal spray, or lozenge in the past year. Conversely, to measure prescription medication use, respondents were asked if they had used Chantix, Varenicline, Wellbutrin, Zyban, or Bupropion in the past year.

**Socio-Demographic Covariates**

Age and sex are included as standard demographic covariates in the model. Age is a categorical variable that distinguishes between the following age groups: (1) 18 to 34; (2) 35 to 44; (3) 45 to 64; and (4) 65 and above. Respondents who were ages 45 to 64 were the omitted reference category, given that tobacco use is high among this age group (Cornelius et al. 2020). Sex is a binary variable, and females were the omitted reference category given that self-identified men tend to use tobacco more than self-identified women (Higgins et al. 2015).
Mediator Measures

The mediating measures are (1) socioeconomic resources that affect well-being and status attainment and (2) tobacco use history and experience.

Prior research shows that socioeconomic inequality is a fundamental driver of racial inequality (Williams and Jackson 2005). The present study defines indicators of socioeconomic resources as insurance status, income, receiving government assistance, education level, and employment status.

The control for insurance status distinguishes between those who are insured (reference category) and uninsured. For income, I distinguish between those who have a low income (ranging from than $10,000 per year to $49,999 per year), middle income (ranging from $50,000 to $99,999 per year, used as the reference), or a high income (ranging from $100,000 or more per year). In addition, the control for receiving government assistance distinguishes between those who do and do not receive welfare, food stamps, unemployment benefits, cash aid, housing assistance, childcare, or Medicaid.

For educational level, I distinguish between those with less than a high school education; a high school education (reference category); some college or associate’s degree; and a four-year college degree and above. Finally, the control for employment status distinguishes between those who are employed (reference category) and unemployed.

Prior studies have shown that racial discrimination is related to tobacco use history (Hicks and Kogan 2018) and that tobacco advertising is concentrated in
communities classified as Black (Seidenberg et al. 2010, Widome et al. 2012). In turn, racism plays a role in tobacco use history and experiences, which can be seen as coping responses to how people are perceived in society. This set of mediator variables measure (1) cigarette or menthol cigarette use; (2) views on Nicotine Replacement Therapy; (3) secondhand smoke exposure; (4) self-rated mental health; (5) experience with tobacco advertising and (6) experience with tobacco cessation advertising.

The cigarette use variable distinguishes between whether, during the previous 12 months, the respondent formerly used cigarettes, used only non-flavored cigarettes, or used only menthol cigarettes. I distinguish menthol cigarette use from regular cigarette use because communities racially classified as Black tend to use these products, which are more addictive at higher rates than other groups (Giovino et al. 2013, Willis et al. 2011).

Further, people attempting to quit using tobacco or electronic nicotine products often do not use nicotine replacement therapy because they may believe that the nicotine within nicotine patches, gums, inhalers, nasal sprays, or lozenges can be harmful or addictive (Bansal et al. 2004, qtd. in Liu 2010). In turn, this variable distinguishes between those who believe that the nicotine in NRT is (1) not harmful, (2) slightly or somewhat harmful, (3) very or extremely harmful, and (4) those who are not aware of nicotine replacement therapy.

The secondhand smoke variable is a binary measure. This measure combines all variables that measured secondhand smoke exposure at home, work, or in close contact with others to determine whether or not respondents had been exposed to smoke. That is,
respondents who reported living, working, or being in close contact with someone who smoked near them were coded as 1, while all others were coded as 0.

The self-rated mental health variable distinguishes between whether respondents reported their mental health – which included stress, depression, and emotional problems – as (1) poor or fair; or (2) good, very good, or excellent. Respondents who reported their mental health as good, very good, or excellent were the omitted reference category.

In addition, the experience with tobacco advertising variable distinguishes between whether or not the respondent saw tobacco ads in their neighborhood or via the media (television, radio, magazines, or newspapers). Similarly, the experience with tobacco cessation advertising variable distinguishes between those who did and did not see tobacco cessation ads on television. Those who reported sometimes, often, or very often seeing tobacco cessation ads on television were coded as having seen tobacco cessation ads. In contrast, those who reported rarely or never seeing tobacco cessation ads on television were coded as not having seen tobacco cessation ads.

Analytic Strategy

I first report descriptive statistics by self-reported racial and ethnic classification for the study’s explanatory and outcome variables. Given that these variables vary by racial and ethnic classification, I model current use of a smoking cessation therapy using binary logistic regression.

Descriptive Results

Table 3.1 provides descriptive statistics for the explanatory and dependent variables by respondents’ self-reported racial and ethnic classification. Results show that
13 percent of respondents racially classified as white currently used smoking cessation therapies, while the same was true for 12 percent of communities classified as “other” (a group which includes people racially classified as Indigenous Americans, Asians, and Pacific Islanders). In contrast, respondents racially and ethnically classified as Black and Hispanic were the least likely to use smoking cessation therapies.

This table also demonstrates that socioeconomic resources and tobacco use experiences varied based on respondents' self-reported racial and ethnic classification. The “other” group (including communities racially classified as Indigenous Americans, Asians, and Pacific Islanders) and samples ethnically classified as Hispanic were younger, on average, than respondents racially classified as Black and white. Communities racially classified as Black and white were slightly overrepresented among older adults between the ages of 45 and 64: the age group most likely to use cigarettes. Further, the “other” group (including communities racially classified as Indigenous Americans, Asians, and Pacific Islanders) were also overrepresented among male respondents in the sample, while communities racially classified as Black were underrepresented.

In addition, communities racially and ethnically classified as Black and Hispanic had fewer socioeconomic resources than the other racially and ethnically classified groups. A higher share of respondents racially classified as Black had a low income, received government assistance, and were unemployed, while most of sample ethnically classified as Hispanic was uninsured. However, a substantial proportion of the sample racially classified as “other” (including Indigenous Americans, Asians, and Pacific
Islanders) had completed some college or more. In contrast, a small proportion of the same sample had less than a high school education.

In addition, tobacco use history, experience, and exposure varied among racially and ethnically classified groups. A higher share of respondents racialized as Black used menthol cigarettes, while respondents racially or ethnically classified as white or Hispanic were overrepresented among those who used non-menthol cigarettes. Communities racially and ethnically classified as Black and Hispanic formed the highest proportion – 49 and 46 percent, respectively – of those who believed that the nicotine in NRT was very or extremely harmful. These racially and ethnically classified groups were nearly twice as likely as respondents classified as white to hold this belief. This gap in beliefs among racially and ethnically classified groups was the largest among all of the variables in the analysis. In contrast, there was no variation by racially and ethnically classified group in how aware respondents were of NRT or in the levels of secondhand exposure to smoke at home, work, or in other close contact with others. There was also little variation among racially and ethnically classified groups in self-rated mental health.

On the other hand, there were differences by racial and ethnic classification in experiences with tobacco and tobacco cessation advertisements. Most respondents racially classified as Black had seen tobacco and tobacco cessation advertisements in their neighborhood or media, while the same was true for a smaller proportion of the group racially classified as “other” (including groups racially classified as Indigenous Americans, Asians, and Pacific Islanders).
Multivariate Results

Table 3.2 examines the association between self-reported racial and ethnic classification and current use of a smoking cessation therapy by estimating a set of binary logistic regression models. The baseline model regresses current use of a smoking cessation aid (NRT or prescription medication) on self-reported racial and ethnic classification. This model replicates the findings in Table 3.1: that respondents racially classified as white and “other” (including groups racially classified as Indigenous Americans, Asians, and Pacific Islanders) had higher odds of currently using smoking cessation therapies as compared to communities racially classified as Black. On the other hand, communities racially classified as Hispanic had lower odds of using a smoking cessation therapy than communities racially classified as Black.

Adding sociodemographic background covariates in model 2 results in an even larger inequality in smoking cessation therapy use among racially and ethnically classified groups. Accounting for compositional differences across groups and the greater tendency for older adults and self-identified women to use smoking cessation therapies at higher rates had no effect on the gap between respondents racially classified as Black, white, and “other” (including people racially classified as Indigenous Americans, Asians, and Pacific Islanders). Thus, respondents racially classified as white and “other” (including those racially classified as Indigenous Americans, Asians, and Pacific Islanders) maintained higher odds of using a smoking cessation therapy relative to communities racially classified as Black. However, including these covariates did help explain some of the lower current use of smoking cessation therapies among respondents.
ethnically classified as Hispanic relative to respondents racially classified as Black, given that respondents ethnically classified as Hispanic had lower odds of currently using a smoking cessation therapy.

Next, after adjusting for socioeconomic resources in model 3, the gap between respondents racialized as white’s and “other’s” (including communities classified as Indigenous Americans, Asians, and Pacific Islanders) current use of cessation therapies relative to respondents racially classified as Black increases. In contrast, accounting for socioeconomic resources slightly reduced the gap between respondents racially and ethnically classified as Hispanic’s and Black’s current use of cessation therapies. Respondents ethnically classified as Hispanic had lower odds of using cessation therapies relative to respondents racially classified as Black. This model demonstrates that inequities in current use of a smoking cessation therapy by racial and ethnic classification held even after considering the differential composition of racially and ethnically classified groups, the lower tendency for uninsured people to use smoking cessation therapies, and the higher tendency for respondents who had received government assistance, experienced unemployment or completed higher education to use a smoking cessation therapy.

Adding indicators of tobacco use history, experience, and exposure in model 4 further increased the effect size of respondents racially classified as white’s (OR = 1.503) and “other’s” (OR = 1.508) (including groups racially classified as Indigenous Americans, Asians, and Pacific Islanders) greater use of smoking cessation therapies. This model best fit to the data. Overall, after considering the higher tendency for those
who use menthol and non-menthol cigarettes and who have poor or fair mental health to use a smoking cessation therapy, respondents racially classified as white’s and “other’s” (including Indigenous Americans, Asians, and Pacific Islanders) advantage in use of behavioral health care remained. This advantage remained after accounting for the lower tendency for people who viewed the nicotine in NRT as very or extremely harmful, who were not aware of NRT, and who had been exposed to secondhand smoke to use a smoking cessation therapy. Similarly, the gap between respondents ethnically classified as Hispanic’s use of behavioral health care (OR = 0.739) compared to people racially classified as Black in the aggregate was also slightly reduced.

Finally, model 5 included controls for tobacco and tobacco cessation advertisement experiences. While model 5 was not the best fit for the data, analyzing these results indicates that seeing tobacco advertisements in one’s neighborhood or in the media were positively associated with using smoking cessation therapies. Accounting for the higher tendency of people who saw tobacco and tobacco cessation advertisements in their neighborhoods to use a smoking cessation therapy, respondents racially classified as white, Indigenous American, Asian, and Pacific Islander maintained greater use of smoking cessation therapies. In contrast, the difference between groups ethnically and racially classified as Hispanic’s and Black’s use of these therapies further decreased.

Taken together, these results demonstrate that if socioeconomic resources and exposure to tobacco were even across racially and ethnically classified groups, communities racially classified as white, Indigenous American, Asian, and Pacific Islander’s greater use of smoking cessation therapies would be even larger, while the
difference in levels of smoking cessation therapy usage between communities ethnically and racially classified as Hispanic and Black would be smaller.

**Discussion**

This study explored how vulnerability to racism, defined as self-reported racial and ethnic classification and, consequently, placement in the racial hierarchy relative to whiteness, shapes current use of and access to smoking cessation therapies. Understanding how racism shapes inequities in the use of and access to behavioral health care can contribute to further parsing out the root causes of health inequities (Link and Phelan 1995; Mays et al. 2007; Williams and Jackson 2005).

While the literature provides critical insights on what shapes cessation prevalence and adherence to smoking cessation therapies (Honjo et al. 2006; Kim et al. 2019; Leventhal et al. 2021; Mills et al. 2021; Zhuang et al. 2015), there is less information on how structural racism shapes the availability of and access to smoking cessation therapies among communities with different racial and ethnic classifications. Additionally, few studies provide information on the cessation experiences of non-daily smokers – among whom people racialized as Black are overrepresented (Nollen et al. 2018) – and further examining how tobacco cessation advertising might be associated with use of smoking cessation therapies. Such studies could provide insights on how these factors affect the use of smoking cessation therapies. Finally, little work connects the stress that may partially drive tobacco use and recovery with mechanisms of racism.

The study's results indicate that communities racially classified as white and as Indigenous American, Asian, and Pacific Islander used smoking cessation therapies more
than communities racially classified as Black. On the other hand, communities ethnically classified as Hispanic had lower odds of using a smoking cessation therapy than communities racially classified as Black. This finding extends recent work that suggests that communities ethnically classified as Hispanic tend to receive less advice to quit smoking from their healthcare professional and use cessation treatments less frequently than communities racialized as Non-Hispanic white (Kohn et al. 2022). Communities ethnically classified as Hispanic may also face language barriers when interacting with healthcare professionals. In addition, they may have concerns about the safety of cessation treatments. As this study demonstrates, they also experience higher rates of uninsurance that may affect their access to healthcare providers who can help them navigate their recovery process (Babb et al. 2020). In addition, communities racialized as Asian tend to have higher rates of successful cessation due to less nicotine dependence and higher rates of formerly using tobacco (Carroll and Cole 2021), which may explain why they tended to use therapies more than communities racialized as Black. They may in turn have driven the “other” group results, given that prior literature suggests that communities racialized as Indigenous American have a higher prevalence of tobacco use and have lower rates of cessation than communities racialized as white (Carroll and Cole 2021).

Further, socioeconomic resources, tobacco use history, experience, and exposure largely widen, rather than eliminating inequities in the use of smoking cessation therapies among racially and ethnically classified groups. Early research suggested that socioeconomic resources explained away inequities in cessation therapy use among
racially and ethnically classified groups (U.S. Department of Health and Human Services 1998, qtd. in Warner 2011). However, this study's findings regarding socioeconomic resources demonstrate that socioeconomic differences did not explain the gap in cessation use among racially and ethnically classified groups.

In line with recent research (Liu 2010), this study finds that those who were uninsured tended to have lower odds of currently using smoking cessation therapies. However, those who had completed some college, a college degree or higher, and received government assistance had higher odds of currently using a smoking cessation therapy. The study's finding that unemployed people also had higher odds of currently using a smoking cessation therapy aligns with recent empirical work, which indicates that receiving unemployment benefits was associated with higher smoking cessation (Fu and Liu 2019).

Further, the study’s findings related to tobacco use history, experience, and exposure both complicate and add more context to results from prior research. For instance, this study found that using menthol and non-menthol cigarettes was associated with significantly higher odds of currently using a smoking cessation therapy. This finding did not align with the mixed results on this relationship in prior research (see, for example, Gandhi et al. 2009; Keeler et al. 2017; and Levy et al. 2011, qtd. in Mills et al. 2021). On the other hand, viewing the nicotine in NRT as very or extremely harmful and not being aware of NRT resulted in lower odds of smoking cessation therapy use. This result connects with the interactive model of racial inequality and critical perspectives on substance dependence.
The study's preliminary results demonstrated that communities racialized as Black were the most likely to believe that the nicotine in NRT was very or extremely harmful, a finding that critical and policy perspectives on substance and nicotine dependence help explain. Communities racially classified as Black may have concerns about NRT's safety (Neptune, Leone, and Kathuria 2020) due to the medical field's historical mistreatment of Black people (Roberts 2011). They may also face stigma due to obtaining treatment for tobacco use or worry about potential surveillance while receiving prescription medication (Hansen and Roberts 2012; Netherland 2012). Other research has also noted that current cessation interventions focus on health care providers asking patients if they smoke, discussing how cessation can be helpful, and providing referrals to cessation resources. This strategy, known as the ask-advise-refer approach, has been shown to be largely ineffective in promoting cessation (Kohn et al. 2022). For communities racialized as Black, who are already more likely to experience discrimination in the healthcare system (Williams and Rucker 2000), this approach may add to the stigma of seeking treatment for nicotine dependence if they already feel uncomfortable sharing challenges with their healthcare provider.

In addition, the study’s findings on secondhand smoke exposure and mental health confirmed and added to findings from prior research. Exposure to secondhand smoke decreased the odds of using a smoking cessation therapy. This study's findings on the relationship between exposure to secondhand smoke and current use of a smoking cessation therapy are consistent with prior research (Kim et al. 2019).
Further, the association between mental illness and smoking has increased over time (Prochaska et al. 2017), and tobacco cessation may be particularly difficult for people using tobacco as a result. However, recent work has demonstrated that using cessation therapies may be associated with improvements in mental health (Taylor et al. 2014). This study's finding that people experiencing poor or fair mental health had higher odds of trying to use cessation therapies compared to those with better mental health aligns with current empirical findings. The findings suggest that those with poor or fair mental health may be using cessation therapies to help improve their mental wellness.

Theoretically, the clinical cascade model (Cranmer et al. 2018; Kay et al. 2016; Morgan et al. 2018) provides helpful insights into understanding the processes through which self-reported racial and ethnic classification produce inequities in the current use of smoking cessation therapies. This study's analysis helps to partly illuminate which groups are prescribed NRT or a prescription medication, which groups fill their prescriptions, and which groups are in the process of currently using the smoking cessation therapy. In addition, this study demonstrates that inequities in smoking cessation therapies may stem from being uninsured, being exposed to more secondhand smoke, and wariness of or lack of awareness around the safety of NRT, particularly given that the majority of the sample in the study did not use smoking cessation therapies.

This study's findings that racial and ethnic inequities in current smoking cessation therapy use widen after accounting for socioeconomic resources, tobacco use history, experience, and exposure also illustrate the tenets of the interactive model of racial inequality by demonstrating how racial and ethnic classification works with other
mechanisms to become an "observed inequality" (Stewart 2008:123). The analysis suggests that the observed inequality in the current use of smoking cessation therapies may begin with inequities in socioeconomic resources and less awareness around the safety of smoking cessation therapies.

Additionally, given that all of the variables in the models are racially patterned, the study's analysis is consistent with CRT’s concept of race - a byproduct of racism - as a macrolevel variable (Bashi and McDaniel 1997; Crenshaw et al. 1995; Ford and Airhihenbuwa 2010; Gilroy 2005:39, qtd. in Roberts 2011:25; Mills 1998). Further, the study’s analysis illustrates how racial inequality is associated with other compounded, intersecting, and overlapping forms of socioeconomic and environmental oppression that result in inequities in the use of recovery options to support smoking cessation. The study also illustrates that the system of racial stratification provides a helpful starting point for understanding variations in outcomes by racial and ethnic classification. It demonstrates that there are complex dynamics at work that affect communities racially classified as nonwhite, including racialized oppression through policies, language barriers, and discrimination in the healthcare system.

Finally, this study also has implications for perspectives on access to behavioral healthcare. Merging the clinical cascade model, the interactive model of racial inequality, critical perspectives on substance dependence, and policy perspectives on nicotine dependence suggest that understanding the path to tobacco cessation can also involve examining the many steps in the process to cessation: intending to, attempting to, or successfully quitting smoking. Thus, investigating these pathways to better explain
various racially and ethnically classified groups' experiences of health inequities provides space for more expansively documenting racism's role in structuring health inequities.

Limitations

This study is not without limitations. First, the study cannot fully explain differences in cessation use among communities racialized as Indigenous American, Asian, and Pacific Islander. Given that these communities are combined into one category in the analysis, the study may mask their unique barriers to cessation use based on their placement in the racial hierarchy (Bonilla-Silva 2004). Further, this study uses cross-sectional data. As a result, this study cannot make inferences about trends in cessation use over time.

Additionally, given that some forms of NRT are available over the counter, there should ideally be few inequities in the use of cessation treatments given their accessibility. However, recent work illustrates that pharmacy deserts tend to be more concentrated in neighborhoods racially and ethnically classified as Black and Hispanic than in white or racially and ethnically diverse areas (Guadamuz et al. 2021). Given that communities racially and ethnically classified as Black and Hispanic in this study tended to have lower rates of cessation therapy use overall, the literature on pharmacy deserts suggests that they may live in areas with less access to pharmacies, which may impact their ability to start cessation treatments.
Implications

The study's findings show that future research can continue to further apply the mechanisms in the clinical cascade model to smoking cessation, among other health outcomes. More information is needed on the differences between who seeks and is able to receive services to support smoking cessation to better understand the processes that create inequities in recovery outcomes. In addition, national-level data suggests that communities that are not racialized as white tend to have lower rates of continuing to abstain from using cigarettes even after using treatment therapies such as NRT (Croghan et al. 2010; Kohn et al. 2022). In turn, future studies can work towards unpacking – both qualitatively and quantitatively – what other factors might shape continuing to adhere to abstaining from smoking. For example, studies could more closely measure how access measures, such as whether people have a usual source of healthcare, and spatial data that indicates whether or not an area is located in a pharmacy desert, could impact the use of cessation treatments.

Future studies can also better quantify racism by using a quantitative model of interactive racial inequality (Stewart 2008) that studies the interactions that work together to produce racial inequities in outcomes. Through this model, researchers can investigate how racial inequality functions as a macrolevel variable that operates in a cycle wherein racism manifests through mechanisms that may lead to inequities in health outcomes. As a result, these studies can improve understandings of how inequities occur as a result of structural racism.
Overall, this study has offered insights into the processes that produce health inequities. Additionally, this study illustrates how racial oppression intersects with other forms of inequality to contribute to limited use of therapies for recovery from cigarette and electronic nicotine product use among communities racially and ethnically classified as Black and Hispanic. As a result, this analysis demonstrates the importance of better understanding how systems of inequality overlap and work together to shape communities' life chances, healthcare use, and healthcare access.
References


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Tables and Figures

Figure 3.1: Conceptual Model
Figure 3.2: Racial Hierarchy – System of Racial Stratification

<table>
<thead>
<tr>
<th>RACIAL HIERARCHY: SYSTEM OF RACIAL STRATIFICATION®</th>
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</thead>
<tbody>
<tr>
<td>TOP OF HIERARCHY: White</td>
</tr>
<tr>
<td>Native-born white Americans</td>
</tr>
<tr>
<td>white immigrants</td>
</tr>
<tr>
<td>BOTTOM OF HIERARCHY: Nonwhite/Other</td>
</tr>
<tr>
<td>Asian and Pacific Islander</td>
</tr>
<tr>
<td>Hispanic</td>
</tr>
<tr>
<td>Native-born Black Americans</td>
</tr>
<tr>
<td>Black immigrants → Classified as Black after 1-2 generations</td>
</tr>
<tr>
<td>Indigenous Americans</td>
</tr>
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</table>

**Note:** "This sketch of the system of racial stratification was adapted from Bashi, Vilna, and Antonio McDaniel. 1997. “A Theory of Immigration And Racial Stratification.” *Journal of Black Studies* 27(5):668–82."
Table 3.1: Descriptive Statistics of Dependent and Explanatory Variables

<table>
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<tr>
<th>Variables</th>
<th>Self-Reported Racial and Ethnic Classification</th>
<th>Black</th>
<th>White</th>
<th>Other*</th>
<th>Hispanic</th>
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<tr>
<td>Current Use of a Smoking Cessation Therapy (Nicotine Replacement Therapy or Prescription Medication)</td>
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<td>Currently Uses Smoking Cessation Therapy (%)</td>
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<td>Does Not Currently Use a Smoking Cessation Therapy (%)</td>
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<td>Age</td>
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<td>Younger Adults, 18-34 (%)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Middle-Aged Adults, 35-44 (%)</td>
<td></td>
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<td></td>
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<tr>
<td>Older Adults, 45-64 (%)</td>
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<tr>
<td>Elderly Adults, 65 and above (%)</td>
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<tr>
<td>Sex</td>
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<td>Female (%)</td>
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<td>Male (%)</td>
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<td>Income</td>
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<tr>
<td>Low-Income (Less than $10,000-$49,999) (%)</td>
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<tr>
<td>Middle-Income ($50,000-$99,999) (%)</td>
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<tr>
<td>High-Income ($100,000 and above) (%)</td>
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<td>Insurance Status</td>
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<td>Government Assistance/Income Recipient</td>
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<tr>
<td>Receives Government Assistance (%)</td>
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<tr>
<td>Does Not Receive Government Assistance (%)</td>
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<td>Education</td>
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<td>High School (%)</td>
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<tr>
<td>Some College (%)</td>
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<td></td>
</tr>
<tr>
<td>College and Above (%)</td>
<td></td>
<td></td>
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<td>Employment Status</td>
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<td>Unemployed (%)</td>
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<tr>
<td>Employed (%)</td>
<td></td>
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</table>
Flavor of Cigarette Used

<table>
<thead>
<tr>
<th></th>
<th>Menthol Cigarette (%)</th>
<th>Non-Menthol Cigarette (%)</th>
<th>Formerly Used Cigarettes (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>55</td>
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<td>24</td>
<td>52</td>
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Beliefs about Nicotine Replacement Therapy

<table>
<thead>
<tr>
<th></th>
<th>Not Harmful (%)</th>
<th>Slightly/Somewhat Harmful (%)</th>
<th>Very/Extremely Harmful (%)</th>
<th>Not aware of Nicotine Replacement Therapy% (%)</th>
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<tbody>
<tr>
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<td>46</td>
<td>47</td>
<td>2</td>
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<tr>
<td></td>
<td>5</td>
<td>65</td>
<td>29</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>60</td>
<td>35</td>
<td>1</td>
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<tr>
<td></td>
<td>4</td>
<td>49</td>
<td>46</td>
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</table>

Secondhand Smoke Exposure

<table>
<thead>
<tr>
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<th>Exposed to Secondhand Smoke (%)</th>
<th>Not Exposed to Secondhand Smoke (%)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>94</td>
<td>92</td>
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<tr>
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<td>93</td>
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<td>8</td>
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<td>7</td>
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</table>

Self-Rated Mental Health

<table>
<thead>
<tr>
<th></th>
<th>Poor or Fair Mental Health (%)</th>
<th>Good, Very Good, or Excellent Mental Health (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20</td>
<td>22</td>
</tr>
<tr>
<td></td>
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<td>78</td>
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<td></td>
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</tr>
</tbody>
</table>

Experience with Tobacco Advertisements

<table>
<thead>
<tr>
<th></th>
<th>Saw tobacco advertisements in neighborhood or media (%)</th>
<th>Did not see tobacco advertisements in neighborhood or media (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>67</td>
<td>66</td>
</tr>
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<td></td>
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<td>42</td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>39</td>
</tr>
</tbody>
</table>

Experience with Tobacco Cessation Advertisements

<table>
<thead>
<tr>
<th></th>
<th>Sometimes/Often-Very Often saw tobacco cessation advertisements in media (%)</th>
<th>Never/Rarely saw tobacco cessation advertisements in media (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>68</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>59</td>
<td>41</td>
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<tr>
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<td>48</td>
</tr>
<tr>
<td></td>
<td>54</td>
<td>46</td>
</tr>
</tbody>
</table>

N | 1,657 | 6,582 | 840 | 1,759


Notes: 4The study investigators combined respondents who identified as Indigenous American, Asian, Native Hawaiian, or another Pacific Islander into one category coded as ‘Other.’

The reference category for current use of a smoking cessation therapy consists of people who have formerly smoked cigarettes. These individuals may have used a smoking cessation therapy in the past that resulted in their no longer using cigarettes.

The “not aware” category for this variable refers to respondents who answered “don’t know” when asked about their beliefs on how harmful they believed the nicotine in Nicotine Replacement Therapy to be.
### Table 3.2: Multivariate Results for Current Smoking Cessation Therapy Use

<table>
<thead>
<tr>
<th>Current Use of Smoking Cessation Therapy &amp;a</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>White (Ref: Black)</td>
<td>1.432***</td>
<td>1.451***</td>
<td>1.504***</td>
<td>1.503***</td>
<td>1.508***</td>
</tr>
<tr>
<td></td>
<td>(3.89)</td>
<td>(3.97)</td>
<td>(4.25)</td>
<td>(3.94)</td>
<td>(3.97)</td>
</tr>
<tr>
<td>Other (Ref: Black)</td>
<td>1.486**</td>
<td>1.743***</td>
<td>1.712***</td>
<td>1.695***</td>
<td>1.705***</td>
</tr>
<tr>
<td></td>
<td>(2.99)</td>
<td>(4.11)</td>
<td>(3.92)</td>
<td>(3.70)</td>
<td>(3.75)</td>
</tr>
<tr>
<td>Hispanic (Ref: Black)</td>
<td>0.570***</td>
<td>0.688**</td>
<td>0.738*</td>
<td>0.739*</td>
<td>0.743*</td>
</tr>
<tr>
<td></td>
<td>(4.19)</td>
<td>(2.74)</td>
<td>(2.20)</td>
<td>(2.15)</td>
<td>(2.11)</td>
</tr>
<tr>
<td>Younger Adults, Ages 18-34 (Ref: Older Adults, Ages 45-64)</td>
<td>0.341***</td>
<td>0.382***</td>
<td>0.397***</td>
<td>0.398***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.47)</td>
<td>(12.61)</td>
<td>(11.87)</td>
<td>(11.77)</td>
<td></td>
</tr>
<tr>
<td>Middle-Aged Adults, Ages 35-44 (Ref: Older Adults, Ages 45-64)</td>
<td>0.742***</td>
<td>0.787**</td>
<td>0.761**</td>
<td>0.764**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.44)</td>
<td>(2.69)</td>
<td>(3.02)</td>
<td>(2.98)</td>
<td></td>
</tr>
<tr>
<td>Elderly Adults, Ages 65 and up (Ref: Older Adults, Ages 45-64)</td>
<td>1.088</td>
<td>0.925</td>
<td>1.008</td>
<td>1.007</td>
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<tr>
<td></td>
<td>(0.73)</td>
<td>(0.65)</td>
<td>(0.67)</td>
<td>(0.66)</td>
<td></td>
</tr>
<tr>
<td>Sex (Ref: Female)</td>
<td>0.578***</td>
<td>0.668***</td>
<td>0.768***</td>
<td>0.769***</td>
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<tr>
<td></td>
<td>(8.71)</td>
<td>(6.17)</td>
<td>(3.90)</td>
<td>(3.88)</td>
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<tr>
<td>Uninsured (Ref: Insured)</td>
<td>0.580***</td>
<td>0.558***</td>
<td>0.563***</td>
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<tr>
<td></td>
<td>(5.22)</td>
<td>(5.56)</td>
<td>(5.47)</td>
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<tr>
<td>Low Income (Ref: Middle Income)</td>
<td>0.946</td>
<td>0.887</td>
<td>0.890</td>
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<td>(0.64)</td>
<td>(1.38)</td>
<td>(1.33)</td>
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<tr>
<td>High Income (Ref: Middle Income)</td>
<td>0.831</td>
<td>0.941</td>
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<td>(1.64)</td>
<td>(0.52)</td>
<td>(0.50)</td>
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<tr>
<td>Receives Government Assistance (Ref: Does Not Receive Government Assistance)</td>
<td>1.508***</td>
<td>1.449***</td>
<td>1.433***</td>
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<tr>
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<td>(5.26)</td>
<td>(4.69)</td>
<td>(4.55)</td>
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<tr>
<td>Less Than High School (Ref: High School)</td>
<td>1.093</td>
<td>1.047</td>
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<td>(0.44)</td>
<td>(0.48)</td>
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<tr>
<td>Some College (Ref: High School)</td>
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<td>1.329***</td>
<td>1.328***</td>
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<tr>
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<td>(3.35)</td>
<td>(3.49)</td>
<td>(3.48)</td>
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<td></td>
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<tr>
<td>College and Above (Ref: High School)</td>
<td>1.348**</td>
<td>1.486***</td>
<td>1.485***</td>
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<td></td>
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<tr>
<td></td>
<td>(2.81)</td>
<td>(3.67)</td>
<td>(3.66)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployed (Ref: Employed)</td>
<td>1.496***</td>
<td>1.303***</td>
<td>1.306***</td>
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<td></td>
<td>(4.80)</td>
<td>(3.43)</td>
<td>(3.46)</td>
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<tr>
<td>Model Description</td>
<td>Coefficient</td>
<td>Standard Error</td>
<td>z-score</td>
<td>p-value</td>
<td></td>
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<td>----------------------------------------------------------------------------------</td>
<td>-------------</td>
<td>----------------</td>
<td>---------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td>Uses Non-Menthol Cigarettes (Ref: Formerly Used Cigarettes)</td>
<td>3.066***</td>
<td>9.93</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Uses Menthol Cigarettes (Ref: Formerly Used Cigarettes)</td>
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<td>10.22</td>
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<tr>
<td>Views NRT as Slightly/Somewhat Harmful (Ref: Views NRT as Unharmful)</td>
<td>0.933</td>
<td>0.45</td>
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<td></td>
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<tr>
<td>Views NRT as Very/Extremely Harmful (Ref: Views NRT as Unharmful)</td>
<td>0.590***</td>
<td>3.99</td>
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<td></td>
</tr>
<tr>
<td>Not Aware of NRT (Ref: Views NRT as Unharmful)</td>
<td>0.557***</td>
<td>4.23</td>
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<td></td>
</tr>
<tr>
<td>Exposed to Secondhand Smoke (Ref: Not Exposed to Secondhand Smoke)</td>
<td>0.507†</td>
<td>1.91</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor/Fair Mental Health (Ref: Good/Very Good/Excellent Mental Health)</td>
<td>1.407***</td>
<td>4.81</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Saw Tobacco Advertisements in Neighborhood or Media (Ref: Did not see Tobacco Advertisements in Neighborhood or Media)</td>
<td>1.136†</td>
<td>1.77</td>
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<tr>
<td>Saw Tobacco Cessation Advertisements in Neighborhood or Media (Ref: Did not see Tobacco Advertisements in Neighborhood or Media)</td>
<td>1.034</td>
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**Observations**: 10,838

**SOURCE**: Population Assessment of Tobacco and Health (PATH) Study, Wave 5 (2018-2019). The analytic sample is restricted to respondents who currently use or quit using cigarettes or electronic nicotine products in the past year with no missing information on the explanatory, mediating, and outcome variables. Unweighted frequencies are shown. T statistics are in parentheses. Models were compared using likelihood ratio tests.† p < .10; * p < .05; **p < .01; *** p < .001 (two-tailed tests).

* Cessation therapies were defined as Nicotine Replacement Therapy (NRT) or a non-nicotine prescription medication (Varenicline or Bupropion). The reference category for current use of a smoking cessation therapy consists of people who have formerly smoked cigarettes or electronic nicotine products. These individuals may have used a smoking cessation therapy in the past that resulted in their no longer using cigarettes or electronic nicotine products.

† The study investigators combined respondents who identified as Indigenous American, Asian, Native Hawaiian, or another Pacific Islander into one category coded as 'Other.'

The "not aware" category for this variable refers to respondents who answered "don’t know" when asked about their beliefs on how harmful they believed the nicotine in Nicotine Replacement Therapy to be.
Appendix

Appendix 3.A: Multivariate Results by Self-Reported Racial and Ethnic Classification and Immigrant Status

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Use of Smoking Cessation Therapy*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Native-Born White (Ref: Native-Born Black)</td>
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<td>1.453***</td>
<td>1.515***</td>
<td>1.552***</td>
<td>1.557***</td>
</tr>
<tr>
<td></td>
<td>(3.63)</td>
<td>(3.56)</td>
<td>(3.86)</td>
<td>(3.77)</td>
<td>(3.79)</td>
</tr>
<tr>
<td>White Immigrant (Ref: Native-Born Black)</td>
<td>0.484</td>
<td>0.421</td>
<td>0.509</td>
<td>0.472</td>
<td>0.485</td>
</tr>
<tr>
<td></td>
<td>(0.99)</td>
<td>(-1.18)</td>
<td>(-0.92)</td>
<td>(-1.01)</td>
<td>(-0.97)</td>
</tr>
<tr>
<td>Native-Born Other (Ref: Native-Born Black)</td>
<td>1.491*</td>
<td>1.692***</td>
<td>1.683**</td>
<td>1.732**</td>
<td>1.739***</td>
</tr>
<tr>
<td></td>
<td>(2.55)</td>
<td>(3.31)</td>
<td>(3.23)</td>
<td>(3.28)</td>
<td>(3.30)</td>
</tr>
<tr>
<td>Native-Born Hispanic (Ref: Native-Born Black)</td>
<td>0.691*</td>
<td>0.807</td>
<td>0.829</td>
<td>0.829</td>
<td>0.829</td>
</tr>
<tr>
<td></td>
<td>(2.36)</td>
<td>(-1.35)</td>
<td>(-1.17)</td>
<td>(-1.15)</td>
<td>(-1.14)</td>
</tr>
<tr>
<td>Hispanic Immigrant (Ref: Native-Born Black)</td>
<td>0.487*</td>
<td>0.499+</td>
<td>0.609</td>
<td>0.606</td>
<td>0.621</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(-1.94)</td>
<td>(-1.37)</td>
<td>(-1.38)</td>
<td>(-1.31)</td>
</tr>
<tr>
<td>Younger Adults, Ages 18-34 (Ref: Older Adults, Ages 45-64)</td>
<td>0.389***</td>
<td>0.429***</td>
<td>0.429***</td>
<td>0.431***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-10.75)</td>
<td>(-9.35)</td>
<td>(-9.17)</td>
<td>(-9.09)</td>
<td></td>
</tr>
<tr>
<td>Middle Aged Adults, Ages 35-44 (Ref: Older Adults, Ages 45-64)</td>
<td>0.807*</td>
<td>0.861</td>
<td>0.821*</td>
<td>0.823†</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.24)</td>
<td>(-1.53)</td>
<td>(-1.98)</td>
<td>(-1.95)</td>
<td></td>
</tr>
<tr>
<td>Elderly Adults, Ages 65 and up (Ref: Older Adults, Ages 45-64)</td>
<td>1.102</td>
<td>0.938</td>
<td>1.015</td>
<td>1.013</td>
<td></td>
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<tr>
<td></td>
<td>(0.75)</td>
<td>(-0.47)</td>
<td>(0.11)</td>
<td>(0.09)</td>
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</tr>
<tr>
<td>Sex (Ref: Female)</td>
<td>0.578***</td>
<td>0.665***</td>
<td>0.767***</td>
<td>0.768***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-7.56)</td>
<td>(-5.41)</td>
<td>(-3.40)</td>
<td>(-3.39)</td>
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</tr>
<tr>
<td>Uninsured (Ref: Insured)</td>
<td>0.583***</td>
<td>0.567***</td>
<td>0.571***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.49)</td>
<td>(-4.88)</td>
<td>(-4.62)</td>
<td></td>
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</tr>
<tr>
<td>Low Income (Ref: Middle Income)</td>
<td>0.918</td>
<td>0.861</td>
<td>0.864</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.87)</td>
<td>(-1.50)</td>
<td>(-1.47)</td>
<td></td>
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</tr>
<tr>
<td>High Income (Ref: Middle Income)</td>
<td>0.708*</td>
<td>0.809</td>
<td>0.813</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.52)</td>
<td>(-1.52)</td>
<td>(-1.49)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Receives Government Assistance (Ref: Does Not Receive Government Assistance)</td>
<td>1.425***</td>
<td>1.378***</td>
<td>1.364***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.97)</td>
<td>(3.56)</td>
<td>(3.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less Than High School (Ref: High School)</td>
<td>1.117</td>
<td>1.081</td>
<td>1.083</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(0.66)</td>
<td>(0.67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Some College (Ref: High School)</td>
<td>1.225*</td>
<td>1.266*</td>
<td>1.266*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.17)</td>
<td>(2.49)</td>
<td>(2.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>College and Above (Ref: High School)</td>
<td>1.265†</td>
<td>1.412**</td>
<td>1.411**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.93)</td>
<td>(2.78)</td>
<td>(2.77)</td>
<td></td>
<td></td>
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<tr>
<td>Unemployed (Ref: Employed)</td>
<td>1.397***</td>
<td>1.257*</td>
<td>1.263**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.81)</td>
<td>(2.55)</td>
<td>(2.59)</td>
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</tr>
</tbody>
</table>

120
Uses Non-Menthol Cigarettes (Ref: Formerly Used Cigarettes)  
3.212***  3.196*** 
(8.40)  (8.36)

Uses Menthol Cigarettes (Ref: Formerly Used Cigarettes)  
3.635***  3.609*** 
(8.81)  (8.75)

Views NRT as Slightly/Somewhat Harmful (Ref: Views NRT as Unharmful)  
0.893  0.872 
(0.64)  (0.77)

Views NRT as Very/Extremely Harmful  
(Ref: Views NRT as Unharmful)  
0.611**  0.616** 
(3.22)  (3.18)

Not Aware of NRT* (Ref: Views NRT as Unharmful)  
0.547***  0.551*** 
(3.78)  (3.73)

Exposed to Secondhand Smoke (Ref: Not Exposed to Secondhand Smoke)  
0.632  0.649 
(1.14)  (1.07)

Poor/Fair Mental Health (Ref: Good/Very Good/Excellent Mental Health)  
1.398***  1.390*** 
(4.09)  (4.01)

Saw Tobacco Advertisements in Neighborhood or Media (Ref: Did not see Tobacco Advertisements in Neighborhood or Media)  
1.143  
(1.62)

Saw Tobacco Cessation Advertisements in Neighborhood or Media (Ref: Did not see Tobacco Advertisements in Neighborhood or Media)  
1.017  
(0.21)

Observations 7,676  7,676  7,676  7,676  7,676

SOURCE: Population Assessment of Tobacco and Health (PATH) Study, Wave 5 (2018-2019). The analytic sample is restricted to respondents who currently use or quit using cigarettes or electronic nicotine products in the past year with no missing information on the explanatory, mediating, and outcome variables.

Unweighted frequencies are shown. T statistics are in parentheses. Models were compared using likelihood ratio tests.

* p < .10; ** p < .05; *** p < .001 (two-tailed tests).

Cessation therapies were defined as Nicotine Replacement Therapy (NRT) or a non-nicotine prescription medication (Varenicline or Bupropion). The reference category for current use of a smoking cessation therapy consists of people who have formerly smoked cigarettes or electronic nicotine products. These individuals may have used a smoking cessation therapy in the past that resulted in their no longer using cigarettes or electronic nicotine products.

The study investigators combined respondents who identified as Indigenous American, Asian, Native Hawaiian, or another Pacific Islander into one category coded as ‘Other.’

The “not aware” category for this variable refers to respondents who answered “don’t know” when asked about their beliefs on how harmful they believed the nicotine in Nicotine Replacement Therapy to be.
CHAPTER 4: THE POLITICS OF PLACE: STRUCTURAL RACISM AND ACCESS TO MENTAL HEALTH CARE

Abstract

Although the sociological and clinical literature has expanded understandings of structural racism, health outcomes, and access to healthcare in critical ways, the dynamics of structural racism at the mesolevel – specifically counties – are less well understood. The purpose of this study is to investigate the relationship between racial-gender equity and access to mental healthcare. This study uses data from a sample of 2,853 counties in the United States. The study combines data sources from the 2021 Area Health Resources Files, the 2021 County Health Rankings, and the Kaiser Family Foundation. Empirically, the study examines the relationship between an index of racial-gender equity and whether or not a county is located in a mental health professional shortage area. The index aggregates population-level measures of unemployment, educational attainment, severe housing cost burden, overall income inequality, and median household income for the total population. It also assesses gaps in these measures between the overall population and groups classified by race and ethnicity and, where possible, sex. The analysis demonstrates that areas with lower equity are more likely to lack an adequate supply of mental health professionals. However, the association was mediated through the county’s socio-political landscape, including the state governor’s political orientation, a county’s urban or rural designation, and home internet access. Having a Democratic governor was the key macrolevel factor that explained the association between racial-gender equity and the availability of mental healthcare. On the
other hand, home internet access was the microlevel downstream factor that explained away the association. Counties with Democratic governors had lower odds of being located in a mental health professional shortage area than counties with Republican governors. Areas with average or higher levels of internet access compared to the national average had decreased odds of being in a mental health professional shortage area than those with low internet access. This study suggests that mesolevel political dynamics mirror structural patterns at the macrolevel that systematically sustain inequities in access to healthcare. Further, the study demonstrates that access to healthcare is a political issue, and it can be restricted or expanded depending on the spatial distribution of inequality. Finally, this work illustrates how the spatial distribution of inequality shapes access to healthcare in racialized social systems and, in turn, clarifies the social sources of inequalities in healthcare access and delivery.

Introduction

The twin pandemics of COVID-19 and systemic racism have exacerbated the prevalence of mental health conditions worldwide, and inequalities in access to healthcare persist (Santomauro et al. 2021; Vahratian et al. 2021; VanderWielen et al. 2015). Twenty-six percent of adults in the United States with a mental health condition reported having an unmet need for mental health care (Han 2019). Prior studies demonstrate that neighborhood and community-level characteristics shape healthcare access (Anderson 2018; Cummings et al. 2017; Kirby and Kaneda 2005; Oluwoye et al. 2021; Sherry et al. 2021; VanderWielen et al. 2015). In particular, scholars have identified residential segregation as a fundamental cause of health disparities (Williams
Health disparities refer to differences in health outcomes and status, environment, quality of, use of, and access to care that warrant careful examination (Carter-Pokras and Bacquet 2002:427). These findings indicate that unpacking how racism manifests spatially can help further explain inequalities in access to mental health care.

Inequality in mental healthcare access affects healthcare utilization and health outcomes. Many studies have provided critical insights on disparities in mental healthcare utilization (for example, see Dinwiddie et al. 2013; Kim 2019; and Smith and Trimble 2016). However, additional information on the availability of mental health care services can elucidate how care-seeking may differ spatially (Cook et al. 2013; Gomez-Vidal and Gomez 2021). In turn, a recent, growing body of work employs spatial analysis to map how neighborhood and community inequality shapes access to mental healthcare (for example, see Anderson 2018; Cummings et al. 2017; Oluwoye et al. 2021; Sherry et al. 2021; and VanderWielen et al. 2015). These studies demonstrate that neighborhoods with a lower income, in rural areas, and with a higher proportion of Black and Hispanic residents tend to have less access to a diverse, financially accessible set of mental health care options.

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Scholars often disagree about the meaning of the term ‘health disparities,’ and as a result there are several meanings of this concept in the literature (Carter-Pokras and Bacquet 2002:428). Throughout this chapter – and in the dissertation as a whole – I use the terms health inequalities and health inequities to highlight that many of the differences in health outcomes and access to care are avoidable. Further, these differences result from a structural cause: the unequal distribution of resources and privilege in multiple domains of society (Carter-Pokras and Bacquet 2002:428). The categories that divide humans are socially, politically, and systematically constructed and maintained on the basis of anti-Blackness. Working from an approach that centers the equality of humanity, there is no disparity by racial classification, class, or gender identity categories. Instead, there are structural inequalities that affect people based on the categories they have been placed in. In turn, I only use the word disparity if it is explicitly stated in the literature I am citing.
The sociological and clinical literature has expanded understandings of access to healthcare in critical ways; however, few studies have examined how an area's racial and gender equity – rather than solely the level of resource or disadvantage in a neighborhood – shapes healthcare access. There is also limited work that describe the dynamics of institutionalized racism at the mesolevel – particularly in counties (Gómez and López 2013; Riley 2018; Sewell 2016). Understanding how local policies, politics, and the supply of health providers shape access to health care can shed light on an underappreciated aspect of inequality – the spatial distribution of unequal contexts in counties. Given that racism is a key driver of health inequalities (Pearson et al. 2021; Williams and Mohammed 2009; Williams and Sternthal 2010), examining indicators of racial and gender equity at the mesolevel can contribute to further unpacking the spatial dimensions of structural racism (Allport 1958; Bonilla-Silva 1997; Feagin 1991; Mills 1997) and inequalities in healthcare access (for example, see Andersen 1995; Cyr et al. 2019; and Levesque et al. 2013).

To address these gaps in the literature, the purpose of this study is to investigate the relationship between racial-gender equity and access to care. Empirically, the study examines the relationship between a county’s level of racial-gender equity and the supply of mental health providers. This study describes racial and gender equity as a process involving every community having sufficient resources to access the same life chances and outcomes (Allies Reaching for Community Health Equity 2022). I operationalize an Index of Racial-Gender Equity and examine its association with whether or not a county is located in a mental health professional shortage area. The data for this study come from
the 2021 Area Health Resources Files (U.S. Department of Health and Human Services 2021), the 2021 County Health Rankings (University of Wisconsin Population Health Institute 2021), and the Kaiser Family Foundation (2022a; 2022b).

Results demonstrate that accounting for a county’s socio-political landscape, including the state governor’s political orientation, a county’s urban or rural designation, and home internet access eliminated the mental health provider supply gap by racial-gender equity. Having a Democratic governor was the primary macrolevel factor that explained this relationship. Counties with Democratic governors had lower odds of experiencing a shortage of mental health professionals than counties with Republican governors. In addition, household internet access, a microlevel indicator, also explained the relationship between racial-gender equity and the mental health provider supply. Areas with average or higher levels of internet access compared to the national average had decreased odds of being in a mental health professional shortage area than those with low internet access.

This work contributes to understandings of how mesolevel political dynamics (Sewell 2016) mirror structural patterns at the macrolevel that systematically sustain inequities in access to healthcare. Further, the study demonstrates that access to healthcare is a political issue, and it can be restricted or expanded depending on the spatial distribution of inequality. The study also illustrates how the spatial distribution of inequality shapes access to healthcare in racialized social systems (Bonilla-Silva 1997) and, in turn, contributes to clarifying the social sources of inequalities in healthcare access and delivery.
Theoretical Context

*Explaining Inequities in Access to Mental Health Care*

Prior studies have shown that place matters in understanding inequalities in access to healthcare (Dinwiddie et al. 2013). For instance, several studies have examined the relationship between racial residential segregation – a fundamental driver of racial inequality (Feagin 1991; Williams and Collins 2001; Williams and Sternthal 2010) – and health (for example, see Dinwiddie et al. 2013; Lee et al. 2020). The results of this literature have been mixed (White et al. 2019). Some studies suggest that living in an ethnic enclave is protective to mental health (Faris 1960; Halpern 1993; Levy and Rowitz 1973, qtd. in Williams and Collins 2001). In contrast, other studies have found that racial residential segregation negatively impacts mental health access depending on a neighborhood's concentration of racially and ethnically classified groups (Dinwiddie et al. 2013).

Building on these insights, a growing body of work examines the relationship between measures of spatial inequality, such as neighborhood composition and community relative position, and the geographic availability of mental health services using spatial analysis (see Anderson 2018; Cummings et al. 2017; Oluwoye et al. 2021; Sherry et al. 2021; VanderWielen et al. 2015). These studies have found that lower-income neighborhoods, rural communities, and neighborhoods with a higher concentration of residents racially and ethnically classified as Black and Hispanic tended to have less access to multiple mental health care options, such as telemedicine (Anderson 2018; Cook et al. 2013; Cummings et al. 2017; Finch et al. 2010; Guerrero
and Kao 2013; Hughes et al. 2019; Kalb et al. 2021; Kirby and Kaneda 2005; Lee et al. 2020; Miranda et al. 2020; Oluwoye et al. 2021; Ramos and Chavira 2019; Sherry et al. 2021; VanderWielen et al. 2015). This literature has also found that the availability of these services could reduce inequities in mental healthcare access, and that a community's social environment shapes health outcomes through differences in access to healthcare (Lillie-Blanton and LaVeist 2012).

Other recent scholarship extends the literature on place and health by emphasizing that place matters because of structural racism (Riley 2018:363, emphasis author’s) and, in turn, examining the spatial distribution of inequality (Bell and Owens-Young 2020; Pinto-Coelho and Zuberi 2015; Sewell 2016; Sewell 2021; Smith and Trimble 2016; Smith-East and Neff 2020; Stewart 2006; Stark and Taylor 1989). This literature also argues for going beyond studying neighborhood or census-tract level disadvantage to examining units of analysis such as cities, counties, and states to understand how institutional dynamics might affect health outcomes (Riley 2018). This literature is in line with other studies that have developed and utilized racial equity and evenness indices within geographical areas to expand understandings of how varying experiences of racial stratification in an area shapes outcomes (McDaniel 2021; Pinto-Coelho and Zuberi 2015; Willie et al. 2021).

Explaining spatial experiences of racial stratification can provide more context for analyses surrounding racial and ethnic realities (Pinto-Coelho and Zuberi 2015). Scholars have recently developed a Racial Equity Index to measure communities' progress towards full access to resources for every racially and ethnically classified group based on
economic and social markers (PolicyLink 2020). Scholars have applied this index in domestic violence and migration work (McDaniel 2021; Willie et al. 2021). The Racial Equity Index provides an aggregate spatial indicator of the many factors that prior studies have identified as key for explaining access to mental services, particularly for people from nonwhite racially and ethnically classified groups (Dinwiddie et al. 2013; Kirby and Kaneda 2006; Rosales and Calvo 2019). In turn, this index can methodologically bolster understandings of healthcare access inequities.

Similarly, the literatures on relative deprivation and structural racism demonstrate that the spatial distribution of inequality can provide insight into the sources of inequities in health outcomes and access to care. The relative deprivation literature argues that people's placement in the social hierarchy stems from their social status and outcomes relative to other people in their immediate community (for example, see Stark and Taylor 1989; Stewart 2006). This literature suggests that understanding the level of inequality in an area can provide insight into often under-recognized sources of disadvantage among communities classified as nonwhite.

**Conceptualizing the Impact of Structural Racism on Access to Mental Health Care**

In theorizing on the sources of unequal access to healthcare, the literature on racism and health emphasizes that structural racism shapes the underlying conditions associated with inequities in accessing mental healthcare among racially and ethnically classified groups (Bonilla-Silva 1997; Brown 2003; Mays et al. 2007; Williams and Mohammed 2009; Williams and Sternthal 2010). At its core, structural racism is a system of assigning meaning to racially and ethnically classified groups that is pervasive at every

Most social science scholarship acknowledges that race and racism are socially constructed. However, quantitative work on race and racism tends to justify – rather than explain – "the process of racial stratification" (Zuberi 2011:101; Zuberi 2001b; Zuberi and Bonilla-Silva 2008). As a result, scholars have argued that Critical Race Theory (CRT), which seeks to identify how racism manifests in society, can guide conceptualizations of race and racism in quantitative work (Brown 2003; Brown 2008; Crenshaw 1995; Ford and Airhihenbuwa 2010; Mills 1998; Zuberi 2000; Zuberi 2001a; Zuberi 2001b; Zuberi 2011).

Critical race theorists have demonstrated that race functions as a system and political strategy (Brown 2003; Bonilla-Silva 1997; Fanon 1967; Mills 1997; Roberts 2011; Zuberi 2001a; Zuberi 2001b) that uses arbitrary measures such as "somatic images" (Zuberi 2001a:147) to justify racism. Racism provides an orienting structure for guiding the institution of white supremacy in assigning differential value, power, and privilege to groups based on their racial and ethnic classification. Given racism's ubiquity in society, its ideology that solidifies the "racial notions and stereotypes" (Bonilla-Silva 1997:474) associated with particular racially and ethnically classified groups becomes seen as common sense. Racism thus provides a rationale for race relations and, in turn, structures of power that shape interactions, institutions, and access to benefits or disadvantages (Mills 1997). In addition, as intersectionality theory describes, racism overlaps with other forms of oppression, such as sexism and classism, to shape outcomes (Crenshaw 1995).
Further, structural theories of race extend CRT by arguing that the United States has a "racialized social system" in which race undergirds the structures governing health, education, employment, housing, mass incarceration, income, wealth, the economy, food security, and politics (Bonilla-Silva 1997:467). The pervasiveness of the racialized social system in society highlights the link between structural and institutional racism. Institutional racism, a term Carmichael and Hamilton (1967) coined, explains that racism becomes most apparent at the community or mesolevel through established stakeholders' "acts, decisions, and policies" that are rooted in anti-blackness (Carmichael and Hamilton 1967:4-5, qtd. in Sewell 2016).

In their theory of the racism-race reification process (R3p) model, Sewell (2016) links structural and institutional racism by conceptualizing how racism's consequences at the individual and household level are "codified" at the mesolevel (Sewell 2016:409). This theory outlines how racial inequities in health outcomes stem from policies and other institutional dynamics at the neighborhood level. Specifically, R3p argues that "institutional (in) actions" tend to place "racially marginalized" communities into segregated spaces that result in harmful risk factors (Sewell 2016:409). In addition, R3p posits that institutional policies are linked to other determinants of health, including racial residential segregation and a household's socioeconomic status. Overall, this theory brings together structural and institutional racism by suggesting that macrolevel forms of racism affect life chances, and that institutional processes such as policies create and sustain racial health inequities at the neighborhood, city, county, and state levels (Bonilla-Silva 1997; Bonilla-Silva 2001; Carmichael and Hamilton 1967; Feagin 2006;
Overall, the racism and health literature suggest that exposure to discrimination, the pervasiveness of racism in healthcare and other societal systems, and institutional policies shape observed inequities among racially and ethnically classified groups in health outcomes and access to care (Boen 2020; Bell and Owens-Young 2020; Feagin 1991; Mays et al. 2007; Riley 2018; Williams and Collins 2001; Williams and Mohammed 2009). This literature also suggests that understanding how structural and institutional racism functions in multiple community-level domains can illuminate how policies systematically shape health outcomes and access to health care.

**Gaps in the Literature**

The literature has provided important insights on where inequities exist in access to mental healthcare. Recent work has also identified several indicators of racial inequity that may shape healthcare access. Further, the literature has theorized and tested how policies shape health outcomes. However, few studies aggregate multiple measures of structural racism to understand how this system shapes the availability of healthcare that can, in turn, affect health outcomes through policies that either advance or curtail racial and gender equity. Understanding the availability of healthcare can provide further insight into the sources of inequities in health outcomes overall.

In addition, the literature on the spatial distribution of inequality sheds light on how experiences differ based on community members' placement in the racial hierarchy,
particularly in highly unequal contexts. However, more research is needed that uses units of analysis directly connected to the effects of institutional policies - such as counties - to determine the circumstances that produce unequal contexts at the mesolevel. Using spatial indicators such as counties as units of analysis may help demonstrate an underappreciated source of inequality that groups' individual-level racial and ethnic classifications may not provide (Gómez and López 2013; Zuberi 2000:183).

Finally, a small but growing body of work explicitly names structural racism and the racial hierarchy as the root cause of inequities in the availability of healthcare and health outcomes more broadly (for example, see Riley 2018; Williams et al. 2019). Further studies are needed that highlight specific conceptual frameworks for understanding structural racism’s – and other forms of oppressions’ (Crenshaw et al. 1995) – impact on the availability of mental healthcare. Given that gaps remain in access to mental healthcare (Han 2019), such studies are particularly salient.

To address these gaps in the literature, this study examines the relationship between a geographical area's level of racial-gender equity and the availability of mental healthcare. Empirically, this study seeks to answer the question: What is the relationship between a county's level of racial-gender equity and the supply of mental health providers? As illustrated in Figure 4.1, the study's conceptual model integrates two structural theories of race: the racialized social system (Bonilla-Silva 1997) and the racism-race reification process (Sewell 2016). This study defines a county's mental health provider supply as the dependent variable and a county's level of racial (and, where possible, gender) equity as the independent variable. I conceptualize racial and gender
equity as the notion that every community has the same level of access to resources based on an understanding of the factors that shape their current placement in the racial and gender hierarchy (Allies Reaching for Community Health Equity 2022).

In order to help explain the supply of mental health providers in a county, the study includes three mediating factors: (1) county health policies, (2) county socio-political landscape, and (3) the county's primary health provider supply. Based on Sewell and Bonilla-Silva's structural theories of race (Bonilla-Silva 1997; Sewell 2016), all of these variables are situated within a racialized social system that undergirds each of the variables in the analysis. The mediating mechanisms help clarify the effects of varying levels of racial and gender equity in a county and how they manifest in health policies, population distribution, provider availability, and population health characteristics that may shape the supply of mental health providers in an area.

Data, Measures, and Methods

Data Sources

To assess how the racialized social system shapes access to mental health services, I draw on multiple national data sources that include equity and health policy indicators. This study's analytical sample comes from the 2021 Area Health Resources Files (U.S. Department of Health and Human Services 2021), the 2021 County Health Rankings (University of Wisconsin Population Health Institute 2021), and the Kaiser Family Foundation (2022a; 2022b).

The Area Health Resources Files are a set of repeated cross-sectional datasets that provide, among other measures, information on medically underserved areas and
populations along with the availability of primary, mental, and dental health care professionals by census tract. The measures in the datasets are based on estimates from the 2020 American Community Survey, 2020 Bureau of Labor Statistics data, and the National Center for Education Statistics' 2018 Integrated Postsecondary Education Data System. In addition, the Area Health Resources Files include geographic shapefiles that describe areas with a health professional shortage and medically underserved areas and populations.

Next, the County Health Rankings are repeated cross-sectional datasets based on a community health model that outlines the relationship between policies and programs, health risk factors, and health outcomes. The Rankings provide raw and ranked county-level data marshaled from multiple sources, including the 2015-2019 American Community Survey five-year estimates, the 2019 Bureau of Labor Statistics dataset, and the 2016 Environmental Public Health Tracking Network dataset. In addition, the Rankings data includes information on county demographic composition, family structure, housing, transit, socioeconomic status, community safety, access to and quality of healthcare, and health behaviors.

Finally, additional socio-political variables in the analysis come from the Kaiser Family Foundation (KFF). The KFF is a nonpartisan organization that provides evidence-based national health policy analysis and information. Its data include variables that measure state governors' political affiliations, Medicaid expansion, and state family and medical leave policies.
**Analytic Sample**

The dataset's full sample size was 3,142, the total number of counties in the United States. Counties with missing observations in the explanatory measure were dropped, reducing the analytic sample to 2,859. The dropped counties were located primarily in mostly rural and completely rural areas. Next, counties with missing observations in the mediator measures were excluded, resulting in a final analytic sample of 2,853.

**Measures**

*Key Explanatory Measure: An Index of Racial-Gender Equity*

To capture variation in racial and gender equity, I constructed an index of racial-gender equity (IREQ). For a detailed description of how I constructed the index, see appendix 4.A. I measure the level of racial-gender equity using a single composite score that measures where a county falls overall, by racial classification, ethnic classification, and, where possible, sex, on three sets of indicators. These indicators are (1) Economic Security (Employment rate, median household income, and the ratio of overall household incomes at the 80th percentile to incomes at the 20th percentile); (2) Readiness (some college education) and (3) Connectedness (Severe housing cost burden, the percentage of households that spend 50 percent or more of their household income on housing). Race and ethnicity subgroup data were available for unemployment and median household income.

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15 Overall, nine percent of the county observations in the racial-gender equity variable were missing. Further analysis revealed that of all the missing observations, a combined 17.5 percent were mostly or completely rural. I employed multiple imputation using the multivariate normal distribution (MVN) technique to determine if these missing cases biased the findings. I found that the substantive findings of the multiply imputed model estimates were similar to the findings I report in this study (see appendix 4.E). As a result, the analysis indicates that there is no selection on the complete cases and that the original study findings are not biased.
income. In addition, sex, race, and ethnicity subgroup data were available for the education indicator. For ease of analysis, I recoded the IREQ, which had scores ranging from 1 to 100, into two categories of racial-gender equity that distinguish between (1) low to moderate racial-gender equity (scores of 35 to 80); and (2) high racial-gender equity (scores of 81 and above). Areas with low to moderate racial-gender equity are the omitted reference category.

Key Outcome Measure

The study operationalizes the county mental health provider supply through a binary measure of whether or not a county has been designated as a mental health professional shortage area (MHPSA). I created this variable by calculating a single average MHPSA score\(^{16}\) for all census tracts in each county, which ranged from 0 to 25.\(^{17}\) The final MHPSA score was then converted into the binary measure. Non-MHPSAs are the omitted reference category.

Mediator Measures

Given that prior literature has suggested that the accessibility of healthcare is produced at multiple levels – including at the system and policy access levels (Cyr et al.

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\(^{16}\) The Health Resources & Services Administration (HRSA) calculates the MHPSA score by assigning a certain number of points to each area in the following categories: (1) Population-to-Provider Ratio (30,000 to 1, or 20,000 to 1 in areas with exceptionally high need); (2) Percent of the population below 100 percent of the Federal Poverty Level (FPL); (3) Percent of people over age 65; (4) Percent of people under age 18; (5) Prevalence of alcohol abuse; (6) Prevalence of substance abuse; and (7) Travel time to the nearest source of care outside the shortage area. For further details on the shortage area calculation, see Health Resources & Services Administration. 2020. “Scoring Shortage Designations | Bureau of Health Workforce.” Retrieved May 11, 2022 (https://bhw.hrsa.gov/workforce-shortage-areas/shortage-designation/scoring).

\(^{17}\) Based on the Health Resources & Services Administration guidelines (Health Resources & Services Administration 2022), the MHPSA score cutoff points are: (1) Low: score of 3 to 12; (2) Moderate: score of 13 to 16; and (3) High: 17 to 25. Illustrated in Appendix 4.C, a histogram of the average MHPSA score demonstrates that the majority of counties were clustered around the moderate to high MHPSA score categories.
2019, Levesque et al. 2013) – the mediating measures are (1) county health policies; (2) county socio-political landscape and (3) county primary health provider supply.

The study includes three indicators of state and county health policies: (1) county uninsured rate; (2) whether the county’s state adopted Medicaid expansion; and (3) whether the county’s state has a family and medical leave policy. The county uninsured rate measures the percentage of the population under age 65 who does not have insurance. This binary variable distinguishes between counties with a high or low uninsurance rate. High uninsurance rates were coded as being above the 2020 national average of 10.4 percent (Kaiser Family Foundation 2020), while low insurance rates were coded as being at or below the national average. Counties with a high uninsurance rate were the omitted reference category.

The analysis also includes a binary variable distinguishing between counties located in states that did, and did not, adopt Medicaid expansion as of January 2022. The federal government implemented Medicaid expansion under the Affordable Care Act to increase the scope of Medicaid’s eligibility criteria and, in turn, help insure more Americans from low-income backgrounds (Obama 2016, Oberlander 2016). However, a number of states chose not to expand eligibility. Not adopting Medicaid expansion was the omitted reference category.

Finally, the analysis also includes an indicator of the presence of paid family and medical leave policies. Such policies provide workers with economic security and the ability to care for their health or an ill or aging family member. Access to paid leave is particularly crucial for self-identified women, who tend to be the primary caregivers for
children or aging parents (Kaiser Family Foundation 2021). The paid leave variable distinguishes between whether or not a county is located in a state that has a family and medical leave policy. Counties located in states without family and medical leave policies were the omitted reference category.

I also include three indicators of a county’s socio-political landscape: (1) political orientation of a county’s state governor; (2) county’s urban or rural designation; and (3) broadband internet access. The county’s state governor political orientation is captured by a binary variable distinguishing between whether a county’s state governor is a Democrat or a Republican. Republican governors are the omitted reference category.

Following Census guidelines on defining rural areas (Ratcliffe et al. 2016), this variable distinguishes between counties that are (1) mostly urban; (2) mostly rural; and (3) completely rural, given that a county's population can have a combination or even distribution of urban and rural areas. Mostly urban areas are the omitted reference category.

Given the rise of telehealth services, understanding overall internet access rates can expand insights on which counties can access virtual mental health care more readily (Hughes et al. 2019, Ramos and Chavira 2019). Thus, the broadband internet access variable measures the percentage of the population who has home internet access. It distinguishes between counties with a high or low internet access rate relative to the 2018 national average of 83 percent (County Health Rankings 2021). Counties with a low internet access rate were the omitted reference category.
Overall, the United States meets less than 70 percent of its population's mental health needs (Kaiser Family Foundation 2021). Understanding how the concentration of primary care providers, who may be able to refer patients to mental health services, varies in a county can further uncover what contributes to the accessibility and availability of services (Cyr et al. 2019, Levesque et al. 2013) and in turn the supply of health care providers. I therefore include an indicator of whether a county constitutes a Medically Underserved Area or Population (MUA/P). Following the Health Resources & Services Administration's guidelines (2020), counties receive this designation based on their Index of Medical Underservice (IMU) Score, which ranges from 0 to 100.\(^\text{18}\) To create a binary MUA/P variable that distinguishes between whether or not an area is a designated MUA/P, I first calculated a single average IMU score for all of the census tracts within each county. In line with the Health Resources & Services Administration criteria, counties with an average IMU score below 62 were coded as designated MUA/Ps, while counties with an average IMU score above 62 are coded as non-MUA/Ps. Non-MUA/Ps were the omitted reference category.

Analytic Strategy

Using ArcGIS software, I first present a sociodemographic map (Pinto-Coelho and Zuberi 2015) of each county’s Racial-Gender Equity score. Next, I include sociodemographic maps visualizing Mental Health Professional Shortage Areas and

\(^{18}\) HRSA calculates the IMU score by assigning points to each area based on the following categories: (1) The number of providers per 1,000 people; (2) Percent of the population at 100 percent of the Federal Poverty Level; (3) Percent of the population age 65 and over; and (4) the infant mortality rate. For more details on how HRSA calculates the IMU score, see Health Resources & Services Administration. 2020. “Scoring Shortage Designations | Bureau of Health Workforce.” Retrieved May 11, 2022 (https://bhw.hrsa.gov/workforce-shortage-areas/shortage-designation/scoring).
Medically Underserved Areas and Populations in each county. As prior studies have shown, visualizing inequality through maps can provide further insight into critically understanding how structural racism operates across space and in other ways that tables and charts alone may not provide (Gómez 2007, qtd. in Gómez and López 2013; Pinto-Coelho and Zuberi 2015). I then report descriptive statistics by racial-gender equity score for the study’s explanatory and outcome variables.

Finally, given that county health policies, socio-political landscapes, and primary health care provider supply also vary based on county racial-gender equity scores, I model the supply of mental health providers using binary logistic regression.

**Descriptive Results**

**Sociodemographic Maps**

To understand the relationship between racial-gender equity and the availability of mental health services, I first evaluate the distribution of the Index of Racial-Gender Equity by U.S. county (Figure 4.2). This map demonstrates that counties with higher racial-gender equity tend to be concentrated in the Northeast, Midwest, and some parts of the West Coast. On the other hand, counties with lower racial-gender equity are concentrated in the South, Southwest, Alaska, and Hawaii. Analyzing this map shows a clear spatial distribution of inequality based on the racial-gender equity index. It suggests that counties with lower racial-gender equity may experience the spatial effects of racism at greater levels than those with a higher racial-gender equity level.

Next, I assess whether a county's level of racial-gender equity maps onto the supply of mental health providers, depicted in Figure 4.3. Most of the United States has a
mental health professional shortage, confirming prior literature (Han 2019) that suggests that there is a gap in mental health needs for the overall population. In addition, counties with a high level of racial-gender equity in the previous map were less likely to be located in this map's mental health professional shortage areas. These counties were again located in the Northeast, Midwest, and some parts of the West Coast. On the other hand, counties with a lower level of racial-gender equity – located in Hawaii, Alaska, the South, and Southwest – were more likely to be in mental health professional shortage areas.

Finally, I explore the distribution of medically underserved areas and populations by county in Figure 4.4. This map shows a stark difference in areas that are and are not medically underserved. Alaska, Hawaii, and most of the South, Southwest, West, and Northwest are medically underserved. Conversely, aside from a few exceptions, counties in the Northeast and most of the Midwest had fewer medically underserved areas or populations than the rest of the country. Further, the index of racial-gender equity maps somewhat well onto medically underserved areas and populations. Counties located in the Northeast and Midwest with higher racial-gender equity were less likely to be located in medically underserved areas or populations. On the other hand, counties in the South, Southwest, and Northwest tended to have lower racial-gender equity. They were also more likely to be located in medically underserved areas or populations.

**Descriptive Statistics**

Table 4.1 illustrates the descriptive statistics of the dependent and explanatory variables by racial-gender equity score. Overall, most counties across the United States
tend to be in mental health professional shortage areas. However, the representation was higher in low or moderate equity areas (58 percent) than in high-equity areas (52 percent). In terms of county and state health policies, the majority of counties tended to have a high uninsurance rate compared to the national average. They also were located in states that were more likely to adopt Medicaid expansion yet were less likely to have no paid family and medical leave policy.

These factors also varied by level of racial-gender equity. Counties with a high level of racial-gender equity were nearly twice as likely as counties with a lower level of racial-gender equity to have a low uninsurance rate and a state family and medical leave policy. They were also more likely to have adopted Medicaid expansion. As for county socio-political landscape factors, most counties were located in states with Republican governors and in primarily urban rather than mostly or entirely rural areas. On the other hand, areas with low to moderate racial-gender equity were 1.4 times more likely than high equity areas to have a Republican governor. Further, low to moderate racial-gender equity areas were nearly twice as likely to be in a mostly rural area and more than twice as likely to be in a completely rural area than high racial-gender equity areas.

In addition, most counties tended to have a lower internet access rate than the national average of 83 percent and had medically underserved areas or populations. On the other hand, counties with high racial-gender equity were more than six times more likely than counties with low racial-gender equity to have an average or high internet access rate above the national average of 83 percent. Finally, low to moderate racial-gender equity counties were more likely than high equity areas to be located in a
medically underserved area or population. Analyzing these findings suggests that there is variation by racial-gender equity in the availability of mental health professionals, in county health policies and socio-political landscape, and in the primary healthcare provider supply.

**Multivariate Results**

Table 4.2 analyzes the relationship between the level of racial-gender equity in a county and location within a mental health professional shortage area by estimating a set of binary logistic regression models.

The baseline model regresses county location in a mental health professional shortage area on the level of racial-gender equity. An analysis of this model suggests that counties with high racial-gender equity have significantly lower odds (OR = 0.749) of being in a mental health professional shortage area compared to counties with low or moderate racial-gender equity.

Model 2 adds indicators of county health policies (uninsurance rate, adopting Medicaid expansion, and having a state family and medical leave policy). Results show the importance of uninsurance rates and Medicaid expansion policies. Counties with low uninsurance rates and those that expanded Medicaid have lower odds of being in a mental health professional shortage area than those in non-expansion states with high uninsurance rates. However, even after accounting for these factors, counties with high equity maintained significantly lower odds (OR = 0.853) of being in a mental health professional shortage area than counties with low to moderate racial-gender equity.
Model 2 accounts for compositional differences between counties with high and low racial-gender equity, along with the greater tendency for high racial-gender equity counties to have a lower uninsurance rate, have adopted Medicaid expansion, and have a state family and medical leave policy. However, these differences largely did not affect the mental health provider supply gap between high and low racial-gender equity areas. Overall, an analysis of model 2 suggests that accounting for county health policy factors increased the mental health provider supply gap based on the level of racial-gender equity.

In Model 3, adding county socio-political landscape indicators made this model the best fit for the data. Accounting for these indicators eliminated the mental health provider supply gap by racial-gender equity. The state governor's political party was the primary macrolevel mediator variable that explained this relationship. In addition, household internet access, a microlevel indicator, also explained the relationship between racial-gender equity and the mental health provider supply. Areas with average or higher levels of internet access compared to the national average had lower odds of being in a mental health professional shortage area than those with low internet access.

Finally, accounting for the primary healthcare provider supply in Model 4 resulted in similar findings to Model 3; the relationship between racial-gender equity and mental health professional shortage areas was no longer significant. Though Model 4 was not the best fit for the data, substantively examining the model highlights that counties located in mostly rural areas had lower odds of being in a shortage area compared to counties located in mostly urban areas. Further, analyzing the model demonstrates that a location
in a medically underserved area increased the odds of a county being in a mental health professional shortage area.

Overall, analyzing these results demonstrates that if county health policies, socio-political landscapes, and primary health care provider supply were equal, there would be no difference in counties' mental health professional supply. Further, the political affiliation of policymakers, the types of policies counties enact, and the distribution of access to the internet that could result in access to telemedicine services explain the relationship between racial-gender equity in a county and the mental health provider supply.

Discussion

Though the literature provides important insights on the sources of inequities in mental health outcomes, more work is needed that tests how structural racism manifests in policies (Riley 2018; Sewell 2016) that shape the geographic availability of healthcare, which can impact broader health outcomes, at the mesolevel. The present study explored this issue by examining the relationship between an area’s level of racial-gender equity and the mental health provider supply. By understanding how racism is made real at the mesolevel, particularly through policies structured on antiblackness, this study contributes to understandings of the role of structural racism in spatially impacting access to healthcare. Further, it highlights how place matters because of structural racism’s manifestation through institutionalized policies.

Overall, an analysis of the sociodemographic maps demonstrated a clear spatial distribution of racial-gender equity across counties in the United States. Counties
primarily in the South and Southwest, Alaska, Hawaii, and parts of the West with low to moderate racial-gender equity experienced the spatial effects of structural racism in greater concentrations than counties in other regions. In addition, counties with low to moderate racial-gender equity were more likely to be in mental health professional shortage areas and medically underserved areas and populations. These findings confirm prior research that areas with lower incomes, in rural communities, and with higher concentrations of residents racially and ethnically classified as Black or Hispanic tend to have less access to healthcare (Anderson 2018; Cummings et al. 2017; Cook et al. 2013; Finch et al. 2010; Guerrero and Kao 2013; Kalb et al. 2021; Kirby and Kaneda 2005; Lee et al. 2020; Miranda et al. 2020; Oluwoye et al. 2021; Sherry et al. 2021; VanderWielen et al. 2015).

Many of the counties located in areas with low to moderate racial-gender equity were also less likely to adopt Medicaid expansion, and 67 percent of the states in which counties with lower racial-gender equity were located had Republican governors (Eagleton Institute of Politics 2021). In turn, analyzing these findings confirms and extends Sewell's (2016) racism-race reification process (R3p) theory that the actions of policymakers shape not only health outcomes but also counties' access to resources and the availability of healthcare.

Further, the sociodemographic map findings align with the relative deprivation literature and Sewell's R3p theory. In counties with lower racial-gender equity on the dimensions of economic security, readiness, and connectedness, institutionalized racism
at the mesolevel and the actions of those in power shape sources of disadvantage (Sewell 2016; Stewart 2006).

The key macrolevel factor accounting for the relationship between racial-gender equity and the mental health provider supply was having a Democratic governor. This finding aligns with and extends the racism-race reification process model's (R3p) tenet that "institutional (in)actions" (Feagin 2013, qtd. in Sewell 2016:419) shape the availability of health care and health outcomes. Further, adopting Medicaid expansion and the uninsurance rate also helped explain the relationship between racial-gender equity and access to care. This finding highlights the R3p model's theory that decision-makers at the mesolevel's political philosophies – and policies in response to them – can either exacerbate or curtail racial inequities (Sewell 2016). The finding also connects R3p with the relative deprivation literature by demonstrating how racial inequality is magnified and made real in highly unequal contexts.

In addition, this finding also confirms the structural theories of race that describe the racialized social system (Bonilla-Silva 1997) and the racial contract (Mills 1997:7). Unpacking the system of structural racism into components that are then aggregated provides an avenue for empirically testing the factors that explain racial-gender (in)equities. The county becomes a space where racialized social systems are enacted. This study shows how structural racism undergirds the structures that govern the domain of access to healthcare. Further, the finding confirms the racial contract theory's concept of racism as a political system based on an agreement among those in power on who is considered human and, in turn, who deserves full access to resources (Mills 1997:7).
In a departure from prior literature (Oluwoye et al. 2021; VanderWielen et al. 2015), the study demonstrates that completely rural counties had lower odds of being in a mental health professional shortage area. Thus, rurality did not necessarily correlate with the level of racial-gender equity. This finding shows that racial-gender equity in an area does not necessarily serve as a proxy for urbanism.

Finally, internet access was the main microlevel factor associated with the availability of mental health care. This finding confirms work from prior studies that indicates that lower internet access may impact patient access to connecting with healthcare providers through telemedicine (Hughes et al. 2019; Ramos and Chavira 2019). In the wake of the COVID-19 pandemic, this result is particularly salient for closing the healthcare access gap.

**Implications**

Overall, the study contributes to the literature in several ways. First, it provides an aggregate measure of structural racism that includes multiple socioeconomic and environmental factors marshaled from multiple data sources. An aggregate measure operationalizes the core tenet of structural theories of race: structural racism is a pervasive system that affects multiple societal institutions. This measure allows for insights into the spatial distribution of inequality in counties, an underappreciated source of inequality.

I also demonstrate the utility of using counties as a unit of analysis (Riley 2018). County-level data allow an examination of mesolevel policy decisions that can impact access to care. Further, the study's sociodemographic maps provide a way to visualize
spatial inequality that tables alone may not convey (Pinto-Coelho and Zuberi 2015). Analyzing the maps also demonstrates that place matters to an extent in the availability of mental healthcare. However, policies and decision-makers play an even more significant role in shaping access to mental healthcare and the level of racial-gender equity in an area. Visualizing how stakeholders' policies codify racism at the mesolevel can help support inferences about the reasons for inequities in health outcomes at the macrolevel.

This research also builds on the relative deprivation literature by highlighting that racially marginalized communities in highly unequal counties may experience a greater burden of structural racism because of the spatial distribution of inequality. It also highlights that internet access, a microlevel factor that could impede access to telemedicine (Hughes et al. 2019; Ramos and Chavira 2019), may also affect the availability of mental health providers.

Finally, the study demonstrates how racism – a political-economic system and tool of white supremacy – is made tangible at the mesolevel. The study also provides insight into how institutional racism manifests in counties by demonstrating the ways that health policies affect the availability of healthcare (Miranda et al. 2020). Inequality is ingrained in the foundation of institutions; it is systemic. Further, inequality is also systematic, given that it methodically operates on the premise of anti-Black racism. By providing insights into where concentrations of spatial inequality do and do not occur, this study illuminates how institutionalized racism operates at the mesolevel, which has implications for how it functions at the macrolevel.

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19 I credit LaSha Patterson-Verona with this observation.
Future research could examine additional political-economic factors that may shape access to healthcare. In particular, studying and collecting data on the policies of county commissioners, city council members, and other local officials could provide further insight into how structural racism functions at the mesolevel. Local election dynamics are understudied (Marschall and Lappie 2018), often due to data limitations (Rice University LEAP 2022). However, with the rise of more local elections data (Rice University LEAP 2022), a better understanding of their dynamics could provide further insight into the effects of governance on the relationship between racial-gender equity and the mental health professional supply.

In addition, future studies could include additional indicators of structural racism such as time poverty (Warren 2003), the concentration of contact with the law or police, and the level of access to public transportation in racial-gender equity indices. These indicators could provide additional context on how the differences between areas with low or high racial-gender equity affect the mental health provider supply.

Finally, future research could continue building on an intersectional approach to indices of structural racism. Barring data limitations on indicator information by racial and ethnic classification, sex, and class, an intersectional index that merges the concepts of structural racism and other compounding forms of inequity could show how evenly resources are distributed in multiple dimensions. By continuing to explore the dynamics of structural racism and access to healthcare, such research can contribute to dismantling this system of stratification.
References


Tables and Figures

Figure 4.1: Conceptual Model
Figure 4.2: Racial-Gender Equity Scores of U.S. Counties
Figure 4.3: Mental Health Professional Shortage Area (HPSA) by U.S. County
Figure 4.4: Medically Underserved Areas & Populations in the U.S.
Table 4.1: Descriptive Statistics of Dependent and Explanatory Variables

<table>
<thead>
<tr>
<th>Variables (%)</th>
<th>Low or Moderate Racial-Gender Equity (Equity Score: 35-60)</th>
<th>High Racial-Gender Equity (Equity Score: 81 and above)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental Health Professional Shortage Area&lt;sup&gt;a&lt;/sup&gt;</td>
<td>58</td>
<td>52</td>
</tr>
<tr>
<td>Low Uninsurance Rate (&lt;10%)</td>
<td>34</td>
<td>67</td>
</tr>
<tr>
<td>County's State Adopted Medicaid Expansion</td>
<td>56</td>
<td>70</td>
</tr>
<tr>
<td>County Has State Family &amp; Medical Leave Policy</td>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>County's State Governor Political Party</td>
<td>Democrat</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Republican</td>
<td>66</td>
</tr>
<tr>
<td>County Urban or Rural Designation&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Mostly Urban (Less than 66.8% Rural)</td>
<td>51</td>
</tr>
<tr>
<td></td>
<td>Mostly Rural (66.9% to 99% Rural)</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>Completely Rural (100% Rural)</td>
<td>24</td>
</tr>
<tr>
<td>Average or High Internet Access Rate (&gt;83%)</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Medically Underserved Area or Population&lt;sup&gt;c&lt;/sup&gt;</td>
<td>93</td>
</tr>
</tbody>
</table>

N 1,658 1,195

Sources: Kaiser Family Foundation, 2022; Area Health Resources Files (Mental Health Professional Shortage Area and Medically Underserved Areas/Populations, 2021; County Health Rankings, 2021.

Notes: <sup>a</sup>The racial-gender equity measure comes from the Index of Racial and Gender Equity, a composite score partially based on the Racial Equity Index (PolicyLink and USC Equity Research Institute 2020) that explains where each county falls overall and by race and ethnicity on the following sets of indicators: (1) Economic Security [Employment rate, median household income, and educational attainment]; and (2) Socio-Spatial Connectedness [broadband internet access]). The indicator names and components are also partially based on the National Equity Atlas’ Racial Equity Index.

<sup>b</sup>The Mental Health Professional Shortage Area (MHPSA) variable comes from the average MHPSA score for each county. The average MHPSA score was calculated by estimating the mean HPSA score for each county's census tracts. The final score was converted into a categorical variable that measures (1) non-shortage areas and (2) designated MHPSAs.

<sup>c</sup>Following 2016 Census guidelines on defining rural areas (Ratcliffe et al. 2016), this study designates counties as (1) mostly urban; (2) mostly rural; and (3) completely rural; given that a county’s population can have a combination of urban and rural areas. The numerical groupings for each category are also based on the Census guidelines.

<sup>d</sup>Medically Underserved Areas and Populations refer to areas or populations in the United States that are experiencing a primary health care service shortage. Following the Health Resources & Services Administration’s guidelines, counties receive this designation based on their Index of Medical Underservice (IMU) Score. This study calculated an average IMU score for all census tracts within each county. Medically underserved counties have an average IMU score below 62, while counties that are not medically underserved have an average IMU score above 62.
Table 4.2: Multivariate Results for Mental Health Professional Shortage Areas

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental Health Professional Shortage Area (Ref: Non-Shortage Area)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Racial Equity (Ref: Low/Moderate Racial Equity)</td>
<td>0.749*** (-3.78)</td>
<td>0.853* (-1.96)</td>
<td>0.908 (-1.08)</td>
<td>0.917 (-0.96)</td>
</tr>
<tr>
<td>Low Uninsurance Rate (Ref: High Uninsurance Rate)</td>
<td>0.583*** (-5.59)</td>
<td>0.624*** (-4.70)</td>
<td>0.629*** (4.61)</td>
<td></td>
</tr>
<tr>
<td>Adopted Medicaid Expansion (Ref: Did Not Adopt Medicaid Expansion)</td>
<td>0.723*** (-3.36)</td>
<td>0.724*** (-3.34)</td>
<td>0.716*** (-3.43)</td>
<td></td>
</tr>
<tr>
<td>Family and Medical Leave Policy (Ref: No Family and Medical Leave Policy)</td>
<td>0.994 (-0.04)</td>
<td>1.148 (0.99)</td>
<td>1.143 (0.95)</td>
<td></td>
</tr>
<tr>
<td>Democratic Governor (Ref: Republican Governor)</td>
<td>0.806* (-2.43)</td>
<td>0.800* (-2.51)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urbanism (Ref: Mostly Urban Area)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mostly Rural Area</td>
<td>0.816* (-2.00)</td>
<td>0.808* (-2.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Completely Rural Area</td>
<td>0.985 (-0.14)</td>
<td>0.975 (-0.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average/High Internet Access (Ref: Low Internet Access)</td>
<td>0.790* (-2.15)</td>
<td>0.796* (-2.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medically Underserved Area (Ref: Not a Medically Underserved Area)</td>
<td></td>
<td></td>
<td></td>
<td>1.170 (1.31)</td>
</tr>
</tbody>
</table>

Observations: 2,853 2,853 2,853 2,853

Sources: County Health Rankings, 2021; Kaiser Family Foundation, 2022; Area Health Resources Files (Mental Health Professional Shortage Area and Medically Underserved Areas/Populations, 2021

T statistics are in parentheses. Models were compared using likelihood ratio tests.

† p < .10; * p < .05; **p < .01, *** p < .001 (two-tailed tests).
Appendices

Appendix 4.A: Index of Racial-Gender Equity Measure Construction

Measure Description

I constructed the IREQ by using the methodology and some indicator names\textsuperscript{20} from the National Equity Atlas’ Racial Equity Index (REI), a new composite indicator of state, county, and metropolitan areas’ progress toward equity across nine economic, educational, and environmental indicators.\textsuperscript{21} The IREQ includes fewer indicators than the REI to allow for more counties in its analysis.\textsuperscript{22}

Exploratory Factor Analysis for the Index of Racial-Gender Equity

To determine which sets of indicators would be most meaningful for constructing the IREQ, I conducted an exploratory factor analysis for four variables of interest: unemployment, some college education, median household income, and severe housing cost burden. Illustrated in Appendix 4.B, an analysis of these variables demonstrated that two factors – the unemployment rate and some college education – explained a combined 74 percent of the total variance observed. Severe housing cost burden and some college education primarily defined the unemployment rate factor. This factor had an eigenvalue of 1.90 and explained 48 percent of the total variance observed. Next, the education factor, which had an eigenvalue of 1.07 and explained 27 percent of the total variance, was defined by median household income and severe housing cost burden. This analysis

\textsuperscript{20} The REI is a composite score made up of an overall prosperity score and an inclusion score that identifies overall progress and gaps by racial and ethnic classification in (1) Economic Vitality (wages, poverty, and unemployment); (2) Readiness (educational attainment, high poverty schools, and percentage of youth ages 16-24 not working or in school); and (3) Connectedness (air pollution exposure, commute time to work, and rent burden).

\textsuperscript{21} The REI uses data from the American Community Survey, the United States Census, the National Center For Education Statistics, and the Environmental Protection Agency.

\textsuperscript{22} The REI includes information on the 430 largest counties in the United States.
suggests that all four variables – particularly unemployment and some college education – were relevant to the IREQ.

Measure Construction

I followed the same methodology as the National Equity Atlas study investigators to construct this study's IREQ. The single composite score for each geographic area that I use for the IREQ is made up of an overall prosperity and inclusion score. I obtained the prosperity scores by identifying the overall population values for each indicator. On the other hand, inclusion scores use the Index of Disparity (Pearcy and Keppel 2002) to measure how evenly prosperity is distributed for groups classified by race, ethnicity, and, where possible, sex. Mathematically, the Index of Disparity "averages the absolute value of the differences between each group and the overall population and expresses it as a percentage of the overall population value" (National Equity Atlas 2022). See Appendix 4.D for the Index of Disparity formula.

After obtaining the raw prosperity and inclusion scores for each indicator, I standardized them to ensure that all variables were measured on the same scale. I then reversed the sign of the standardized values for unemployment, severe housing cost burden, the ratio of household income inequality, and all the index of disparity variables so that higher values would indicate more inequality. Next, I normalized the indicator values using min-max scaling to have a more interpretable range of 0 to 1. I then reset the values from 0 to 100 to easily divide the index into categories and follow the REI's methodology of expressing scores as "a percentage of the range between the minimum
and maximum score” (National Equity Atlas 2022). Further, I reset values below 1 to 1 so that the final range was from 1 to 100.

Next, I calculated the geometric mean\(^{23}\) of the resulting scores across the indicators in each category (Economic Security, Readiness, and Connectedness) to obtain final inclusion and prosperity scores for each category. I then calculated the geometric mean of the category scores to arrive at overall inclusion and prosperity scores for each county. Finally, I calculated the geometric mean for each region's overall prosperity and inclusion scores to obtain a single composite score for each county. This final set of scores represents the values of the IREQ.

\(^{23}\) In contrast to the arithmetic mean, the geometric mean is calculated by multiplying a set of values and then taking the \(n^\text{th}\) root of the resulting product. The National Equity Atlas study investigators chose to use the geometric mean to ensure that counties would only receive a high Racial Equity Index score if they had high prosperity and inclusion scores for each indicator (National Equity Atlas 2022).
### Appendix 4.B: Exploratory Factor Analysis Results for Index of Racial-Gender Equity Measure

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor 1 (Unemployment Rate)</th>
<th>Factor 2 (Educational Attainment)</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Rate</td>
<td>-0.673</td>
<td>0.376</td>
<td>0.406</td>
</tr>
<tr>
<td>Educational Attainment (Some College)</td>
<td>0.850</td>
<td>0.132</td>
<td>0.260</td>
</tr>
<tr>
<td>Median Household Income</td>
<td>0.852</td>
<td>0.008</td>
<td>0.274</td>
</tr>
<tr>
<td>Severe Housing Cost Burden*</td>
<td>0.031</td>
<td>0.956</td>
<td>0.085</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Variance Explained (%)</th>
<th>Cumulative Variance Explained (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Rate</td>
<td>48</td>
<td>48</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Household Income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Severe Housing Cost Burden*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sources: Kaiser Family Foundation, 2022; Area Health Resources Files (Mental Health Professional Shortage Area and Medically Underserved Areas/Populations, 2021); County Health Rankings, 2021.

Notes: Factor loadings were rotated using the orthogonal varimax (Kaiser off) technique for ease of interpretation.

*The severe housing cost burden item measures the percentage of households that spend 50 percent or more of their household income on housing.
Appendix 4.C: Distribution of Average Mental Health Professional Shortage Area (MHPSA) Score

\[ ID = \frac{\sum [r_i - R]/n}{R} \cdot 100 \]
## Appendix 4.E: Multiple Imputation Results

### Appendix 4.E: Multiple Imputation Results, Odds Ratios of Mental Health Shortage Areas by Racial Equity

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental Health Shortage Area (Ref: Non-Shortage Area)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Racial Equity (Ref: Low/Moderate Racial Equity)</td>
<td>0.749***</td>
<td>0.853*</td>
<td>0.906</td>
<td>0.916</td>
</tr>
<tr>
<td></td>
<td>(-3.78)</td>
<td>(-1.96)</td>
<td>(-1.10)</td>
<td>(-0.98)</td>
</tr>
<tr>
<td>High Uninsurance Rate (Ref: Low Uninsurance Rate)</td>
<td>1.714***</td>
<td>1.616***</td>
<td>1.603***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.59)</td>
<td>(4.70)</td>
<td>(4.71)</td>
<td></td>
</tr>
<tr>
<td>Adopted Medicaid Expansion (Ref: Did Not Adopt Medicaid Expansion)</td>
<td>0.723***</td>
<td>0.720***</td>
<td>0.712***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.36)</td>
<td>(-3.41)</td>
<td>(-3.50)</td>
<td></td>
</tr>
<tr>
<td>Family and Medical Leave Policy (Ref: No Family and Medical Leave Policy)</td>
<td>0.994</td>
<td>1.154</td>
<td>1.148</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.04)</td>
<td>(1.02)</td>
<td>(0.99)</td>
<td></td>
</tr>
<tr>
<td>Democratic Governor (Ref: Republican Governor)</td>
<td>0.805*</td>
<td>0.800*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.45)</td>
<td>(-2.52)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Urbanism (Ref: Mostly Urban Area)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mostly/Completely Rural Area</td>
<td>0.890</td>
<td>0.882</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.38)</td>
<td>(-1.49)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Internet Access (Ref: Average/High Internet Access)</td>
<td>1.26*</td>
<td>1.253*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.13)</td>
<td>(2.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medically Underserved Area (Ref: Not a Medically Underserved Area)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.172</td>
<td></td>
<td>(1.33)</td>
<td></td>
</tr>
</tbody>
</table>

### Observations

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>2,853</td>
<td>2,853</td>
<td>2,853</td>
<td>2,853</td>
</tr>
</tbody>
</table>

**SOURCES:** County Health Rankings, 2021; Kaiser Family Foundation, 2022; Area Health Resources Files (Mental Health Professional Shortage Area and Medically Underserved Areas/Populations, 2021

T statistics are in parentheses. Models were compared using likelihood ratio tests.

† p < .10; * p < .05; **p < .01; *** p < .001 (two-tailed tests).

Note: *Overall, nine percent of the county observations in the racial equity variable were missing. Further analysis revealed that all the missing observations, a combined 17.5 percent of them were mostly or completely rural. To determine if these missing cases biased the findings, I used multiple imputation using the multivariate normal distribution (MVN) technique. These results are from my analysis using the multiply imputed data.*
CHAPTER 5: CONCLUSION

This dissertation has shown that structural racism is a system that pervades all domains of society. It demonstrates the critical role that stakeholders play in maintaining systems of inequality through policy. Further, the dissertation unpacks how some of the components of structural racism affect health outcomes, healthcare utilization, and access to care.

This dissertation has several implications. First, structural racism, at its core, centers on systematically maintaining white supremacy. Thus, its dimensions are complex and can be challenging to pinpoint. This dissertation contributes to research in this area by examining aspects of structural racism in one domain, health, to provide insights into how this system may function in other areas of society.

In addition, by empirically testing critical perspectives on racism, this dissertation shows how racism permeates each aspect of society. The chapters help highlight the work of critical theorists, which suggests that placement in the racial hierarchy – and the benefits and resources associated with it – are an outcome of the process of racial stratification, a tool of white supremacy.

Future research can study other political-economic dynamics that may explain access to care. Studies can also empirically test measures of racialized oppression – whether through policy, treatment inequities, or measures of equity for racially and ethnically classified groups. Such studies can enrich understandings of the components of structural racism in empirical work. Further, future research can continue to consider the effect of place on health inequities, particularly through spatial analysis of city, county, and state dynamics.
This dissertation has demonstrated that structural factors such as racial inequities in treatment and potential forms of harm such as potential contact with the law or police can affect behavioral health outcomes. In addition, the dissertation shows that anti-Black racism codified into health and drug policies shapes inequities in behavioral health care utilization at the patient level and access to mental healthcare at the county level. Overall, this dissertation has shown that unpacking the impact of structural racism’s many components on healthcare use and healthcare access can illuminate the factors that drive the sources of inequities in health outcomes.