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ABSTRACT

UNDERSTANDING RACIALIZED COVID-19 HEALTH DISPARITIES: INTERACTIONS OF PHYSICAL ENVIRONMENT, SOCIAL STRUCTURE, AND MENTAL HEALTH CONSEQUENCES

By

SURESH NATH NEUPANE

AUGUST, 2024

Committee Chair: Dr. Erin Ruel

Major Department: Urban Studies

This dissertation examines the uneven impacts of the COVID-19 pandemic on racialized populations through differential exposure and differential effects. It analyzes how variations in physical and social environments contribute to disparities in COVID-19 mortality among racialized groups and explores the differential effects on mental health across racial lines.

The first chapter investigates the impact of urban physical and social factors, such as air pollution and social vulnerability, on COVID-19 mortality disparities. It finds that environmental hazards, particularly urban air pollution, increase mortality risks for Blacks and Hispanics. Data from five sources, including the CDC's COVID-19 Case Surveillance, and EPA's EJscreen, were used, covering 1,526,418 cases.

The second chapter examines the urban-rural divide in COVID-19 health outcomes, considering physical and social environments. The chapter identifies significant differences in mortality driven by variations in healthcare access and demographics. The study highlights the need to address healthcare disparities and environmental justice to mitigate the pandemic's impact on rural areas. Data from sources, including the CDC's and County Health Rankings & Roadmaps, were analyzed, with a final sample of 1,611,874 observations.

A multilevel logistic regression analysis was conducted for both chapters. Chapter 1 examined the relationship between air pollution, socioeconomic and health variables, and COVID-19 mortality in urban settings, while Chapter 2 focused on the urban-rural divide. The logistic regression model accounted for the hierarchical structure of the data, with individual-level observations nested within counties.

The third chapter explores the differential effects of COVID-19 on mental health, focusing on how socioeconomic factors and racial inequalities influence anxiety and depression. The study finds that despite higher SES Blacks do not benefit equally in mental health outcomes compared to Whites. Data from the Household Pulse Survey were used, covering 885,495 observations.

This dissertation shows that racial minorities face increased risks of COVID-19 health outcomes due to environmental and social vulnerabilities, demonstrating how physical and social environments, combined with pre-existing conditions, shape health outcomes for racialized populations. These groups also experience mental health consequences influenced by SES. This dissertation highlights the need to address systemic inequities and environmental risks to improve health outcomes for vulnerable populations.

UNDERSTANDING RACIALIZED COVID-19 HEALTH DISPARITIES: INTERACTIONS OF PHYSICAL ENVIRONMENT, SOCIAL STRUCTURE, AND MENTAL HEALTH CONSEQUENCES

BY

SURESH NATH NEUPANE

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

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2024

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Urban Studies in the Andrew Young School of Policy Studies of Georgia State University.

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AUGUST, 2024

Dedication

To my beloved parents, Bhagawati Neupane and Kashinath Neupane.

Acknowledgments

Reflecting on my journey, I am immensely grateful to my advisor, Dr. Erin Ruel, for her support. She has played a crucial role in helping me pursue my passion for quantitative research in social science. Without her guidance, I would not have had the confidence to take on this challenge. Her encouragement has been a constant source of motivation for me. I am truly grateful for her mentorship and the opportunity to learn from her expertise.

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Introduction

The global COVID-19 pandemic has had a profound impact on communities worldwide, disproportionately affecting racial minorities due to a host of factors, including but not limited to unequal access to healthcare, vaccine hesitancy, and systemic racism within the healthcare system (Willems et al., 2022). Furthermore, variations in pandemic impact are also observed across geographic landscapes, with higher mortality and infection rates in rural areas compared to urban regions (Cuadros et al., 2021; Karim & Chen, 2021). The COVID-19 pandemic's fallout, marked by massive job losses and the constant fear of COVID-19 infections, exacerbated its potential impact on the mental health of the population (Cao et al., 2020; de Miquel et al., 2022; Georgetown University, Center on Education and the Workforce, 2022; Tull et al., 2020).

An inquiry from an urban health perspective appears to be the most effective approach in explaining the relationship between urban environments and population health, as both are conditioned by urban life (Vlahov et al., 2007). This underscores the importance of considering both social and physical environments in shaping the well-being of urban residents (L. Liu, 2019; Northridge & Sclar, 2003; Ompad et al., 2008).

This dissertation, built upon a socio-epidemiological perspective, emphasizes such vital roles played by the physical and social dimensions of the urban environment, in examining the COVID-19 health impact among racialized populations. In this research, each article investigates the racialized disparities in health outcomes, which can be attributed to two distinct pathways: differential exposure and differential effect (Jackson & VanderWeele, 2019). Differential exposure encompasses the study of unequal social or environmental exposures and their impact on health outcomes, a focus of inquiry in Chapters 1 and 2. Likewise, differential effect pertains to disparities in health outcomes arising from socioeconomic factors. Chapter 3 specifically focuses on exploring the differential effect on mental health due to the influence of social and economic conditions on mental health during the COVID-19 pandemic (Assari, 2018; Diderichsen et al., 2019).

Chapter 1 probes into the link between physical and social factors of the urban environment, and racial disparities in COVID-19 mortality outcomes. Specifically, the study examines how factors like air pollution and environmental hazards impact racial groups' vulnerability to the virus. This study's theoretical justification is based on the extensive literature linking the physical environment to population health, with poor urban health outcomes associated with negative physical environments created by pollutants from hazardous waste, air, and other sources (Laumbach et al., 2015; Manisalidis et al., 2020; Satterthwaite, 1993), and urban infrastructures built for the well-being or economic benefits of communities (Ompad et al., 2008). Research suggests that the physical environment can play a significant role in COVID-19 outcomes (Bluhm et al., 2022; Collins et al., 2022), but its intersection with racial disparities requires further investigation.

Simultaneously, the chapter investigates the role of social structural factors such as social vulnerability and racial residential segregation in shaping COVID-19 mortality disparities. The pandemic's impact extends beyond individual behaviors, and understanding how social vulnerability interacts with race is essential (Barry et al., 2021; Dasgupta et al., 2020). By considering both the physical and social dimensions, this chapter aims to shed light on the multifaceted nature of racial disparities in COVID-19 outcomes.

In Chapter 2, the focus shifts to understanding the urban-rural divide in COVID-19 health outcomes. Urban and rural environments have distinct characteristics that likely influence disparities in COVID-19 outcomes. The pandemic's impact in urban areas, characterized by high population density, economic activities, and unique social dynamics, differs from its impact in rural settings (Huang et al., 2021; Ma et al., 2023). Research has shown that rural ethnic minorities, particularly Blacks and Hispanics, face unique socioeconomic disparities compared to rural Whites, contributing to differences in urban-rural distribution (C. V. James, 2017; U.S. Department of Agriculture, 2020b). Rural areas with larger Black and Hispanic populations have also exhibited pronounced racial disparities in COVID-19 fatality ratios, highlighting the need for a deeper understanding of these disparities (Millett et al., 2020; Iyanda et al., 2022). Urban health research, which also involves comparing cities, examining urban-rural health, and conducting area-level comparisons (Galea et al., 2005), justifies studying urban-rural health disparities. This study uncovers the role of factors such as healthcare access, food environment, income inequality, and controlling for physical environmental conditions, that shape COVID-19 disparities across these geographical settings.

Finally, Chapter 3 focuses on the racialized differential effects of COVID-19 on mental health, considering social and economic factors. This study aims to bring to light the disparities in mental health outcomes, particularly during the COVID-19 pandemic. This chapter investigates how the pandemic, with its various stressors such as job losses, COVID-19 infections, and financial hardship, among other socioeconomic status (SES) and demographic factors, has led to an increase in anxiety and depression among racialized populations. Furthermore, it examines the effects stemming from health events, seeking to determine the extent of mental health disparities among racialized populations during the COVID-19 pandemic.

Chapter I: Examining the Effects of Urban Physical Environment and Social Structural Factors on Racial Disparities in COVID-19 Mortality

1.1 Introduction

The coronavirus disease (COVID-19) caused by SARS-CoV-2 virus, emerged as a global pandemic in early March 2020, resulting in over 1.1 million deaths and nearly 100 million infections in the United States alone by May 11, 2023, when the national emergency ended (CDC, 2023a; USAFacts, 2022). Racial minorities, particularly Black patients, experienced heightened risks of hospitalization and death (Mackey et al., 2021; Poulson et al., 2021), prompting an investigation into social and environmental factors influencing COVID-19 health outcomes. As the pandemic began to cripple the world with unprecedented challenges, understanding infectious disease dynamics became crucial. This study examines the relationship between macro-environmental elements like air pollution, social vulnerability, and individual-level COVID-19 mortality. Focusing on racial minorities, the research sheds light on the potential pathways contributing to racialized health disparities.

Research indicates that the influence of macro-environmental factors extends beyond individual behaviors to shape health outcomes. Investigating connections between the physical environment, including air pollution (Bluhm et al., 2022; Collins et al., 2022), and social elements such as social vulnerability (Barry et al., 2021; Dasgupta et al., 2020) is vital to understanding racial disparities in COVID-19. In addition, considering individual-level variables is essential, given disease expression and neighborhood impact on health through individual-level processes (Diez Roux, 2001).

Probing health equity involves understanding how race and social determinants contribute to urban health disparities. While health equity research often targets chronic conditions (Cooper, 2001; Kimm et al., 1996), the pronounced impact of COVID-19 on racial minorities (Clark et al., 2020; Krishnamoorthy et al., 2021) underscores the need to explore social determinants driving infectious disease disparities. Unlike chronic diseases, the airborne transmission nature of COVID-19 affects all races and genders. Still, racial disparities seen in COVID-19 mortality prompt investigation into whether factors causing chronic health disparities also affect unequal infectious disease outcomes. For instance, the enduring prevalence of residential segregation, a marker of systemic racism, has links to racialized chronic health outcomes (Bailey et al., 2021; Hart et al., 1998; Hayanga et al., 2013; Kramer & Hogue, 2009) and similarly shaped the health impact of COVID-19 (Neupane & Ruel, 2023). The argument of the significance of systemic structural inequities as key drivers of health disparities is further supported by Dressler et al., (2005), who assert that attributing racial disparities in chronic conditions solely to biological and lifestyle differences is inadequate. Moreover, health disparities are interconnected with social determinants of health (SDOH), underscoring the importance of investigating how disparities reflect the influence of race as a social category (D. R. Williams, 2012).

In order to understand the specific urban factors encompassing both physical and social environments, this study addresses the following research question: How do urban environments, characterized by underlying physical (e.g., pollution) and social mechanisms (e.g., social vulnerability, crime) contribute to disparities in COVID-19 mortality among racial groups?

The unit of analysis of this study is at the individual level, incorporating nationwide data that also includes county-level geographic information. By integrating five datasets—such as those from the CDC's Case Surveillance Task Force, the Surveillance Review and Response Group's dataset on COVID-19, and the Environmental Protection Agency's environmental justice dataset —and employing multilevel modeling techniques, this study demonstrates how specific urban physical and social factors contribute to disparities in COVID-19 mortality among racialized groups. This study acknowledges the limitations[1] of using county-level measures, which can introduce biases due to the use of spatially aggregated data.

This research aims to highlight the links between urban environmental elements and racial disparities in COVID-19 mortality. By integrating both the physical and social aspects of urban settings, this study demonstrates how these factors collectively influence health outcomes. By combining factors such as underlying medical conditions with prominent environmental and social drivers, this study seeks to illuminate the challenges faced by racial minority communities during the pandemic.

1.2 Literature Review

Numerous studies have linked negative physical environments in urban areas to poor health outcomes for residents (Laumbach et al., 2015; Manisalidis et al., 2020; Satterthwaite, 1993). The accumulation of effects of built environments on health may play a significant role in shaping the health outcomes of urban populations (Spring, 2018). Understanding the impact of the physical environment on population health, including the associations between urban pollution, and health outcomes, provides insights for improving urban spaces and promoting the health of urban populations.

1.2.1 COVID-19

COVID-19 is a zoonotic virus that spreads between humans and animals (CDC, 2020b). COVID-19 is very contagious and spreads mainly from person to person through respiratory

[1] A robust discussion of the limitations of using county-level measures in both Chapters 1 and 2 is provided at the end of Chapter 2 before the start of Chapter 3.

droplets (CDC, 2020a). The COVID-19 pandemic, which began in December 2019, claimed more lives than any other pandemic since the HIV/AIDS and the 1918 “Spanish flu” pandemics over the past century (Sampath et al., 2021). Viruses continuously mutate, resulting in new variants such as the COVID-19 Delta and Omicron, which were identified and monitored as concerning in early 2021 or 2022 (CDC, 2020b).

The development of the COVID-19 vaccine saw a significant impact in controlling infections across the globe, with some vaccines exceeding a 90% reduction in documented infections (Ioannidis, 2021). The recent rollout of the COVID-19 vaccine across the globe, with more than 5.51 billion people (71.8% of the world’s population) receiving a dose of the COVID-19 vaccine as of January 8, 2023 (Holder, 2023), showed a promising global response to the pandemic.

Vaccine hesitancy, which has been on the rise due to autism concerns and social media misinformation, has been exacerbated during the COVID-19 pandemic, particularly in racialized populations with a justified mistrust rooted in historical medical abuses such as the Tuskegee experiments (H. J. Larson et al., 2022; Puri et al., 2020; Washington, 2006). Notably, a study by Zhang et al., (2023) revealed key associations: Black participants exhibited 3 times higher odds of vaccine hesitancy compared to their white counterparts, individuals identifying their religion as "Other" had 2.8 times higher odds relative to those of Catholic or Orthodox faith, and Republicans displayed 2.3 times greater odds in comparison to Democrats.

The spread of COVID-19, vaccine development, and vaccine hesitancy issues, particularly among racialized groups, underscore the need for multilayered public health strategies. Recognizing and addressing these challenges are essential steps in developing policies that aim to reduce racial disparities in health outcomes and ensure equitable access to healthcare resources in urban settings.

1.2.2 COVID-19 Disparities

The COVID-19 pandemic has disproportionately impacted racial minorities, with Black and Hispanic individuals experiencing higher relative risks of testing positive, of hospital admissions, and facing increased risks of death compared to White individuals (Aschmann et al., 2022; Lundberg et al., 2022; McLaren, 2020; Millett et al., 2020; Magesh et al., 2021; Sze et al., 2020). For example, at the individual level, Blacks, Hispanics, and Asians were twice as likely as Whites to experience severe COVID-19 outcomes (Shortreed et al., 2023). Black patients had a 20% higher odds of dying from COVID-19, while Hispanic patients had a 51% higher odds of mortality, compared to Whites (Isath et al., 2023). Native Americans and Native Alaskans also face higher COVID-19 mortality (Bassett et al., 2020).

At aggregate population levels, we witness similar findings, predominantly Black counties, which represent nearly 20% of US counties, experienced threefold infection rates and nearly sixfold death rates compared to predominantly White counties (Garg et al., 2020; Hooper et al., 2020; Millett et al., 2020; Scott, 2020; Yancy, 2020). Furthermore, Black counties with an increased prevalence of comorbidities, such as diabetes (14%) and hypertension (45%), also exhibited a heightened susceptibility to COVID-19 mortality (Kodsup & Godebo, 2023). Moreover, Dukhovnov & Barbieri, (2021) reveals a changing socio-economic gradient in COVID-19 mortality in U.S. counties during the pandemic, with affluent areas initially experiencing higher mortality rates that later reversed, leading to a 2.58-fold increase in COVID-19 mortality in lower quintile counties compared to the top quintile in September–December 2020.

While this paper focuses on racial disparities in COVID-19, it should be noted that there were gender (Carethers, 2021; Chaturvedi et al., 2022; Danielsen et al., 2022) and age (Elezkurtaj et al., 2021; Harrison et al., 2020; Pennington et al., 2021; Zhou et al., 2020) disparities as well with men and older adults being at greater risk of mortality. Therefore, I control for gender and age in the analysis.

1.2.3 Explanations or Causes of Disparity in COVID-19 Infections

1.2.3.1 Risk Factors and Proximate Causal Explanations. Proximate causal explanations for COVID-19 mortality are pre-existing medical conditions and greater risk of exposure due to being an essential worker (Banerjee et al., 2020; Fung et al., 2021; Mutambudzi et al., 2021). Studies have shown that vaccination status is also a proximate causal factor in preventing COVID-19, as vaccines provide strong protection against the disease (Baden Lindsey R. et al., 2021; Polack Fernando P. et al., 2020) COVID-19-related cases are frequently associated with preexisting medical conditions, often compounded by SARS-CoV-2-induced lung damage, and bacterial superinfection—common in the viral influenza (Cataño-Correa et al., 2021; Elezkurtaj et al., 2021; Morens et al., 2008; van der Sluijs et al., 2010). Consistently, underlying health conditions pose greater COVID-19 severity. Ssentongo et al., (2020)'s meta-analysis further supports the association between common comorbidities like cardiovascular disease, hypertension, diabetes, and others, and an elevated mortality risk from COVID-19.

Studies have shown that comorbidities, including cardiovascular disease, hypertension, diabetes, and cancer, contribute to the potential emergence of racial disparities in COVID-19 outcomes among minority populations (Alcendor, 2020; Kodsup & Godebo, 2023; Williamson et al., 2020; Holman et al., 2020). For instance, Wiley et al., (2022) found that comorbidities such as obesity, hypertension, diabetes, and chronic kidney condition, or CKD, were more common in

Black COVID-19 patients and that explain racial disparities as mediators rather than confounders, suggesting that these disparities result from a complex relationships of race, social factors, and lifelong health conditions. Moreover, clinical research has also shown that minorities such as Hispanics, Blacks, or Asians are more likely to experience adverse lung problems due to COVID-19 infections, than Whites (Joseph et al., 2020).

During the lockdown, essential workers, driven by the need to secure their livelihoods, faced increased vulnerability due to both COVID-19 exposure and economic instability, with 22.7% earning less than US$50,000 annually (Capasso et al., 2022; Mutambudzi et al., 2021). The pandemic disproportionately impacted the young, the less educated, and racialized minorities such as Blacks and Hispanics, primarily due to their overrepresentation in essential worker roles across various occupations, where they encountered heightened exposure risk in jobs characterized by face-to-face contact and limited remote work options (Gwynn, 2021; Montenovo et al., 2022; The Lancet, 2020). Unfortunately, I cannot account for whether or not an individual was an essential worker in this study. I hypothesize that differences in co-morbidities explain some of the racial COVID-19 mortality gap.

> Hypothesis 1: COVID-19 mortality disparities may be partly attributed to variations in co-morbidities, as individuals with underlying conditions are more likely to succumb to the virus.

1.2.4 Urban Physical Environment

Ambient air pollution, including particulate matter ($PM_{2.5}$) and hazardous air pollutants (HAPs), which is also known as urban air toxics, has been extensively studied in relation to their association with various health outcomes (H. R. Anderson, 2009; Beatty & Shimshack, 2014; Pope et al., 1995). In urban areas, where the majority of the world's population resides, air pollution poses a significant health risk (Attademo & Bernardini, 2017, 2020). Multiple diseases and health risks have been associated with air pollution (Finch & Morgan, 2020; Moitra et al., 2022; Münzel et al., 2021; Rappold et al., 2012).

The federal Clean Air Act (CAA) recognizes the impacts of air pollution on human health and has established regulations to address them (EPA, 2007). The Environmental Protection Agency (EPA) sets standards for six common air pollutants, known as "criteria pollutants," including particulate matter (PM) and ground-level ozone, which pose threats to both the environment and human health (EPA, 2007). In addition, the CAA regulates a list of 187 HAPs, such as benzene (found in gasoline), perchloroethylene (emitted from some dry cleaners), and methylene chloride (used as solvent and paint stripper), among others that pose serious health risks, including cancer (Environmental Protection Agency, 2007). Unlike criteria pollutants, no safe exposure threshold has been established for HAPs (Willis & Hystad, 2019).

1.2.4.1 Particulate Matter ($PM_{2.5}$). The presence of $PM_{2.5}$, among other air pollutants, in urban areas poses a threat to the health of individuals due to their chronic and acute effects, with $PM_{2.5}$ being particularly concerning as it consists of fine inhalable particles smaller than 2.5 micrometers (Kampa & Castanas, 2008; U.S. Environmental Protection Agency, 2019). The tiny size of these particles (for comparison, human hair is around 70 micrometers in diameter, making it more than 30 times larger than each $PM_{2.5}$ particle) makes them easily inhaled into the bloodstream, and they can be composed of hundreds of different chemicals (U.S. Environmental Protection Agency, 2019). Exposure to $PM_{2.5}$ has been associated with a wide range of severe health consequences, including respiratory and cognitive health issues (Achilleos et al., 2019; Brook et al., 2010; Cheung et al., 2020; Cleary et al., 2018; Dedoussi et al., 2020; Ji et al., 2020; Pope III et al., 2019; Schwartz & Dockery, 1992; Stieb et al., 2012).

Air pollution, particularly $PM_{2.5}$, impacts public health, with over 4 in 10 Americans exposed to unhealthy air quality and about 141 million individuals residing in counties with elevated levels of air particulate matter or ozone, posing risks to respiratory health (American Lung Association, 2022). Globally, long-term $PM_{2.5}$ exposure led to 4.1 million deaths in 2019, with over 32% attributed to respiratory diseases, representing a twofold increase in $PM_{2.5}$ -related deaths compared to 1990 (Y. Wu et al., 2021). Detrimental effects extend beyond respiratory issues to cardiovascular diseases and lung cancer (Al-Aly & Bowe, 2020; Bowe et al., 2019; Cohen et al., 2017). Notably, a comprehensive Health Effects Institute review highlighted increased asthma prevalence in children exposed to air pollution, revealing an elevated risk of asthma onset (RR: 1.33, 95% CI: 0.90–1.98) associated with long-term $PM_{2.5}$ exposure, along with an 11% increased risk of low birth weight linked to $PM_{2.5}$ exposure during pregnancy (Health Effects Institute, 2022).

The mechanism by which infectious agents contribute to chronic conditions lies in their capacity to trigger inflammation, prompting a healthcare policy reorientation towards early intervention (O'Connor et al., 2006). Exposure to $PM_{2.5}$ has been linked to an increased risk of developing cardiovascular and respiratory diseases, lung cancer, and an increased risk of mortality due to various causes, including but not limited to chronic kidney disease, COPD, diabetes, and hypertension (Basith et al., 2022; Bowe et al., 2019; Brook et al., 2010; Kampa & Castanas, 2008). $PM_{2.5}$ pollution induces cardiovascular risk by activating blood clotting mechanisms and disrupting nerve control of heart function, illustrating the complex influence of urban air pollution on cardiovascular health (Chen et al., 2017). This $PM_{2.5}$ pollution also compromises respiratory immunity, leading to increased inflammation and cellular damage, thus escalating the risk of respiratory infections (Loaiza-Ceballos et al., 2022).

The adverse effects of $PM_{2.5}$, however, are widespread, impacting individuals regardless of their underlying health status. For instance, Lin et al., (2021) found that long-term exposure to $PM_{2.5}$ is positively linked to hypertension, and notably, in individuals with lower educational attainment, $PM_{2.5}$ is also positively associated with diabetes (OR = 1.11) and overweight (OR = 1.07). These findings emphasize a link between $PM_{2.5}$ and underlying conditions that could influence COVID-19 mortality outcomes.

> Hypothesis 2: Individuals living in areas with higher $PM_{2.5}$ or HAP air pollution levels experience elevated COVID-19 mortality in comparison to individuals living in areas with cleaner air.

1.2.4.2 Hazardous Air Pollutants (HAP). Urban air toxics, or HAPs, are another type of pollutant with adverse health effects. HAPs have been linked to diseases such as asthma (Tart, 2002) and cardiovascular disease (Howell et al., 2019), both of which are conditions that elevate the risk of mortality and hospitalization from COVID-19, thereby potentially mediating the racial disparity gap in COVID-19 outcomes (Fitero et al., 2022). HAPs are pollutants that are known or suspected to cause cancer, originating from large stationary sources such as industrial facilities, and power plants; small area sources such as gas stations, and dry cleaners; and mobile sources such as motor vehicles (EPA, 2018). Carrillo et al., (2018) found that exposure to chlorine, one of the HAPs, was positively associated with pediatric asthma risk among 2,930 school-age children in Hidalgo County, Texas. The study found that air-toxic exposure to chlorine was associated with a 22% increased likelihood of having asthma. Chlorine gas exposure can occur due to traffic or rail accidents, spills, or other disasters, and can result in breathing problems such as wheezing (White & Martin, 2010).

Studies have shown disproportionate impacts of HAP on racial minorities concerning various poor health outcomes (W. James et al., 2012; S. Wilson et al., 2015). Chakraborty, (2021) shows that Blacks and those from low SES groups are disproportionately concentrated in counties experiencing both elevated COVID-19 incidence and high respiratory risks due to HAP exposure, suggesting a compounded vulnerability to both pandemic-related and environmental health risks.

Previous research has linked air pollution to COVID-19 health outcomes at the area level, as shown by X. Wu et al., (2020) and Petroni et al., (2020). Additional ecological studies have corroborated these findings, particularly in terms of hospitalization and mortality rates. This study, however, expands the understanding further by examining the association between air pollution covariates and individual-level COVID-19 patients with underlying conditions.

The following hypotheses investigate the interaction between race and pollution, highlighting how these factors together amplify the risk more than individually. Hypotheses 3 and 4 propose that racial minorities residing in areas with high levels of $PM_{2.5}$ and HAPs are at an increased risk of COVID-19 mortality. This focus underscores the compounded health risks that arise from the combination of systemic racial disparities and exposure to widespread air pollutants.

Hypothesis 3: Racial minorities, particularly Black or Hispanic individuals residing in areas with high levels of HAP or $PM_{2.5}$ are at an increased risk of COVID-19 mortality.

Hypothesis 4: Individuals with underlying health conditions and living in areas of higher $PM_{2.5}$ pollution exposure face increased COVID-19 mortality risk.

1.2.4.3 Traffic Proximity. Living in close proximity to heavily trafficked roads has consistently been linked to an increased risk of asthma symptoms and hospitalizations (Baumann et al., 2011; Bowe et al., 2021; Brender et al., 2011; Comunian et al., 2020; Khorram-Manesh et al., 2021; Kravitz-Wirtz et al., 2018). Kim et al., (2008) found that residential proximity to traffic, determined by factors such as traffic density and distance to major roads, was associated with a higher likelihood of current asthma and bronchitis, with individuals living within 75 meters of a freeway or highway having 3.8 times higher odds of having current asthma compared to those living farther away. Hauptman et al., (2020) observed in a recent study of urban school-aged children with asthma that living and attending school closer to major roadways was linked to increased asthma symptom days, healthcare utilization, and poor asthma control, with a 100-meter increase in distance from major roadways resulting in 29% fewer asthma symptom days per 2-week period. Another study in a Texas school district, Chakraborty, (2022) shows a positive association between the percentage of children from racial minorities such as Black, Hispanic, and Asian and higher traffic proximity, suggesting the vulnerability of racial minorities to traffic pollution-related health outcomes. These findings emphasize the role of traffic proximity in attenuating the racial disparity gap in health outcomes and underscore the importance of its impact on individual health, particularly for respiratory diseases like asthma, which may potentially increase susceptibility to COVID-19 infection (Skevaki et al., 2020).

Hypothesis 5: Controlling for close proximity to vehicular traffic should attenuate though not eliminate the association between COVID-19 mortality and race.

Hypothesis 5 examines attenuation by proposing that controlling for traffic proximity should reduce the association between race and COVID-19 mortality. This hypothesis aims to identify if traffic pollution specifically contributes to racial disparities, suggesting that the localized impact of traffic-related air pollution near heavily trafficked roads can exacerbate the health outcomes for racial minorities. By controlling for traffic proximity, the goal is to isolate the effect of race on COVID-19 mortality from the compounding effect of traffic pollution.

1.2.4.4 Proximity to Waste Treatment Facilities. Living near hazardous waste treatment, storage, and disposal facilities (TSDFs) has been linked to chronic health issues and infectious disease outbreaks, exacerbating pre-existing conditions (Henn et al., 2016; Landrigan et al., 2015; Webber & Stone, 2017), potentially serving as a contributing factor in the racial disparity gap in COVID-19 outcomes. These facilities can spread contamination through water and volatile chemicals, leading to vapor intrusion via groundwater and soil pathways (Johnston & MacDonald Gibson, 2015). For example, Fazzo et al., (2017) associated exposure to oil industry waste with health problems, including respiratory and neurological symptoms. Carpenter et al., (2008) demonstrated that residing near hazardous waste sites, especially those with persistent organic pollutants or POPs[2], significantly increased rates of infectious respiratory disease (RR = 1.09) and chronic obstructive pulmonary disease (RR = 1.19) among urban residents of all ages, highlighting the impact of environmental contaminants on respiratory health. Concerns about potential infections underscore the need to investigate the connection between hazardous waste sites and COVID-19 mortality.

Furthermore, evidence indicates that hazardous waste facilities are disproportionately located in areas with racial minorities, contributing to health disparities (United Church of Christ Commission on Racial Justice, 1983). Exposure to contaminated sites may worsen vulnerabilities in patients with medical conditions, exacerbating health inequities among different racial groups

[2] POPs encompass intentionally produced chemicals used in agriculture, disease control, manufacturing, and industry, like PCBs and DDT, as well as unintentionally produced chemicals like dioxins from industrial processes and combustion (EPA, 2014).

(Ferguson et al., 2021; Forastiere et al., 2007; Sharma & Balyan, 2020). These findings emphasize the need for comprehensive research to understand how proximity to TSDFs mediates racial health disparities, particularly in the context of COVID-19 outcomes.

An ecological study, Hendryx & Luo, (2020) established an association between hazardous waste treatment sites and COVID-19 fatality rates, revealing that each unit increase in TSDF exposure corresponded to a 0.52 increase in death rate, implying that proximity to TSDF could enhance susceptibility to COVID-19 (Hendryx & Luo, 2020). However, the ecological design of the study warrants further investigation. In my research, I intend to expand further by analyzing individual-level COVID-19 patients with underlying conditions.

Hypothesis 6: Controlling for close proximity to waste treatment facilities should attenuate though not eliminate the association between COVID-19 mortality and race.

1.2.4.5 Poor Housing. Unhealthy and poor housing conditions not only affect individuals but also have broader implications for public health (Baker et al., 2017; Boch et al., 2021). Zock et al., (2002) and Boch et al., (2020) show the link between poor housing facilities, such as exposure to molds and pests, and increased risk of respiratory diseases like asthma. Likewise, Shaw (2004) stresses the impact of housing conditions on health, arguing that the relationship between housing and health can be traced back to the period of industrialization when crowded, poorly ventilated housing in industrial centers in the West led to poor health outcomes. For instance, Boch et al., (2021) found that poor housing quality, as characterized by poor infrastructures such as holes in walls, problems with pets and pests, and plumbing issues, is associated with poor health outcomes among children. Children living in such conditions were 16% more likely to have poor health outcomes and 11% more likely to make medical visits due to health problems (Boch et al., 2021). Furthermore, a recent study showed that housing problems, such as overcrowding, high rent or mortgage, or lack of facilities, were associated with higher rates of COVID-19 infections among children (Yuan et ., (2022).

Studies on social determinants of health in urban settings show that poor housing conditions often cluster in specific areas due to residential segregation, disproportionately affecting racial minorities and leading to adverse health outcomes (Hood, 2005; Massey & Denton, 1993; S. G. Meyer, 2000; D. R. Williams & Collins, 2001a). These findings suggest that addressing poor housing conditions can potentially play a role in attenuating the racial disparity gap in health outcomes.

> Hypothesis 7: Individuals residing in areas with poor housing conditions exhibit a higher risk of COVID-19 mortality compared to those living in areas with well-maintained housing.

1.2.5 Urban Social Environment

Systemic disparities, like racial residential segregation limiting opportunities and neighborhood features, drive health inequities (Diez Roux & Mair, 2010; Massey & Denton, 1993; D. R. Williams & Collins, 2001b). Racial minorities, especially Blacks, face disproportionate health impacts due to systemic inequalities and social determinants of health (Islami et al., 2022; Zavala et al., 2021). To address these, we must confront structural inequalities linked to resource access, especially in urban settings (Islami et al., 2022; Zavala et al., 2021). In this study, I follow the framework Yen & Syme, (1999), which categorizes epidemiologic research on the social environment's health impact into three areas: community socioeconomic status' significance, social structure's effect (like residential segregation), and environmental quality assessment, often using violent crime rates. These efforts uncover links and mechanisms driving health disparities and behaviors.

Ellen et al., (2001) highlight the complex neighborhood effect mechanism between neighborhood environments including their physical and social environments that interact with individual and family characteristics, affecting behavior, and individual health outcomes. The authors note methodological challenges in this research such as isolating neighborhood influences, defining and measuring local conditions, and considering non-linear effects and delayed manifestation of health effects (Ellen et al., 2001). Jakobsen et al., (2022) build upon this, advocating for a deeper analysis of neighborhood social-interactive mechanisms, a 'black box' where social structures and interactions potentially influence health outcomes. They call for research that moves beyond mere correlations to unearth concrete causal pathways, emphasizing the need to more comprehensively understand how the quality of social interactions within neighborhoods can shape health disparities (Jakobsen et al., 2022).

The study of neighborhood effects on health is also complicated by methodological challenges, particularly concerning selection bias—where individuals' choices or constraints about where to live may influence the observed health outcomes. Galster, (2008) points to the need for more precise measures of neighborhoods and individual characteristics to advance research in this area. Despite methodological advances, such as the use of inverse probability[3] of treatment to address time-varying treatments (Do et al., 2013; Kravitz-Wirtz, 2016; Wodtke et al., 2016), distinguishing between correlation and causation remains difficult. The Moving to Opportunity (MTO) studies, for example, have faced criticism for potential selection bias and the challenge of isolating the effects of improved neighborhood conditions from other factors (Clampeit-Lundquist & Massey, 2008; Ludwig et al., 2008; Sampson, 2008). These studies

[3] The inverse probability treatment weighting adjusts for confounding in observational studies by weighting individuals according to the propensity score.

illustrate the complexity of assessing the true impact of neighborhoods on health outcomes and the need for refined research methods to better understand these relationships.

1.2.5.1 Community Socioeconomic Status. SES, with its links to factors such as income, employment, and education, is considered a powerful social determinant of health (Mechanic, 2007; D. R. Williams & Collins, 1995). Community-level SES has also been utilized as a predictor of population health outcomes in research (Gillcrist et al., 2001; Heitzer et al., 2022). Both individual and aggregate-level SES have been widely used in population health research (R. T. Anderson et al., 1997; Braudt et al., 2019; Tumin et al., 2018). Understanding individuals' SES as a determinant of health encompasses more than access to resources for mitigating risk or managing diseases (Link & Phelan, 1995). It also involves complex social-interactive mechanisms that influence well-being. For instance, Jakobsen et al., (2022) demonstrates that neighborhood SES affects mental health through complex social mechanisms, specifically showing that in neighborhoods with higher SES, elevated levels of trust correlate with better mental health.

1.2.5.2 Income Inequality. The concepts of health inequalities and health inequities, which refer to disparities and structural differences in health outcomes among certain groups such as race and gender, are shaped by factors such as SES and race. These disparities are perpetuated by institutional policies that result in discrimination in areas such as employment and education (Fiscella & Williams, 2004). Income inequality influences health outcomes by reflecting income's impact on health (Pickett & Wilkinson, 2015), and life environments shape health trajectories over time, involving cumulative effects and early-life inequalities due to unfair conditions (Kawachi et al., 2002).

Research into health service utilization and socioeconomic characteristics of urban areas has sought to understand health inequalities across races and ethnicities, underscoring the critical influence of social class or SES in determining health outcomes (Illsley, 1990; Pickett & Wilkinson, 2015; D. R. Williams & Collins, 2001b). The concept of social class or SES is employed to assess health across social groups, connecting individual traits with broader advantages or disadvantages (Deaton & Lubotsky, 2003; Honjo, 2004). Reflecting on the urban dynamics of poverty, Wilson, (1996) identifies the demographic shifts in the urban core during the 1970s, notably the exodus of middle-class Blacks and the relocation of manufacturing jobs, led to employment voids and significantly contributed to economic and racial segregation in inner-city neighborhoods, transforming residential patterns and deepening urban inequality. Robinson III, (2016) expands on this by contesting the notion that urban poverty stems solely from structural disadvantages. He argues that neoliberal policies promoting market logic, market-based solutions for social and economic issues, and privatization have profoundly shaped urban life, particularly in housing and education, thereby exacerbating economic inequalities in urban environments.

1.2.5.3 Social Vulnerability. The concept of social vulnerability is intertwined with area-level socioeconomic elements encompassing accessibility to knowledge, technology, and resources, especially in the context of health disparities (Link, 2008). Furthermore, Cutter, (1996) emphasizes that vulnerability is socially constructed, and shaped by historical, cultural, social, and economic dynamics that influence disaster resilience. Among the factors consistently contributing to social vulnerability, socioeconomic status, along with age, gender, and race, is crucial, as underscored in the literature (Cutter et al., 2003). Fallah-Aliabadi et al., (2022) show that the COVID-19 pandemic has not only exposed but also exacerbated social vulnerability, with marginalized and disadvantaged communities bearing the worst burden. Social vulnerability is often attributed to factors like age, socioeconomic status, race, housing conditions, access to healthcare, and information technology (Fallah-Aliabadi et al., 2022).

Hypothesis 8: Black individuals residing in communities with higher levels of social vulnerability may experience a higher rate of COVID-19-related fatalities compared to their White and other racial counterparts.

1.2.6 Social Structure

1.2.6.1 Racial Residential Segregation. Racial and socioeconomic disparities significantly influence healthcare access and outcomes, particularly due to racial residential segregation and its impact. Despite legislative efforts, persistent racial residential segregation in US cities exacerbates the disproportionate burden of COVID-19 on minority populations already facing economic challenges and poor health (Acevedo-Garcia et al., 2003; D. R. Williams & Purdie-Vaughns, 2016). Understanding the effects of this segregation is vital for addressing disparities and enhancing health outcomes.

Rooted in historical migrations and discriminatory practices, racial residential segregation remains a pressing issue in US urban areas, fostering racial segregation and Black ghettoization (Jargowsky, 2020; Massey & Denton, 1993; S. G. Meyer, 2000). Linked to broader inequality systems, segregation has long impacted minority populations. Despite civil rights legislation and the Fair Housing Act of 1968, the gap in health and socioeconomic status between minorities and non-minorities has improved slowly (Kramer & Hogue, 2009; Krysan & Crowder, 2017). Racial residential segregation impacts health not just through socioeconomic status (SES) differences, but also via broader mechanisms like restricted access to quality education and employment, community disinvestment, and the stress associated with living in segregated environments, which can all contribute to health disparities across racial lines (D. R. Williams & Collins, 2001; Wang et al., 2022). It limits opportunities for maintaining good health within minority communities, exposing them to poverty and inadequate housing, both detrimental to health (Hood, 2005; Massey & Denton, 1993; D. R. Williams & Collins, 2001), confining minorities to disadvantaged urban areas. Prior research (Neupane & Ruel, 2023) suggests that racial residential segregation serves as a mechanism in shaping health disparities related to COVID-19 mortality outcomes, potentially limiting access to essential resources. Therefore, this study controls for racial residential segregation in the analysis.

1.2.6.2 Quality of Environment. The neighborhood environment plays a pivotal role in residents' health outcomes (Suglia et al., 2016). Residential instability and violence are linked to low socioeconomic status (SES), with socially cohesive neighborhoods showing lower violence levels (McNeill et al., 2006; Sampson et al., 1997). Neighborhood quality explains disparities in both SES and health; studies indicate that neighborhood disadvantage and perceptions of unsafety are linked to racial disparities in body mass index (BMI), potentially connecting obesity to physical and social environments (Fish et al., 2010; Ruel et al., 2010). Additionally, residing in environments of poor quality is associated with adverse physical and mental health symptoms (Chaix et al., 2007; Freedman et al., 2011; Giurgescu et al., 2015; Mair et al., 2008). For instance, a study shows that exposure to violent crime is associated with physiological stress pathways that can compromise safety and well-being, potentially leading to cardiovascular disease (Eberly et al., 2022).

1.2.6.3 Crimes. Criminal homicides, defined by the FBI as intentional acts causing death, are closely tied to community safety and often occur in disadvantaged areas, negatively impacting community health (B. Dong et al., 2020; Federal Bureau of Investigation, 2022; Lodge et al., 2021). Poverty and social disorganization contribute to crime and neighborhood deterioration, while strong social cohesion and collective efficacy in neighborhoods correlate with reduced violence and stability (Browning & Cagney, 2003; Sampson et al., 1997; W. J. Wilson, 1994, 1996). Persistent stress from neighborhood violence impacts biological characteristics, increasing health risks such as heart disease (Theall et al., 2017).

Economic disadvantage, neighborhood disorganization, and specific characteristics further contribute to compromised community well-being, with violent crimes consistently linked to negative health outcomes, particularly affecting racial minorities (Browning et al., 2006; Galster, 2012; Kalesan et al., 2014; Smith et al., 2020). Exposure to violence heightens mental anxiety and undermines healthy lifestyle choices, ultimately resulting in diminished well-being (Kimmel, 2014; Tan & Haining, 2016). Proximity to violence was found to be connected to sleep health in high-crime neighborhoods, contributing to health disparities (Richardson et al., 2021).

> Hypothesis 9: Individuals living in areas characterized by lower socio-environmental quality, including higher crime rates, are more susceptible to COVID-19 mortality outcomes.

In sum, this study explores the limited existing research on the link between urban environmental elements, including $PM_{2.5}$ and hazardous air pollutants, and COVID-19 mortality at the individual level, especially within racialized populations with pre-existing medical conditions. Building upon prior research (Comunian et al., 2020; Pansini & Fornacca, 2021), this study examines individual patient data to investigate further into the connections between $PM_{2.5}$ pollution and COVID-19 impacts.

While Austin et al., (2023) have demonstrated a positive association between air pollution and COVID-19 mortality, an attempt to establish a causal relationship relies on observational data and fixed effects models. This study goes further for a more holistic understanding of environmental influences on individual-level COVID-19 mortality among racial groups using broader urban factors, encompassing both physical and social aspects. This study uses better measures ranging from individual-level biological traits of underlying medical conditions to environmental factors such as $PM_{2.5}$ and the social vulnerability index, to better grasp the nuanced environmental effects on diverse COVID-19 patient groups.

1.2.7 Hypotheses

Hypothesis 1: COVID-19 mortality disparities may be partly attributed to variations in co-morbidities, as individuals with underlying conditions are more likely to succumb to the virus.

Hypothesis 2: Individuals living in areas with higher $PM_{2.5}$ or HAP air pollution levels experience elevated COVID-19 mortality in comparison to individuals living in areas with cleaner air.

Hypothesis 3: Racial minorities, particularly Black or Hispanic individuals residing in areas with high levels of HAP or $PM_{2.5}$ are at an increased risk of COVID-19 mortality.

Hypothesis 4: Individuals with underlying health conditions and living in areas of higher $PM_{2.5}$ exposure face increased COVID-19 mortality risk.

Hypothesis 5: Controlling for close proximity to vehicular traffic should attenuate though not eliminate the association between COVID-19 mortality and race.

Hypothesis 6: Controlling for close proximity to waste treatment facilities should attenuate though not eliminate the association between COVID-19 mortality and race.

Hypothesis 7: Individuals residing in areas with poor housing conditions exhibit a higher risk of COVID-19 mortality compared to those living in areas with well-maintained housing.

Hypothesis 8: Black individuals residing in communities with higher levels of social vulnerability may experience a higher rate of COVID-19-related fatalities compared to their White and other racial counterparts.

Hypothesis 9: Individuals living in areas characterized by lower socio-environmental quality, including higher crime rates, are more susceptible to COVID-19 mortality outcomes.

1.3 Data & Methodology

This study merged five secondary datasets to evaluate the influence of physical and social environments on racial disparities in urban COVID-19 mortality. The datasets covered all urban, suburban, and rural areas in the United States that cover a period from January 1, 2020, which marks the earliest reported COVID-19 case, until April 15, 2021. I limited the study to urban and suburban settings areas as low populations in rural areas can compromise existing indices such as segregation. The hierarchical logistic regression models were run using R.

1.3.1 Data

This study combined five different datasets. The first, COVID-19 mortality dataset comes from CDC's Case Surveillance Task Force & SRRG[4]. The restricted data were made available for limited use upon completion of the registration information and data use restrictions agreement (RIDURA). The dataset itself was released on April 30, 2021, with access provided through CDC's GitHub portal. The COVID-19 case surveillance database includes patient-level data reported from various U.S. states, territories, or autonomous reporting entities following a COVID-19 diagnosis. Individuals are included based on COVID-19 case reports, which are submitted using standardized forms. The dataset contains individual-level demographic variables, such as race and ethnicity, disease severity, clinical data, lab results, and comorbidities. The geographic identifiers in the dataset represent the state and county of residence of the individuals. The dataset, however, lacks information on socioeconomic variables at the individual level. Nevertheless, they stand as the only available datasets containing individual-level information on COVID-19 patients with underlying medical conditions.

The dataset consists of 23,723,384 individuals diagnosed with COVID-19 infections. In this dataset, any unanswered responses (blanks) were reclassified as "Unknown" and treated as missing values, which were removed during the final analysis. For example, in the question "Did the patient die as a result of this illness?", responses consist of "Yes," "No," or "Unknown" and all values of "Unknown" were excluded. The same approach was applied to other variables with "Unknown" responses. The dataset may include vaccinated individuals, as the Pfizer-BioNTech COVID-19 vaccine received emergency use authorization in December 2020 and was made

[4] For this analysis, the CDC dataset is preferred due to its detailed individual-level information, including crucial underlying medical conditions, unlike the broader scope of data from other institutions such as Johns Hopkins University.

available to the general public by mid-April (U.S. Department of Health & Human Services, 2020).

This study acknowledges the existence of a subset of COVID-19 cases that remain unrecorded due to the absence of interaction with the healthcare system in the United States. Therefore, this dataset is primarily representative of the more severe cases of COVID-19 that require medical intervention, a factor that may introduce a form of selection bias (Neupane & Ruel, 2023). This focus provides a robust foundation for analyzing the severity of the pandemic. The cases that remain unreported typically represent asymptomatic or mild instances that may not seek medical attention but yet spread COVID-19 (Gao et al., 2021). As shown in Table 1, after removing rural counties, and unknowns on death and race, a final sample size of 1,526,418 was used for the analysis.

Table 1. Adjustments to Merged Datasets

Adjustments	Individual N	County N
Starting sample	24,441,351	3,153
After removing rural counties	23,580,458	2,124
Valid starting sample	23,580,458	2,124
Removing unknown on race	15,240,385	1,996
Removing unknown on death outcome	8,956,200	1,752
Removing unknown on pre-existing conditions	1,663,563	879
Removing unknown on Ejscreen dataset	1,536,052	767
Removing unknown on RWJF dataset	1,527,715	753
Removing unknown on SVI removal	1,527,715	753
Removing item nonresponse	1,526,418	753
Final analysis sample	1,526,418	753

The second dataset, which includes environmental indicators was obtained from EPA's environmental justice (EJ) screening tool, called EJscreen (U.S. Environmental Protection Agency, 2019). The most recent dataset released in 2022 was obtained from the web portal.

EJscreen is the best data publicly available that provides a nationally consistent dataset with census block group level granularity on various environmental indicators. However, the EJscreen dataset has limitations such as that it does not have other important variables of environmental concerns such as drinking water quality and indoor air quality that are linked with the population health outcomes. The EJscreen is a national dataset that aggregates information from diverse sources, including EPA's Office of Air Quality Planning and Standards, the Office of Pollution Prevention and Toxics, and the Highway Performance Monitoring System. The environmental factors obtained from EJscreen data are provided at the block group level. The data is averaged to the county level for the analysis. Aggregating to a county level addresses EJscreen's limitations by combining data from multiple block groups, as recommended by EPA, to mitigate uncertainty in small geographic areas like single Census block groups, where estimates may be less accurate due to their size (Environmental Protection Agency, 2022).

The third dataset, which is obtained from the County Health Rankings & Roadmaps (CHR&R), a program of the University of Wisconsin Population Health Institute, was utilized to incorporate the housing problems variable, as well as factors such as violent crime, racial residential segregation, and income inequality associated with social environments. CHR&R is a national dataset sourced from organizations like the National Center for Health Statistics, Bureau of Labor Statistics, U.S. Census Bureau, U.S. Department of Housing and Urban Development, and the American Community Survey. The 2023 CHR&R data is presented at the county level.

The fourth dataset was the CDC's Social Vulnerability Index dataset. The CDC dataset with SVI was downloaded using the county FIPS code level of a geographic unit. The EJscreen, CHR&R, and SVI datasets were merged into the Case Surveillance dataset with COVID-19 variables by county-level Federal Information Processing System (FIPS) Codes. The county

FIPS code in the Case Surveillance dataset is assigned based on the individual's place of residence.

The final dataset utilized for this study was the 2013 Rural-Urban Continuum Codes (RUCC), which provides an urban-rural classification framework. For the purposes of this research, I focused on urban and suburban counties (USDA Economic Research ServiceUSDA Economic Research Service, 2023). Consequently, a total of 1,084 nonmetropolitan counties (codes 7-9), defined by characteristics such as populations up to 19,999 that are not adjacent to a metropolitan area, as well as completely rural areas with populations less than 2,500, were excluded. The RUCC has been employed in various studies to examine patterns of migration or health outcomes across counties with different levels of urbanization (*see* McCormack et al., 2019; Moore et al., 2014; Winkler & Johnson, 2016).

1.3.2 Constructs

A binary dependent variable, COVID-19 death, is measured at the individual level, where death from COVID-19 equals 1 and survival is 0. Variables representing physical and social environments are measured at a county level to explain the disparities in individual-level COVID-19 mortality outcomes. The environmental indicators of the EJscreen data used for the study included particulate matter ($PM_{2.5}$), hazardous air pollutants or air toxics (HAP), proximity to treatment storage and disposal facilities (TSDF), and traffic proximity.

1.3.3 Independent Variables. Previous studies, such as those conducted by (Hendryx & Luo, 2020) and (Ross et al., 2022), have employed EJscreen variables with a weighted average approach, which I replicated. To calculate the average value at the county level, this block-group data were weighted based on the ACS population estimate at the block-group level. The EJscreen variables, except for TSDF proximity, which was already weighted, were multiplied by their corresponding populations. Each block group's weight was then determined by dividing its total population by the sum of the total population. For analysis purposes, all the physical environmental variables were grand mean-centered, and higher values indicate higher levels of pollution or greater exposure to pollution. Research has utilized measures of air pollution at the county level, focusing on particulate matter like $PM_{2.5}$ and a range of hazardous air pollutants (Petroni et al., 2020; Reid et al., 2021).

1.3.3.1 $PM_{2.5}$. The independent variable, $PM_{2.5}$, is an annual average concentration in micrograms per cubic meter. $PM_{2.5}$ is 2.5 microns or less in diameter and power plants, vehicular exhaust, and industrial facilities are the common sources of such air pollutants (Leffel et al., 2021). $PM_{2.5}$ data are based on 2019 estimates by EPA's Office of Research and Development. According to the EPA, different levels of $PM_{2.5}$ concentrations are found across the country, making residents vulnerable to varying degrees of inhalation. The block group-level $PM_{2.5}$ values were aggregated for a county-level analysis.

1.3.3.2 Air Toxics. The hazardous air pollutants (HAPs) or air toxics respiratory hazard index is the Environmental Protection Agency (EPA) data from the 2019 Air Toxics Screening Assessment, or AirToxScreen. The NATA estimates are the only air toxic data available nationwide and the data are calculated based on the ratio of exposure concentration to a health-based reference concentration or RfC (EPA, 2022a; Niehoff et al., 2019). An RfC is used to assess inhalation risks, where concentration refers to levels in the air(Environmental Protection Agency, 2022). The measure of RfC is units of milligrams of chemical per cubic meter of air (mg/m3). HAP respiratory hazard index (HI) for multiple pollutants represents the sum of individual hazard quotients (HQs), which are the ratios of yearly average ambient concentrations to the reference concentrations (RfCs) where negative health outcomes are expected to occur.

For example, according to the 2019 AirToxScreen, DeKalb County, Georgia has a value of 0.5. This value represents the cumulative HQs for several component chemicals that impact respiratory health such as acetaldehyde (0.14), acrolein (0.07), formaldehyde (0.19), and diesel particulate matter (0.05), among other contributing substances (US EPA, 2022). Higher values of urban air toxics indicate higher levels of pollution.

1.3.3.3 Proximity to TSDF. The TSDF proximity is a count of all commercial hazardous waste facilities within 5 km (or nearest neighbor outside 5 km), each divided by distance in kilometers, presented as population-weighted averages of blocks in each block group (Environmental Protection Agency, 2015). In other words, each block group is assigned a score, the population-weighted sum of the block-level proximity score. According to EPA, the proximity score is the number of facilities per kilometer of distance from the average person. For example, one facility exactly 2 km away gets ½ score while three facilities exactly 4 km away get a score of ¾. The TSDF data is EPA's 2021 estimate. It is important to include proximity to TSDF in the study because the harmful substances at such facilities may be exposed to humans living in the area in different forms such as inhalation or via contaminated water through various sources. The TSDF variable was cube-root transformed to mitigate the effects of data skewness.

1.3.3.4 Traffic Proximity. The traffic proximity and volume is an indicator used by the EPA to develop a new EJSCREEN tool. The PTRAF at the county level is an aggregate of all census block data within a county and is weighted by the number of people in the corresponding blocks. The variable is reported as the average count of vehicles per meter per day within 500 meters of a census block centroid divided by distance in meters. The centroid is the center point of a census block. The closest traffic is given more weight through inverse distance weighting. For example, a single highway with 16,000 annual average daily traffic (AADT) at 400 meters distance would result in a score of 16,000/400=40. The PTRAF was calculated from 2019 U.S. Department of Transportation traffic data retrieved in September 2021 (Environmental Protection Agency, 2022).

According to EPA, the centroid of 500 meters was selected to be large enough to capture the majority of road segments with traffic data that could potentially have a significant impact on local residents. An inverse distance weighting, meaning closest traffic was given more weight while distant traffic less. For instance, traffic 500 meters away would only get one-tenth as much weight as traffic 50 meters away (Environmental Protection Agency, 2022). The PTRAF variable was cube-root transformed to address the skewness.

1.3.3.5 Severe Housing Problems. The severe housing problem variable is a percentage of households within a county with one or more housing problems such as housing units lacking complete kitchen or plumbing facilities, the household being overcrowded, or the household being severely cost-burdened. The unit lacking complete kitchen units is defined as units lacking a sink with running water, a stove, or a refrigerator. Likewise, units lacking hot and cold piped water, and a flush toilet or shower are considered incomplete plumbing facilities. Similarly, overcrowded households are defined as units with more than 1 person in a room, and housing costs, which include utilities, that exceed 50% of monthly income are considered to have a severe cost burden for the purpose of calculating severe housing problems. The severe housing problem percentage is calculated as one of the above-mentioned problems divided by the total number of households in the county. The housing problem variable was transformed by taking a cube root to address the skewness.

All the social environmental variables were grand mean centered to adjust the scale of measurement, and for easier interpretation of the coefficients of predictors.

1.3.3.6 Social Vulnerability Index. The Centers for Disease Control and Prevention (CDC) developed the Social Vulnerability Index (SVI), a county-level percentile-based measure that assesses relative vulnerability using 15 social factors categorized under SES, household composition, minority status, language, housing type, and transportation. This study utilized the overall SVI variable, RPL_THEMES, which serves as a comprehensive vulnerability measure. The SVI values range between 0 and 1, with 0 indicating the lowest disadvantages or highest advantaged county, and 1 representing the county with the highest level of disadvantage. Therefore, higher SVI values correspond to higher levels of disadvantages in a county. The SVI is applied to every U.S. census tract or county level, using data from the American Community Survey (ACS), 2014-2018 estimate (CDC, 2023d). The purpose of the SVI, according to the CDC, is to assist health officials and emergency response planners in identifying and mapping communities in need of support.

The inclusion of poverty, unemployment, income, and lack of high school education in the SES sub-component of the SVI suggests that additional social determinants like SES could impact COVID-19 mortality, therefore, I also assessed whether SVI or SES, is a more effective predictor, and determine if the impact of SVI is primarily driven by SES. While both SVI and SES had moderate effect sizes in the interaction terms, SVI was chosen for its comprehensive scope, despite not being statistically significant in the main effect. The SVI has been utilized in various studies to examine the impact of social and physical environments and social determinants of health on population health outcomes in the United States (Barry et al., 2021; Dasgupta et al., 2020; Lehnert et al., 2020; Paro et al., 2021; Schmidt et al., 2021).

1.3.3.7 Residential Segregation. Residential segregation between non-White and White racial groups is assessed using the dissimilarity index, which indicates higher segregation levels with greater values. The county-level indices are linked to individual-level observations using county-FIPS codes. The dissimilarity index measures the geographic evenness of racial distributions, ranging from zero (completely even distribution) to one hundred (completely uneven distribution) across census tracts within counties. It represents the proportion of non-Whites required to relocate to White tracts in order to equalize the racial distributions.

1.3.3.8 Crime Rates. This study uses homicide rates to represent the crime rates in counties. According to the CHR&R portal, the rate of homicides is determined by dividing the number of deaths due to homicide per 100,000 population. A higher rate of homicide indicates a greater prevalence of violent incidents in a given county. The CHR&R used data from the National Center for Health Statistics - Mortality Files covering the 2014-2020 period to estimate the homicide rates (County Health Rankings & Roadmaps, 2023). The crime variable was cube-root transformed to reduce skewness and make the data more symmetric.

1.3.3.9 Income Inequality. The study utilizes the ratio between the median household income at the 80th percentile and the 20th percentile in each county as an index for income inequality based on the ACS 2015-2019 estimate. The 80th percentile represents the income level where 20% of households have higher incomes, while the 20th percentile represents the income level for the bottom 20% of the population. Higher index values indicate a larger income gap between individuals at the higher and lower ends of the income distribution.

1.3.3.10 Race and Underlying Medical Conditions. The individual-level variable, race is classified into five groups—Whites, Blacks, Hispanics, Asians, and Others (which include American Indian. Alaska Native, Asian, Multiple/Other, Native Hawaiian/Other Pacific Islander, and Hispanic/Latino). A series of dummy variables were created to represent the race variable.

The individual-level data mentions the presence or absence of underlying comorbidity or disease (medical conditions) of COVID-19-infected patients. Therefore, dichotomizing the variable, the patient with an underlying medical condition was coded as "Yes" = 1 and "No" = 0.

1.3.4 Control Variables. At level 1, I control for age and gender. The gender variable was dichotomized into males (0), as a reference category, and females (1). The individual-level data on age is stratified 10 years apart, starting from 0-9 years up to 80+ years old. Therefore, I dichotomized age by dividing it into two groups: 60 and younger (0) and over 60 years old (1). To account for changes due to COVID-19 vaccinations, I included a 'period effects,'(Alwin & McCammon, 2003) with a binary variable, vaccine availability, coded as 1 for post-vaccine introduction and 0 for the pre-vaccine phase. This control variable helps delineate the influence of vaccines on the progression and impact of the pandemic. Additionally, a continuous 'wave' variable serves as a control for the progression of the epidemic over time measured in months. The first month starts at zero and increasing with each month from January 1, 2020, up to April 15, 2021, covering the 15-month study period.

1.3.4 Statistical Analysis

A multilevel logistic regression random intercept analysis was conducted to examine the relationship between the physical and social environmental factors[5] and COVID-19 mortality. Taking into account the clustering of individuals within counties, this analysis enables the

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[5] Diagnostics indicate that treating variables like $PM_{2.5}$, traffic pollution, and TSDF proximity separately is appropriate. The significant odds ratio of 1.47 of $PM_{2.5}$, points to an increased mortality risk. Similar significance in other variables suggests combining them into an index could mask individual effects. Notably, significant interaction terms like 'Hispanic × TSDF proximity' (OR: 1.18) emphasize the need to understand environmental impacts across different demographics, an insight that would be compromised by using an index.
Alternatively, the development of an environmental risk index was initially considered. This index was intended to integrate variables like $PM_{2.5}$, hazardous air pollutants (HAP), proximity to treatment, storage, and disposal facilities (TSDF), and traffic proximity into a composite measure. Following the recommendations of DeVellis & Thorpe (2021), each indicator within this index was to be standardized and weighted equally, reflecting the cumulative environmental health risk at the neighborhood level.

examination of individual-level predictors including race, gender, age, and underlying conditions, as well as county-level predictors such as $PM_{2.5}$, urban air toxics, proximity to TSDF, poor housing, and vehicular traffic proximity, social vulnerability, racial residential segregation, violent crime, and income inequality, in relation to the dependent variable of COVID-19 death. To capture non-linear trends in COVID-19 mortality over time, the wave variable (months from baseline) was squared to include in the hierarchical logistic regression models. This method identifies potential non-linear patterns, enhancing the analysis of the pandemic's dynamics by including both the wave and its squared term.

The *lme4* package in R was used for these analyses. The analysis used nAGQ = 1, the Laplace approximation for glmer models, chosen for its balance between accuracy and computational efficiency. With our study's large sample, the difference between nAGQ = 0 and higher is small, making nAGQ = 1 suitable for efficient and precise results (Gilbert, 2023; Q. Wu et al., 2019).

The following random intercept model was run:

$$Log\ (P_{ij} /(1-P_{ij}))= \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_j + \gamma_{11}W_jX_{ij} + \mu_{0j} + r_{ij} \quad \textbf{(1)}$$

where $\gamma_{00} \sim N(\beta_0, \sigma^2)$

where P_{ij} represents the probability of death occurring for individual i in county j, γ_{00} is the intercept, $\gamma_{10}X_{ij}$ represents the individual-level predictor variables, $\gamma_{01}W_j$ represents the county-level predictors and $\gamma_{11}W_jX_{ij}$ represents the cross level race by particulate matter interaction terms. Finally, there are two random terms in the model. The random term μ_{0j} is the unmodeled level-2 variability for each county j and r_{ij} allows for individual variation within county j.

It is important to note that the choice of multilevel logistic regression analysis is appropriate for this study as it accounts for the nested structure of the data (individuals within counties) and allows for the examination of both individual-level and county-level predictors, providing a more comprehensive understanding of the role of physical and social environments in determining COVID-19 mortality.

1.5 Results

Descriptive statistics for the analysis sample are displayed in Table 2. The top portion of the table presents descriptive statistics for individual-level variables. Starting from January 1, 2020, through the end date of April 15, 2021, of the sample data used for this study, the COVID-19 death toll was 6%. Females represented a slight majority of the sample at 53%. On the racial composition of the dataset, Whites constitute a majority at 63%, followed by Hispanics at 18%, Blacks at 12%, Asians at 3%, and other racial groups at 5%. Individuals aged 60 years or older represent 24% of the sample.

Table 2. Descriptive Statistics of Variables Included in Analyses

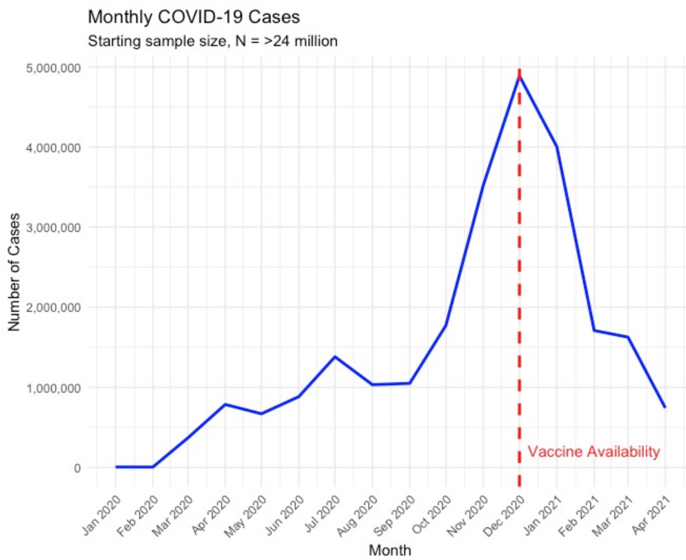
Individual level	***N***	**%**	**Range**
COVID-19 death	84,297	6	0-1
COVID-19 survival	1,442,121	94	
Female	816,317	53	0-1
Male	710,101	47	
White	955,325	63	0-1
Black	182,329	12	0-1
Hispanic	273,854	18	0-1
Asian	45,511	3	0-1
Other racial groups	69,399	5	0-1
Age 60 and over	365,156	24	60–80+
Under age 60	1,161,215	76	0-59
Underlying conditions	639,790	42	0-1
No underlying conditions	886,628	58	

Table 2. Descriptive Statistics of Variables Included in Analyses (continued)

Vaccine availability	439,150	29	0-1
Vaccine unavailability	1,087,268	71	
Wave	16		0-15
N-individual	1,526,418		
County level	**Mean**	**SD**	**Range**
$PM_{2.5}$	7.29	1.59	2.75-11.10
Urban Air Toxic	0.25	0.10	0.05-0.70
Traffic proximity	54.06	123	0-2959.20
Hazardous proximity	0.43	1.10	0-23.24
Crime	342	222	31-1820
SVI	0.50	0.27	0-1
Housing problems	15	4	6-39
Income inequality	4	1	3.1-9.1
Segregation	39	10	6-68
Number of People living in each county	621,251	694,632	6,049-5,265,398
N-county	753		

Of the total sample size, 42% of individuals have underlying medical conditions, indicating a large portion of the population is at high risk. Seventy-one percent of the sample consists of individuals from the pre-vaccine period, or prior to the vaccine availability in December 2020. The sample data captures the monthly wave of COVID-19 cases over a period of 16 months, ranging from 0 (representing January 2020) to 15 (representing April 2021). This temporal range allows for an observation of the pandemic's progression. Figure 1 illustrates the monthly wave of infections[6] within the sample population, offering a comparative view of the periods before and after vaccines became available.

Figure 1. The Wave of COVID-19 Cases



The second part of Table 2 shows county-level descriptive statistics. At the county level, the mean annual average concentration of $PM_{2.5}$ is 7.29 micrograms per cubic meter, with a standard deviation of 1.59, indicating variability across counties, and ranging from 2.75 to 11 micrograms per cubic meter. Likewise, the mean for Urban Air Toxic is 0.25 respiratory reference concentration (RfC), which is an annual average ambient concentration in milligrams per cubic meter, with a standard deviation of 0.10 and ranges from 0.05 to 0.70. Traffic proximity has a mean value of 54.06 with a standard deviation of 123, reflecting the density of

[6] The most pronounced surge occurred during the period leading up to the peak in December 2020, which coincided with Wave 11. This period also marks the availability of vaccines starting in December 2020, representing a critical turning point in the fight against COVID-19.

traffic across counties, and a range that extends from 0 to 2959. The proximity to TSDF averages at 0.43 with a standard deviation of 1.10 and spans from 0 to 23.24.

Crime rates have a mean of 342 with a standard deviation of 222, showcasing the variance in crime rates from 31 to 1820 across counties. The Social Vulnerability Index has an average of 0.50, with a standard deviation of 0.27, and a full range from 0 (least vulnerable) to 1 (most vulnerable). The percentage of households within a county with one or more housing problems averages around 15%, with a range spanning from 6% to 39%. Income inequality has a mean of 4 with a standard deviation of 1, ranging from 3 to 9, which is indicative of the disparities in income distribution within counties.

The average residential segregation, measured using the dissimilarity index across counties is 39, suggesting that on average, to achieve even racial distribution, 39% of the population of color would need to move across census tracts within the county. The range of this index is between 6 (indicating very low segregation) and 68 (indicating higher levels of segregation).

The average number of individuals per county cluster is reflected in the mean number of county residents at 621,25, with a very wide range that goes from a small cluster of 6,049 to an extensive one of over 5 million. The total number of counties included in the analysis is 753.

Table 3. Regressing Wave, Vaccine Availability, and Demographics with COVID-19 Death

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	OR	*CI*	*OR*	*CI*	*OR*	*CI*	*OR*	*CI*
wave	0.88*	0.88 – 0.89	0.68*	0.68 – 0.69	0.68*	0.67 – 0.69	0.71*	0.70 – 0.72
wave squared			1.01*	1.01 – 1.01	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01
Vaccine availability			1.59*	1.53 – 1.66	1.62*	1.56 – 1.69	1.36*	1.31 – 1.42
Black					0.72*	0.70 – 0.74	1.03*	1.01 – 1.06
Hispanic					0.33*	0.32 – 0.34	0.70*	0.68 – 0.72

Table 3. Regressing Wave, Vaccine Availability, and Demographics with COVID-19 Death (continued)

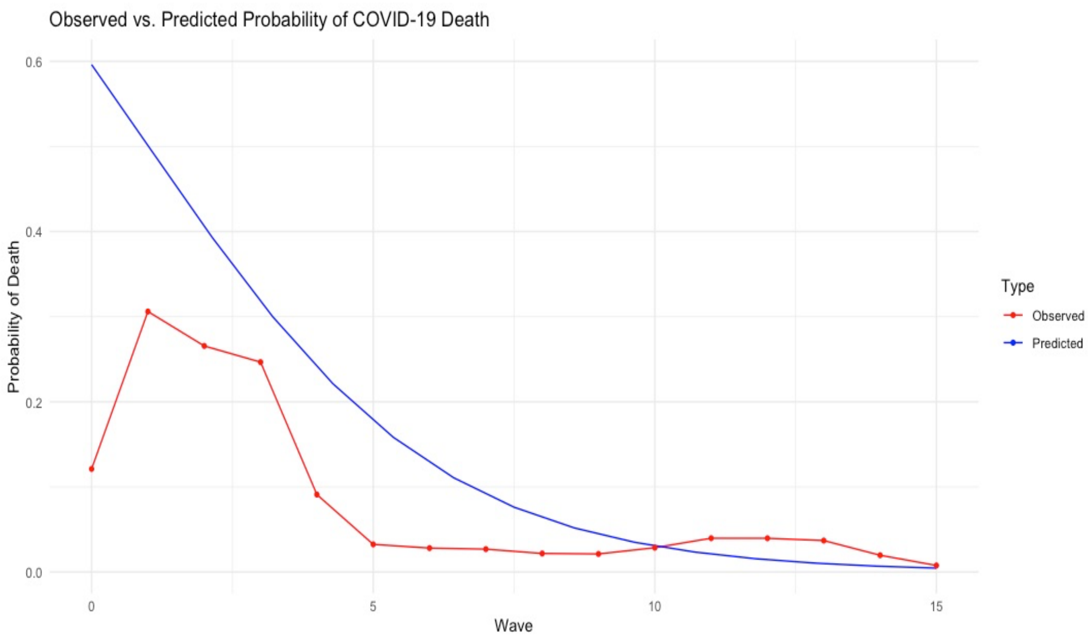
Asian			0.60*	0.58 – 0.63	0.92*	0.87 – 0.97
Others race			0.71*	0.62 – 0.81	1.33*	1.16 – 1.54
Female					0.69*	0.68 – 0.71
Over 60					25.66*	25.02 – 26.32
Random Effects						
σ^2	3.29	3.29	3.29		3.29	
τ_{00}	4.72 county	4.66 county	4.75 county		3.78 county	
ICC	0.59	0.59	0.59		0.53	
N	753 county	753 county	753 county		753 county	
Observations	1,526,418	1,526,418	1,526,418		1,526,418	
Marginal R^2 / Conditional R^2	0.022 / 0.598	0.027 / 0.597	0.042 / 0.608		0.248 / 0.650	
-2LL	454545.2	451290.5	444260.6		342332	
AIC	454551.2	451300.5	444278.6		342354	
BIC	454587.9	451361.7	444388.7		342488.7	

Note: References categories are White and male

Table 3 presents the regression models assessing the relationship between temporal variables, wave, vaccine availability, and demographic factors, and COVID-19 mortality outcomes. Model 1, which includes only the wave variable, indicates a 12% reduction in COVID-19 mortality as the pandemic progressed over the months. In Model 2, the wave variable has an odds ratio of 0.68, suggesting a more substantial decrease in mortality risk over time when compared to Model 1. The wave-squared variable's odds ratio of 1.01 signifies a non-linear trend in the temporal relationship with COVID-19 mortality. Surprisingly, vaccine availability is associated with a 59% increase in mortality odds, as indicated by an odds ratio of 1.59 (CI: 1.53 – 1.66), pointing to higher mortality post-vaccine availability net of the monthly decline in mortality as demonstrated by the wave variable.

In Model 3, the wave variable shows a steady decline in mortality risk over successive waves (OR: 0.68, CI: 0.67 – 0.69). The wave squared term, with an odds ratio of 1.01 (CI: 1.01 – 1.01), suggests minor increases in risk, possibly due to infection rebounds or wave intensity variations. Figure 2 plot visually confirms these findings, showing both observed and predicted death probabilities, validating the model's accuracy in capturing temporal trends.

Figure 2. Comparison of Observed and Predicted COVID-19 Mortality Over Time



Model 3 also integrates race into the analysis, initially suggesting that racial minorities, including Black, Hispanic, Asian, and Other races, are less likely to die from COVID-19 compared to Whites. However, this relationship evolves in Model 4, which consolidates insights from all three models along with age and gender factors. In Model 4, Black and Other racial groups are observed to have a 3% and 33% increased risk of COVID-19 mortality, respectively, when compared to Whites. Additionally, individuals over 60 years old are at more than a 25-fold higher risk of dying from COVID-19, while females are 31% less likely to succumb to the disease.

Table 4, continuing the model progression, assesses the impact of physical and social environmental factors on COVID-19 mortality. Model 5, building on previous models and incorporating variables for physical and social environments, underscores the significance of underlying medical conditions in COVID-19 mortality. Individuals with comorbidities face an over 11-fold increase in mortality risk. The model also reveals a 39% heightened risk of death from COVID-19 for individuals in high $PM_{2.5}$ areas and a more than 5-fold increase for those in areas with severe housing problems. Additionally, higher Social Vulnerability Index (SVI) areas are associated with a nearly 2-fold increased mortality risk. Contrarily, high income inequality areas show a 38% decreased risk of COVID-19 mortality, an unexpected finding.

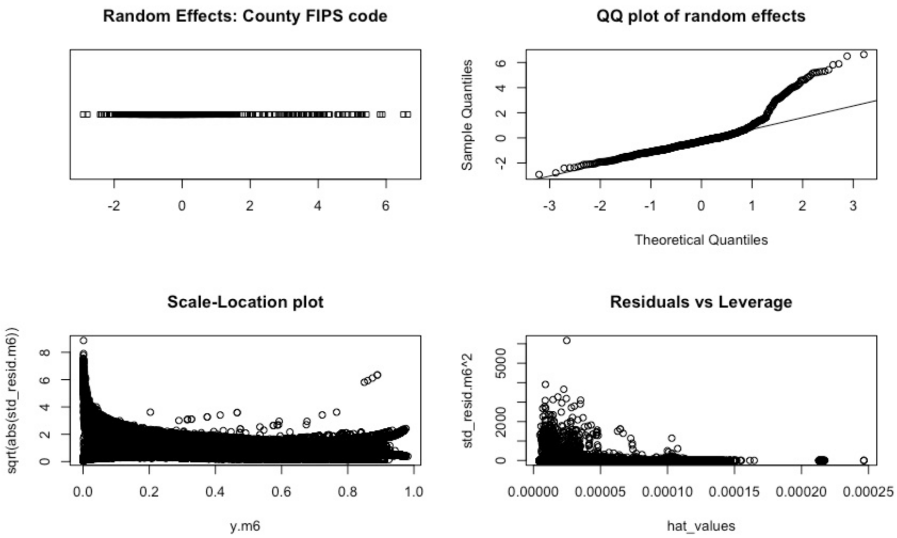
Table 4. Physical and Social Environment Factors and COVID-19 Death

	Model 5		**Model 6**	
Predictors	*OR*	*CI*	*OR*	*CI*
wave	0.76*	0.75 – 0.77	0.76*	0.75 – 0.77
wave squared	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01
Vaccine availability	1.28*	1.23 – 1.33	1.28*	1.23 – 1.34
Black	0.95*	0.93 – 0.98	0.88*	0.84 – 0.92
Hispanic	0.72*	0.69 – 0.74	0.64*	0.61 – 0.67
Asian	0.95	0.90 – 1.01	0.98	0.93 – 1.04
Others race	1.24*	1.07 – 1.44	1.27*	1.10 – 1.48
Female	0.69*	0.68 – 0.70	0.69*	0.68 – 0.70
Over 60	15.13*	14.74 – 15.53	15.10*	14.71 – 15.50
Underlying conditions	11.61*	11.13 – 12.10	11.59*	11.11 – 12.09
$PM_{2.5}$	1.39*	1.25 – 1.55	1.45*	1.29 – 1.62
Hazardous Air Pollutants	0.81	0.43 – 1.54	0.51*	0.27 – 0.98
Traffic proximity	1.39*	1.18 – 1.63	1.41*	1.20 – 1.66

Table 4. Physical and Social Environment Factors and COVID-19 Death (continued)

TSDF proximity	1.05	0.96 – 1.15	1.04	0.95 – 1.14
Crime	0.92	0.83 – 1.02	0.92	0.83 – 1.02
SVI	1.92*	1.37 – 2.69	1.92*	1.33 – 2.79
Housing problems	5.63*	3.93 – 8.07	5.65*	3.98 – 8.04
Income inequality	0.62*	0.51 – 0.76	0.62*	0.51 – 0.75
Segregation	0.98*	0.97 – 1.00	0.98*	0.97 – 0.99
Underlying conditions × $PM_{2.5}$			0.97*	0.94 – 0.99
Black × $PM_{2.5}$			1.02	0.99 – 1.05
Hispanic × $PM_{2.5}$			0.95*	0.92 – 0.98
Black × Traffic proximity			0.95*	0.92 – 0.99
Hispanic × Traffic proximity			0.93*	0.89 – 0.96
Black × TSDF proximity			1.01	0.99 – 1.02
Hispanic × TSDF proximity			1.02*	1.01 – 1.04
Black × Hazardous Air Pollutants			4.33*	2.95 – 6.35
Hispanic × Hazardous Air Pollutants			18.92*	12.48 – 28.68
Black × SVI			1.29*	1.14 – 1.45
Random Effects				
σ^2	3.29		3.29	
τ_{00}	2.67		2.70	
ICC	0.45		0.45	
N county	753		753	
Observations	1,526,418		1,526,418	
Marginal R^2 / Conditional R^2	0.471 / 0.708		0.472 / 0.710	
-2LL	319840.5		319628.7	
AIC	319882.5		319690.7	
BIC	320139.5		320070.1	

Figure 3. Diagnostic Plots for Model 6



Model 6 reveals complex dynamics influencing COVID-19 mortality, consistently showing the effects of wave progression and vaccine availability across all models. Model 6 has the lowest model fit statistics and therefore, is the best-fitting model.

Figure 3 presents diagnostic plots based on Model 6, which indicate minor deviations in the quantile-quantile and scale-location plots. However, considering the large dataset used in this study, these deviations do not undermine the model's validity. According to Ghasemi & Zahediasl, (2012), minor deviations from normality in large sample sizes are not of substantial concern, thereby supporting the reliability of our model's findings.

Figures 4 and 5 show the marginal effects of selected independent variables on the likelihood of COVID-19 mortality, holding all other covariates constant at their mean values in the model. These plots were generated using the ggpredict() function from the ggeffects R package, which calculates the average predicted probability of the outcome across the range of observed data for a given predictor while accounting for the distribution of other predictors in the model (Lüdecke, 2018). The resulting figures display the marginal effect of each factor with solid lines encapsulated by shaded areas denoting the 95% confidence intervals around these estimates.

Figure 4. Interactions Between Race, Pre-Existing Conditions and $PM_{2.5}$

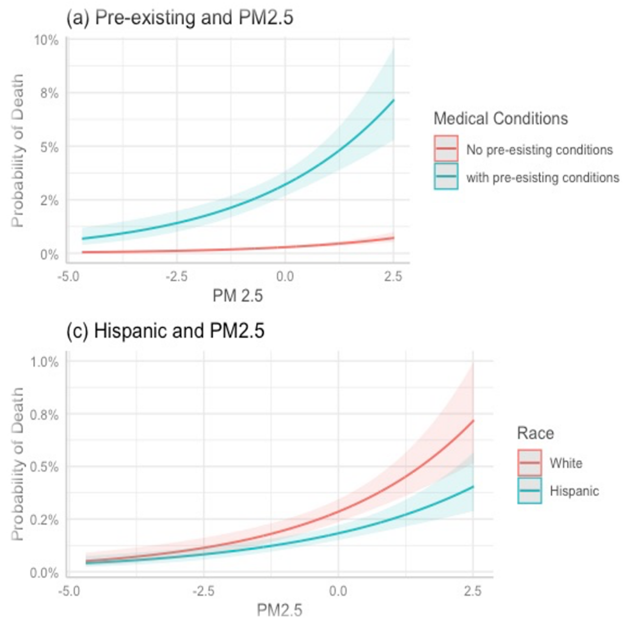


Figure 5. Interactions Between Race, HAP, and Traffic Proximity

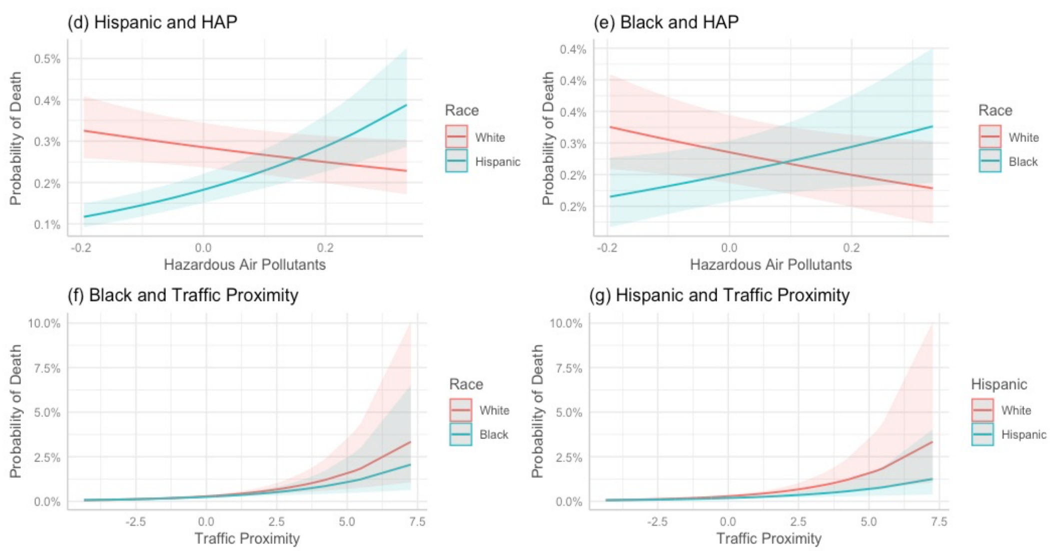
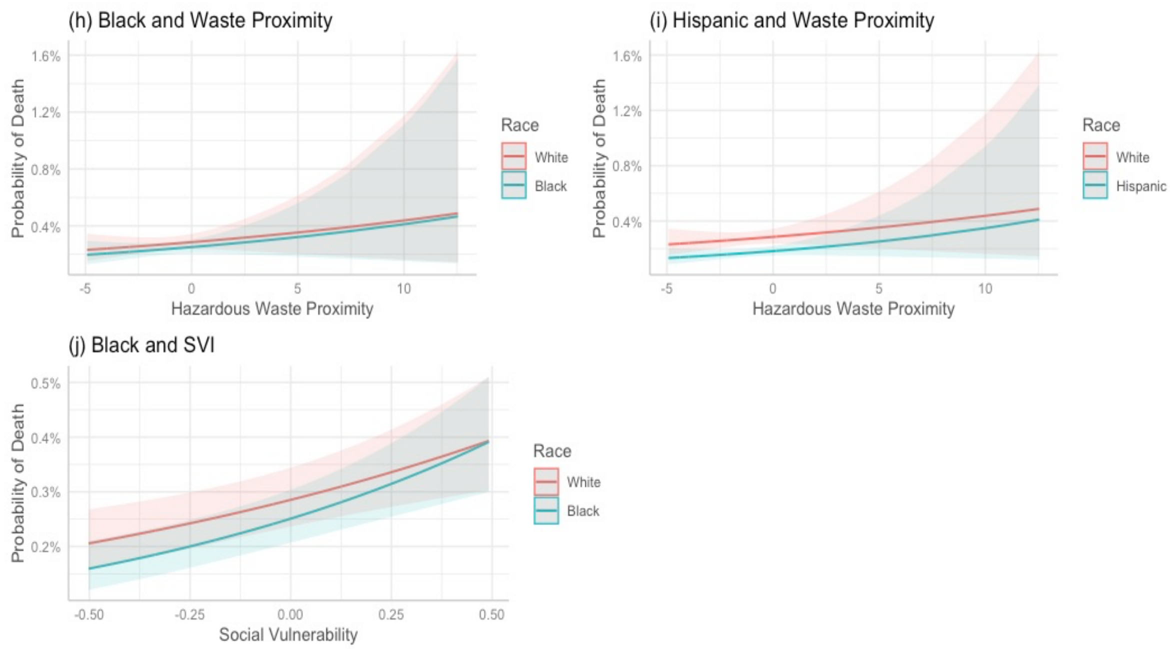


Figure 6. Interactions Between Race, Proximity to Waste Treatment Facilities, and SVI



In Model 6, racial minorities, notably Black (OR: 0.88, CI: 0.84 – 0.92) and Hispanic (OR: 0.64, CI: 0.61 – 0.67), living in counties with average levels of pollutants HAP and SVI exhibit a reduced likelihood of COVID-19 mortality compared to Whites. However, as HAP increases by one unit above the mean, the risk of mortality increases by 333% for Blacks and over 1700% for Hispanics. Figures 5 (d) and (e) illustrate that the probability of death for Hispanics and Blacks respectively increases more steeply than for Whites as exposure to hazardous air pollutants rises. Consistent with previous models, the results also show that females have a 31% lower mortality risk than males (OR: 0.69, CI: 0.68 – 0.70), aligning with gender disparities reported in the literature (Carethers, 2021; Chaturvedi et al., 2022; Danielsen et al., 2022).

The Model 6 results show that both $PM_{2.5}$ (OR: 1.45, CI: 1.29 – 1.62) and traffic proximity (OR: 1.41, CI: 1.20 – 1.66) are significantly associated with increased odds of

COVID-19 mortality, contributing to a 45% and 41% increase in the likelihood of mortality, respectively, when adjusting for other factors. This suggests that individuals in areas with $PM_{2.5}$ levels above the mean are at a significantly higher risk of death from COVID-19 compared to those in areas with average or below-average $PM_{2.5}$ levels. For $PM_{2.5}$ exposure, Hispanics exhibit a 5% reduced likelihood of COVID-19 mortality compared to Whites, with no significant association observed for Black individuals.

Surprisingly, individuals with underlying medical conditions residing in high $PM_{2.5}$ areas have a slightly reduced mortality risk (OR: 0.97, CI: 0.94 – 0.99). In the marginal effects plot, as illustrated in Figure 4 (a), the steepness of those with pre-existing conditions suggests a higher baseline probability of death, which aligns with the substantial main effect odds ratio of pre-existing conditions. However, the fact that those with or without pre-existing conditions both rise with increasing $PM_{2.5}$ levels, yet the interaction effect is less than 1 (OR: 0.97), suggesting that the additional risk imposed by $PM_{2.5}$ is not as large for those with pre-existing conditions as one might expect. This finding thus indicates a subdued interaction effect, contrary to the strong main effects observed independently for pre-existing conditions and $PM_{2.5}$, potentially suggesting that $PM_{2.5}$ does not uniformly increase risk across health statuses.

Age is also a significant predictor of COVID-19 mortality, with the study findings indicating that individuals over 60 years old have a 15-fold increased risk of death (OR: 15.10, CI: 14.71 – 15.50) when compared to younger individuals. The results also show that segregation (OR: 0.98, CI: 0.97–0.99) has a negligible but slightly negative association with COVID-19 mortality.

Model 6 shows that COVID-19 mortality disparities may be partly attributed to variations in comorbidities, as individuals with underlying conditions are more likely to die due to COVID-

19. The odds ratio for underlying conditions shows that individuals with comorbidities are about more than 11-fold (OR: 11.59, CI: 11.11 – 12.09) more likely to die from COVID-19 than those without, holding all the other variables constant.

The results suggest that environmental factors such as proximity to vehicular traffic and waste treatment facilities (TSDF) partially influence racial disparities in COVID-19 mortality. For example, the study found that the interactions between Black and Hispanic and traffic proximity show a slight reduction of 5% (OR: 0.95, CI: 0.92 – 0.99) and 7% (OR: 0.93, CI: 0.89 – 0.96) reductions in mortality respectively, indicating that the association between COVID-19 mortality and race is weakened but not eliminated when controlling for traffic proximity. The finding suggests while proximity to heavy vehicular traffic increases COVID-19 mortality risk across all groups, accounting for this factor slightly reduces racial disparities in mortality, yet such disparities persist despite considering environmental exposures. Likewise, the study shows that for Hispanics, proximity to TSDF slightly increases the COVID-19 mortality risk (OR: 1.02, CI: 1.01 – 1.04) though it has no significant effect on Whites. Similarly, no such associations between TSDF proximity and Blacks were observed.

Model 6 findings indicate that individuals residing in areas with severe housing issues—characterized by inadequate kitchen or plumbing facilities, overcrowding, or substantial financial burdens due to housing costs—experience a 465% increase (OR: 5.65, CI: 3.98 – 8.04) in the likelihood of mortality.

Similarly, the finding shows that Black individuals living in more socially vulnerable areas, measured by SVI, which includes area-level factors like SES, have a 29% higher risk of COVID-19 mortality (OR: 1.29, CI: 1.14 – 1.45) compared to those in areas with lower vulnerability. The interaction plot (Figure 6 j), however, shows a nuanced relationship between

SVI and the predicted probability of COVID-19 along racial lines. The initial increase in social vulnerability corresponds with a marked difference in mortality risk between Black and White populations. Yet, as vulnerability increases, the disparity in risk diminishes, indicating that in highly vulnerable areas, the mortality risk between the two groups converges.

This study measures income inequality by comparing median household incomes at the 80th and 20th percentiles, highlighting disparities within counties. Despite expectations that greater inequality worsens health outcomes, findings indicate a 38% lower mortality risk (OR: 0.62, CI: 0.51 – 0.75) with higher inequality, suggesting other factors like local health policies or community resources may influence health disparities. Finally, the results showed that there was no association between crime rates and COVID-19 mortality.

Most variables in Model 6, chosen for analysis, exhibit VIFs below 2, highlighting minimal multicollinearity concerns. However, high VIFs are anticipated for the wave and wave-squared variables due to their inherent correlation. The robust dataset of over 1.5 million observations ensures reliable estimates, even with higher VIFs in race-environment interactions such as Black × Traffic proximity (VIF: 6.80, SE: 0.01) and Hispanic × Traffic proximity (VIF: 7.83, SE: 0.01). These interactions show significant impacts on COVID-19 mortality with small standard errors and significant p-values, indicating that multicollinearity does not affect the model's reliability. This is further supported by low AIC values and narrow confidence intervals, endorsing the inclusion of these factors in the analysis.

1.5.1 **Sensitivity Analysis**

To manage the dataset gaps and the possibility of non-random missing data, such as from mild or asymptomatic cases that did not maintain medical contact, a sensitivity analysis was conducted, the results of which are presented in Table 5. The various models in the table explore different assumptions about the missing data entered as "unknown," providing an understanding of the robustness of the primary analysis in Table 4, Model 6.

Table 5. Sensitivity Analyses

	Multiple imputation of the outcome, Model S1	**Mortality Assumption for Unknowns, Model S2**	**Survival Assumption for Unknowns, Model S3**	**Random subsample, Model S4**	**Table 4 Model 6**
wave	0.71*	0.98*	0.70*	0.75*	0.76*
Wave squared	1.01*	1	1.01*	1.01*	1.01*
Vaccine availability	1.18*	1.11*	1.08*	1.30*	1.28*
Black	0.91*	0.96*	0.87*	0.89	0.88*
Hispanic	0.63*	0.79*	0.63*	0.61*	0.64*
Asian	0.91	0.96*	0.93*	0.97	0.98
Others race	1.03	0.91*	1.03	1.37	1.27*
Female	0.76*	0.89*	0.69*	0.77*	0.69*
Over 60	8.43*	2.35*	13.33*	14.99*	15.10*
Underlying conditions	6.59*	2.28*	9.30*	10.40*	11.59*
$PM_{2.5}$	1.05	1.57*	1.23*	1.21	1.45*
HAP	0.91	0.31	0.58	1.82	0.51*
Traffic proximity	1.11*	1.81*	1.05	1.08	1.41*
TSDF proximity	1.09*	0.84	1.08*	1.13*	1.04
Crime	0.92*	1.24	0.90*	1.05	0.92
SVI	1.25	0.7	1.60*	0.68	1.92*
Housing problems	1.93*	4.64	1.09	3.57*	5.65*
Income inequality	1.01	0.68	1	0.84	0.62*
Segregation	1	0.97*	1	1	0.98*
Underlying conditions × $PM_{2.5}$	1.05*	1.25*	0.86*	0.91	0.97*
Black × $PM_{2.5}$	1.01*	1.01	0.99	1.1	1.02
Hispanic × $PM_{2.5}$	0.98*	0.96*	0.98	1.21*	0.95*
Black × Traffic proximity	1	0.93*	0.99	1.11	0.95*
Hispanic × Traffic proximity	0.99*	0.99	0.98	0.88	0.93*
Black × TSDF proximity	0.99	1.04*	0.98*	0.99	1.01
Hispanic × TSDF proximity	1.01*	1.05*	1.01	1.07	1.02*

Table 5. Sensitivity Analyses (continued)

Black × HAP	1.96	1.16	5.48*	0.42	4.33*
Hispanic × HAP	5.96*	0.23*	7.03*	2.26	18.92*
Black × SVI	1.20	1.14*	1.19*	2.20*	1.29*
N	2,031,398	2,031,398	2,031,398	50,000	1,52,6418

Model S1 utilizes the 'mice' package in R for multiple imputations, treating missing outcomes as randomly distributed. The varied outcomes could stem from the treatment of missing data as both deaths and survivals. The process was repeated to create five separate imputed datasets, encapsulating the variability in the potential imputations and thus providing a more robust inference. The multiple imputation Model S1 aligns well with Table 4 Model 6 for some key predictors such as race, gender, Traffic proximity, underlying conditions, housing problems, and interaction terms such as Hispanic × HAP and Hispanic × TSDF proximity, indicating that the missing data on the death variable is likely random. The differences in odds ratios between the imputed Model S1 and the selected final Model 6 show the influence of missing data on the estimated relationships. For instance, the lower odds ratios for variables such as age ‘over 60' and 'underlying conditions' in Model S1 indicate that these factors' impact on COVID-19 mortality could be overrepresented in the final selected Model 6 if cases with more severe outcomes were systematically missing from the dataset. These patterns suggest the presence of younger individuals or less severe cases among the missing data. Similarly, the 'Hispanic × HAP' interaction showing lower odds in Model S1 compared to Model 6 suggests the possibility that the full extent of HAP exposure's impact on Hispanic populations might be overstated in the complete case analysis of Model 6.

Model S2 assumes mortality for unknowns on the death variable. The lower odds ratio for age ‘over 60’ and underlying conditions in Model S2 (OR: 2.35 and 2.28 respectively), compared to Model 6 (OR: 15.10 and 11.59 respectively), suggests that assuming all unknown outcomes are survivals underestimates the mortality risk for the older population, possibly missing cases were younger individuals with less severe outcomes. Therefore, Model 6 potentially overestimated the age and underlying conditions effect.

Model S3 is fairly consistent with Model 6, the selected model for analysis indicating that the missing cases were potential survival. The slightly lower odds ratio for environmental variable such as $PM_{2.5}$, in Model S3, compared to Model 6, suggests that the effects of environmental factors on COVID-19 mortality might be underestimated in Model 6. Likewise, the interactions between Black and environmental factor HAP in Model S3 show higher odds ratios than in Model 6, suggesting that the actual impact of HAP on mortality among Black is even greater than estimated in Model 6, under the assumption that unknowns were treated as survivals.

Finally, the comparison between Model S4, which represents a random subsample of fifty-thousand cases, and the final Model 6 indicates that key predictors such as gender, age over 60, underlying conditions, housing problems, environmental factors like TSDF proximity, and interaction term such as Black × SVI show similar patterns, although some variations exist. These differences highlight the influence of sample size on the robustness of model findings. Model 6, with a larger dataset, likely offers more generalizable results compared to the smaller, randomized subsample in Model S4.

1.6 Discussion

The findings of this study present a complex picture of the multidimensional factors affecting COVID-19 mortality, highlighting that individual demographics, comorbidities, and various physical environmental, and social structural factors are significant contributors. The study indicates that while both Black and Hispanic populations experience a differential impact from environmental pollutants compared to Whites, the nature of these impacts varies with each pollutant, underscoring the importance of public health strategies that account for race-specific environmental interactions.

A key finding that expands the current literature is recognizing differential exposure as a risk factor due to environmental hazards, particularly urban air toxics like hazardous air pollutants (HAPs), confirming Hypothesis 3 posed in this study. While living in average levels of HAP, $PM_{2.5}$ and SVI showed a reduced COVID-19 mortality among racial minorities, particularly Blacks and Hispanics, their risk of mortality increases substantially with each unit increase of air pollution exposures such as HAPs. Blacks living in areas with high HAP exposure were over four times more likely to die from COVID-19 compared to Whites, and similarly, Hispanics in high HAP regions face over eighteenfold the risk of COVID-19 mortality. This finding aligns with the broader literature which suggests that racial minorities are often subjected to worse environmental conditions due to HAP, potentially exacerbating health disparities (W. James et al., 2012; S. Wilson et al., 2015). Moreover, these findings expand Chakraborty's, (2021) study, which indicates that Blacks and individuals from low SES backgrounds are significantly overrepresented in counties with elevated COVID-19 incidence and respiratory risks from HAPs, emphasizing a compounded vulnerability related to both pandemic-related and environmental health risks.

These results not only support Hypothesis 3 but also align with Hypothesis 2, highlighting the broader impact of air pollution. Partially in line with Hypothesis 2, which proposed that residents in high air pollution areas—characterized by contaminants like $PM_{2.5}$ or HAP—face greater COVID-19 mortality risks than those in areas with cleaner air, the study confirms that elevated $PM_{2.5}$ exposure correlates with increased mortality. These findings align with existing research on the harmful health impacts of air pollution (Health Effects Institute, 2022). Conversely, the main effect of hazardous air pollutants (OR: 0.51, CI: 0.27 – 0.98) shows a negative association with COVID-19 mortality, suggesting that Whites in high HAP areas might experience lower mortality. This could be due to the lower prevalence of underlying health conditions among Whites, which increases mortality risk. Wiley et al., (2022) found that comorbidities such as obesity, hypertension, diabetes, and CKD were more prevalent in Black COVID-19 patients, contributing to higher mortality rates in these populations.

The significant role of comorbidities is further underscored by this study's findings on their associations with COVID-19 mortality. This study, supporting Hypothesis 1, found that comorbidities increase the risk of COVID-19 mortality substantially, with individuals with underlying conditions being more than 11 times more likely to die from COVID-19 than those without comorbidities. This finding aligns with similar other studies (Holman et al., 2020; Ssentongo et al., 2020). Likewise, age emerged as a significant determinant of COVID-19 mortality, with individuals over 60 years being markedly at higher risk, echoing the age-related vulnerabilities established by previous literature (Elezkurtaj et al., 2021; Harrison et al., 2020; Pennington et al., 2021; Zhou et al., 2020). This study also resonates with the gender disparities reported by Carethers, (2021), showing that females have a 31% lower risk of COVID-19 mortality compared to males.

This study revealed that individuals with pre-existing health conditions residing in areas with heightened levels of $PM_{2.5}$ do not exhibit the expected increased mortality risk, challenging the assumptions of Hypothesis 4. Instead, they demonstrate a marginally reduced risk (3%), signaling a subdued interaction effect. This unexpected result suggests that the health risk increments attributable to $PM_{2.5}$ pollution may not be as pronounced among those already facing health challenges, countering the assumption that $PM_{2.5}$ exposure uniformly increases mortality risk for all individuals with comorbidities.

The study further substantiates the connection between other environmental health risks and COVID-19 mortality. Consistent with Hypothesis 5, controlling for close proximity to vehicular traffic attenuates the association between COVID-19 mortality and race. Specifically, individuals living closer to high-traffic areas had a 41% increased likelihood of dying from COVID-19 (OR: 1.41, CI: 1.20 – 1.66). This finding echoes the findings of Kim et al., (2008) and suggests that environmental pollutants from traffic can exacerbate health issues, potentially increasing vulnerability to severe outcomes from respiratory infections such as COVID-19. The interactions between race and traffic proximity revealed that the associated risks were slightly reduced for Black and Hispanic populations. For Black individuals, the odds ratio was 0.95 (CI: 0.92 – 0.99), and for Hispanic individuals, it was 0.93 (CI: 0.89 – 0.96). This indicates that controlling for traffic proximity reduces the risk of COVID-19 mortality for these racial groups, but does not completely eliminate racial disparities. These findings support Hypothesis 5, showing that traffic proximity contributes to but does not fully account for racial disparities in COVID-19 mortality.

Conversely, for Hypothesis 6, the impact of proximity to hazardous waste treatment sites was not statistically significant for the main effect, indicating that this factor does not significantly influence COVID-19 mortality rates. The interactions between race and TSDF proximity revealed no significant effect for Black individuals (OR: 1.01, CI: 0.99 – 1.02) but a slight increase in risk for Hispanic individuals (OR: 1.02, CI: 1.01 – 1.04). This suggests that while TSDF proximity might have a marginal impact on racial disparities in COVID-19 mortality for Hispanic populations, it does not fully account for these disparities.

Housing problems emerged as another significant social environmental variable, confirming Hypothesis 7, with individuals living in areas characterized by housing issues being over five times more likely to die from COVID-19, underscoring the need to prioritize housing conditions in public health interventions. This finding adds to the literature that suggests that inadequate housing, characterized by overcrowding or lack of essential amenities, is a public health issue, especially in the context of infectious diseases like COVID-19 (Ahmad et al., 2020; Donadio et al., 2021).

This study's examination of the social determinants of COVID-19 mortality highlights the significant role of differential vulnerability. The findings indicate that the Social Vulnerability Index (SVI) alone significantly affects COVID-19 mortality, with individuals nearly twice as likely to die from COVID-19 (OR: 1.92, CI: 1.33 – 2.79). In addition, the interaction with Black populations further revealed crucial insights, supporting Hypothesis 8. Blacks in areas of high social vulnerability were found to be 29% more likely to succumb to COVID-19 (OR: 1.29, CI: 1.14 – 1.45), underlining the profound effects of structural social vulnerabilities. Interestingly, the mortality risk between Black and White individuals tends to converge in areas with the highest social vulnerability, as shown in the marginal effects plot (Figure 6(j)). This trend suggests that extreme vulnerability may have a leveling effect on racial disparities in health outcomes. Nevertheless, it also emphasizes the disproportionate burden that structural vulnerabilities place on certain groups, contributing to health inequities even when risk factors are widely shared across populations (Diderichsen et al., 2019; Fallah-Aliabadi et al., 2022).

The study also reveals an inverse association between income inequality and COVID-19 mortality, suggesting that areas with higher income inequality might experience a reduced mortality risk, which is an unexpected finding. Similarly, the study did not find any association between higher crime rates, a marker of lower socio-environmental quality, and COVID-19 mortality, thus not supporting Hypothesis 9.

Overall, these results indicate that addressing COVID-19 health disparities necessitates a multifaceted public health strategy that accounts for factors from individual demographics and biological traits to structural, social, and environmental influences. The findings highlight the need to consider a wide range of urban elements, both physical and social, to effectively reduce the unequal effects of COVID-19 on different populations.

Chapter II: Examining the Urban-Rural Divide in COVID-19 Health Outcomes Controlling for Physical and Social Environments

2.1. Introduction

The coronavirus disease (COVID-19), caused by SARS-CoV-2 virus, emerged as a global pandemic, claiming millions of lives, including over 1.1 million deaths in the United States alone within a span of three years (CDC, 2023b). Across geographic areas in the U.S., COVID-19 disparities have been evident, with rural regions experiencing higher rates of mortality and infection compared to urban areas (Cuadros et al., 2021; Karim & Chen, 2021). Specifically, rural areas in the U.S. experienced significantly higher COVID-19 incidence rates compared to urban areas, witnessing an alarming increase of over 80% in rural incidence and a mortality increase of more than 50% during the period from June to August 2020, while urban areas experienced a decline in mortality during the same period after initial rise (Cuadros et al., 2021). This shift indicates the unique vulnerability of rural areas to COVID-19, emphasized by their insufficient healthcare resources and demographic challenges, (Miller et al., 2020; Cuadros et al., 2021). These seemingly unusual COVID-19 outcomes between rural and urban areas necessitate further investigation and analysis.

The United States has experienced remarkable urban growth over the past few decades, resulting in a decline in the rural population and an increase in socioeconomic challenges in these areas (K. M. Johnson & Lichter, 2019). According to the 2020 Census, the urban population increased by 6.4%, with urban areas now accounting for 80% of the U.S. population, down slightly due to new urban classification criteria that increased population thresholds and incorporated housing unit density, but not due to migration from urban to rural areas (US Census

Bureau, 2022). As a result, urban areas have become denser, with the population density increasing from 2,343 in 2010 to 2,553 in 2020 (US Census Bureau, 2022).

Conversely, rural areas in the United States have seen a decrease in net migration since 2000, leading to a pronounced natural decrease in population, especially in farming, mining, and rural manufacturing counties, exacerbating existing economic disparities with urban areas (Johnson, 2012; Randolph et al., 2023).

Rural ethnic minorities, notably Blacks and Hispanics, encounter unique socioeconomic disparities compared to rural Whites, resulting in differences in urban-rural distribution (C. V. James, 2017; U.S. Department of Agriculture, 2020b). While there have been disparities in COVID-19 testing rates and financial hardships between rural and urban areas (Monnat, 2021), racial variances are particularly pronounced in COVID-19 fatality ratios in rural areas, especially in counties with larger Black and Hispanic populations (Millett et al., 2020; Iyanda et al., 2022). This underscores the need to investigate how diverse factors might differentially account for racial disparities in COVID-19 health outcomes between rural and urban regions.

Understanding the dynamics of urban areas is crucial as distinct features such as condensed residences and higher population density, contribute to increased transmission rates of COVID-19 (Huang et al., 2021). Moreover, Ma et al., (2023) shows the relatively slower recovery rates observed in central urban areas, compared to non-core areas. This phenomenon underscores the significance of factors like concentrations of points of interest such as sports centers, in the recovery process. Urban areas, distinguished by their high population density and economic activities, have been a focal point for investigating various dimensions of the COVID-19 pandemic, including environmental quality, socio-economic impacts, transportation, and urban design implications (Sharifi & Khavarian-Garmsir, 2020). Therefore, understanding the unique physical and social environments of urban areas is essential for a more nuanced grasp of the far-reaching impact of COVID-19 on diverse communities. For instance, Millett et al., (2020) demonstrated that black urban counties disproportionately experienced elevated COVID-19 rates and deaths, emphasizing the potential influence of socioeconomic factors. These studies suggest an assumption of how various elements that are distinct in urban and rural settings come together to shape COVID-19 outcomes. Moreover, studies have consistently shown the disproportionate impact of COVID-19 on racial minorities, resulting in higher infection rates (Magesh et al., 2021; Webb Hooper et al., 2020) and increased mortality (Aburto et al., 2022; Aschmann et al., 2022; Lundberg et al., 2022; Tai et al., 2021) when compared to White individuals. These disparities prompt a critical inquiry into how this unequal burden is pronounced in urban or rural settings. Understanding the distinctive physical and social dynamics of urban and rural areas is essential for gaining insights into the extensive impacts of COVID-19, with a central emphasis on racial disparities, a key focus of this paper.

This study thus aims to investigate the following research questions: Do demographic factors explain urban-rural disparities in COVID-19 mortality? For instance, we know that in urban areas racialized minorities, low SES individuals, older individuals and those with pre-existing conditions have a greater likelihood of COVID-19 mortality (Hawkins et al., 2020; Clark et al., 2020). Research also shows that the social and physical environments of urban areas are associated with greater COVID-19 mortality (Hu et al., 2021). Do the social and physical environments also explain the urban-rural divide in COVID-19 mortality like they explain the racialized COVID-19 mortality disparities in urban areas? Finally, how do the interactions among race, urbanicity, and key social or environmental factors, influence COVID-19 mortality disparities across urban and rural settings? This question seeks to highlight the complex relationships of sociodemographic and environmental elements across urban and rural landscapes, examining whether the effects of race and socioeconomic status on COVID-19 mortality are moderated by these individuals' residing contexts and access to resources.

This study addresses a gap in the existing literature by systematically exploring the impact of the urban-rural divide on COVID-19 mortality, with a focused examination of how demographic factors—including race, age, and pre-existing health conditions—along with both social and physical environmental factors, explaining if these factors contribute to narrowing or exacerbating the urban-rural divide. The study elucidates the multifaceted mechanisms driving the observed differences in COVID-19 mortality, placing a special focus on the distinctions in racialized impacts of the pandemic.

The study thus utilizes multilevel logistic regression analysis to explore whether racialized COVID-19 mortality disparities vary by urbanicity, controlling for factors such as pre-existing medical conditions, and social and physical environmental influences that contribute to the variation or consistency of these disparities.

2.2 Literature Review

2.2.1 COVID-19

COVID-19, caused by the highly contagious SARS-CoV-2 virus, is a zoonotic virus, which means it can spread between people and animals (Feng et al., 2023; Zhou et al., 2020). While primarily affecting the respiratory system, the transmission of the virus occurs through respiratory droplets and small particles (CDC, 2020b). The pandemic's severity is highlighted by its toll, surpassing many historical pandemics, such as HIV/AIDS and the 1918 "Spanish flu" (Sampath et al., 2021). The virus continually mutates, leading to the identification of monitored variants like Delta and Omicron (CDC, 2020b). The introduction of COVID-19 vaccines has significantly curtailed infections globally, with some vaccines showing over 90% efficacy in reducing documented cases (Ioannidis, 2021). As of mid-March 2023, approximately 5.5 billion individuals globally have been administered at least one dose of a COVID-19 vaccine, which accounts for around 72.3 percent of the global population (Holder, 2023).

2.2.2 Explanations or Causes Of COVID-19

2.2.2.1 Risk Factors and Proximate Causal Explanations. Individuals experiencing severe cases of COVID-19 frequently exhibit infections such as SARS-CoV-2-induced lung damage or bacterial superinfections, as seen in viral influenza (Morens et al., 2008; Omoush & Alzyoud, 2022; van der Sluijs et al., 2010). The presence of coinfections and superinfections, whether bacterial or viral, in COVID-19 patients, can considerably influence the disease's severity and outcomes, potentially resulting in heightened mortality and critical illness (Omoush & Alzyoud, 2022).

Studies have established a strong association between pre-existing medical conditions and the severity of COVID-19, often leading to fatal outcomes (Ejaz et al., 2020; Kompaniyets et al., 2021). Rural residents, in contrast to their urban counterparts, face a higher likelihood of experiencing health challenges such as heart disease, chronic respiratory disease, stroke, and cancer (National Institute for Health Care Management, 2022). Pre-existing health conditions significantly increase the risk of severity and mortality in COVID-19, especially in the context of infectious diseases (Aguiar & Stollenwerk, 2020; Clark et al., 2020). This association was also evident in the infectious H1N1 pandemic in 2009 (Adlhoch et al., 2019; Koh et al., 2016; Maine Center for Disease Control & Prevention, 2009). Moreover, S. Jain et al., (2009) show that 73% of H1N1 patients with pre-existing medical conditions faced an elevated risk, while Badawi & Ryoo, (2016) demonstrate the prevalence of diabetes, hypertension, and cardiac diseases among patients affected by another infectious disease, the Middle East respiratory syndrome coronavirus (MERS-CoV). A meta-analysis Ssentongo et al., (2020) further validated the association between common comorbidities like cardiovascular disease, hypertension, diabetes, and others, and an increased mortality risk from COVID-19. Urban-rural differences were also seen in vaccination rates with 49% of adults in rural counties being fully vaccinated, compared to 63% in urban counties as of January 2022 (National Institute for Health Care Management, 2022).

2.2.2.2 Urban-Rural Residence. Urban health research, which encompasses city comparisons, urban-rural health examinations, and neighborhood-level analyses (Galea & Vlahov, 2005), provides a strong basis for the study of health disparities between urban and rural populations. This research explores the differences in health outcomes between urban and rural areas, taking into account the diverse social and physical characteristics that influence the health of urban populations. Moreover, it acknowledges the substantial impact of urban resources, infrastructure, and socioeconomic factors on these health disparities (Ompad et al., 2008; Salgado et al., 2020).

Rural areas show higher mortality rates for conditions like cancer, respiratory issues, diabetes, heart diseases, and infant mortality, with a total average mortality rate of 841 per 100,000, significantly surpassing the urban figure of 713 (Randolph et al., 2023). Chronic conditions like cardiovascular disease (Abrams et al., 2021), hypertension (Heindl et al., 2023), and diabetes (Callaghan et al., 2020; Dugani et al., 2021; Mercado et al., 2021) have been instrumental in explaining the urban-rural health divide, while also serving as risk factors for severe COVID-19 outcomes (Peña et al., 2021). The urban-rural disparity in access to healthcare is also notable, with a lower percentage of rural residents living within 15 miles of an acute care hospital compared to their urban counterparts (Randolph et al., 2023).

Various studies have highlighted the significant impact of urban rurality on the prevalence of chronic conditions, with certain predictors playing crucial roles in explaining health disparities in rural and urban areas. For instance, the percentage of uninsured population (Gaffney et al., 2022), access to primary care physicians (Elson et al., 2021; Gaffney et al., 2022), food environment (Fonge et al., 2020; N. I. Larson et al., 2009), and income inequality (Thiede et al., 2020) have been identified as factors contributing to disparities in chronic conditions. These disparities have been particularly pronounced among racial minorities, resulting in poor outcomes.

Studies have shown that rural children are more likely to be overweight than urban children, despite the former exhibiting higher physical activity levels (A. Johnson & Mohamadi, 2015; J. Liu et al., 2008). J. Liu et al., (2008) found that rural children in the United States had a higher prevalence of overweight (16.5%) compared to urban areas (14.3%), with only 25.2% being physically inactive in rural areas versus 29.1% in urban areas. This indicates the influence of other pathways for obesity, such as socioeconomic status (Davis et al., 2011; J. Liu et al., 2008) and physical limitations, which are particularly prevalent in rural areas (Davis et al., 2011). Understanding these factors is essential in answering whether racial COVID-19 health outcome disparities exhibit consistency or variation between both urban and rural settings.

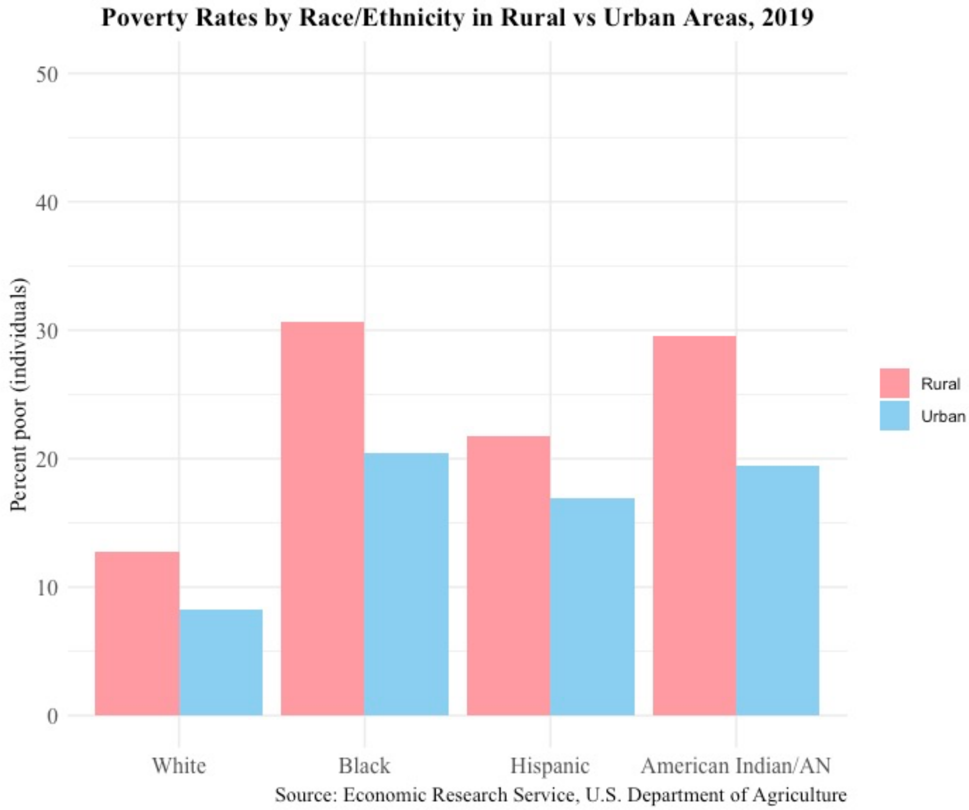
The urban-rural divide in health outcomes, particularly in the context of COVID-19 mortality, thus underscores the need for a nuanced understanding of how demographic factors and environmental conditions contribute to these disparities. When examining urban-rural health comparisons, it is essential to consider the dynamic nature of urban areas and cities, as they undergo continuous changes that influence the health of their populations (Galea & Vlahov, 2005). Urban areas provide benefits like economic growth and resource accessibility, but they also face challenges such as pollution and disease transmission (Dye, 2008). Conversely, health inequalities persist in rural areas due to varying levels of urbanization, socioeconomic factors, and demographic differences among residents (Eberhardt & Pamuk, 2004).

An examination of the demographic composition is essential to understand the potential for racialized differences in health outcomes across urban and rural areas. Compared to rural Whites, rural ethnic minorities tend to be economically poor and have lower levels of education (C. V. James, 2017), creating a potential burden of diseases. For instance, rural older adults (aged 85 and older) have a higher disease burden and use more prescription medications compared to their urban counterparts, with significant differences in disease accumulation (Goeres et al., 2016).

Rural counties also lag behind urban and suburban areas in employment among prime-age workers—those 25 to 54 years old—with only 71% employed in rural areas compared to 77% in urban and suburban counties, a decline since 2000 resulting in a decreased share of the nation's workforce within this demographic (Mitchell, 2018). Other demographic distinctions are evident as well, with rural areas having a higher percentage of residents over the age of 65 than urban areas, indicative of an aging population in these rural communities (U.S. Department of Agriculture, 2018).

2.2.2.3 Urban-Rural Race and Poverty Composition. In 2013, rural poverty reached 18.4%, which was the highest in the 30-year peak, but between 2013 and 2018, it dropped by 2.3 percentage points, benefiting about 1 million rural residents, according to the U.S. Department of Agriculture (2020).

Figure 7. Comparing Urban and Rural Poverty by Race



The decline in the poverty rates was seen among all racial groups. The steepest decline was among the rural Black population, going from 37.3% in 2013 to 30.7% in 2019, although they still had the highest poverty rate among rural groups (U.S. Department of Agriculture, 2023). Likewise, the data showed that Hispanics had the lowest rate, 21.7% among rural minorities. Although Whites had a historically lower rate, 12.7% in 2019, falling by 1.3 percentage points from 2018, the majority of the rural poor are White, accounting for 73.4% of the rural poor in 2018 (U.S. Department of Agriculture, 2020a). As shown in Figure 1, In 2019, urban Whites in the U.S. had the lowest poverty rate at 8.2%, Hispanics at 16.9%, and Blacks the highest at 20.4%, slightly above American Indians and Alaska Natives, against a backdrop where rural poverty rates stood at 15.4% compared to urban areas at 11.9% (U.S. Department of Agriculture, 2023).

Acknowledging the urban-rural divide's complexity, this study progresses to incorporate urban status, adding layers of race, and further expanding the model with primary care physician rates, income inequality, particulate matter ($PM_{2.5}$), and the food environment index. This addition of variables aims to show the factors at play, from individual to county levels, in defining COVID-19 mortality disparities.

2.2.2.4 Disparities in COVID-19 Outcomes. The focus of this paper is to examine how racialized COVID-19 disparities play out in urban and rural settings due to their distinct characteristics. However, it is important to note that there are gender and age disparities in terms of COVID-19's impacts as well. Studies have shown that men are more likely than women to die of COVID-19 infections (Carethers, 2021; Chaturvedi et al., 2022; Danielsen et al., 2022). For instance, Danielsen et al., (2022) show that the odds of death due to COVID-19 were 1.14 times higher for men compared to women, with no significant change in the pre-existing gender disparities in all-cause mortality rates during the COVID-19 pandemic. Likewise, as in chronic conditions like cardiovascular disease and type 2 diabetes that grow more common as individuals age (Prasad et al., 2012), numerous studies have established that age is a strong predictor of COVID-19 mortality, with the elderly population experiencing the heaviest burden of fatalities linked to the virus (Elezkurtaj et al., 2021; Li et al., 2020; Pennington et al., 2021; Zhou et al., 2020). Moreover, studies have also shown that older adults exhibit weakened vaccine responses, characterized by lower seropositivity, which indicates the detectable antibody (to COVID-19 in this particular case), rates, and levels of antibody, which are biomarkers of immunity against COVID-19 (Bayram et al., 2021; Fernandes et al., 2023). Compared with rural Whites, ethnic minorities living in rural areas tend to be younger (C. V. James, 2017) suggesting this might be a protective factor for rural areas.

Research has shown there are racial group differences in COVID-19 health outcomes, as studies have shown the disproportionate impacts of the pandemic on racial minorities (Aschmann et al., 2022; Lundberg et al., 2022; Sze et al., 2020). For instance, Magesh et al., (2021) found that Blacks have a significantly higher relative risk (RR) of testing positive for COVID-19 compared to Whites (RR = 3.54), while Hispanics have an even higher RR (RR = 4.68). Studies have also revealed that Blacks have 3.57 times increased risk of dying from COVID-19 compared to Whites, while Latinx individuals face an 88% increased risk of death (Carethers, 2021; Gross et al., 2020). The presence of comorbidities such as diabetes, hypertension, or cardiovascular diseases also plays a significant role in exacerbating the racial disparities observed among minority groups, such as Black and Hispanic populations, in relation to COVID-19 outcomes when compared to Whites (Alcendor, 2020; Kodsup & Godebo, 2022; Williamson et al., 2020).

Monnat (2021) highlights the disparities in COVID-19 outcomes between rural and urban regions, showing that residents in rural areas are subject to more adverse effects. These residents faced lower testing rates (34.8% in rural vs. 42.3% in urban areas), more significant financial difficulties, such as a higher incidence of late rent or mortgage payments (40.2% in rural vs. 33.1% in urban), and an increased probability of testing positive for COVID-19 (OR=1.56) (Monnat, 2021). The demographic distinctions of racialized minorities in rural areas being younger, and their White counterparts generally older, point to a critical intersection of age and race in shaping COVID-19 vulnerabilities. These observations guide our hypothesis formulation, focusing on the urban-rural divide while considering the compounded effects of social and physical environmental factors.

H1: Individuals residing in urban areas have a higher likelihood of COVID-19-related death compared to rural areas.

H2: In urban areas, racial minorities, particularly Blacks and Hispanics will experience higher COVID-19 mortality rates compared to Whites, independent of any assumed protective effects of younger age demographics typically in rural settings.

H3: Controlling for pre-existing underlying conditions will attenuate the COVID-19 mortality disparity between urban and rural residents.

H4: Controlling for age will attenuate the urban-rural disparity in COVID-19 mortality, with individuals over 60 in urban areas exhibiting lower odds of death compared to those in rural areas.

2.2.2.5 Uninsured Population. Residents in rural counties face disparities in access to healthcare services. Gaffney et al., (2022) in their study of individuals with chronic obstructive pulmonary disease (COPD) revealed that 12.6% of rural residents were uninsured, and in rural areas, 23% of individuals with COPD were considered inadequately insured, meaning they faced financial barriers to accessing necessary medical care, while in urban areas, the percentage of such inadequately insured individuals was at 20% at a statistically significant level (Gaffney et al., 2022). In terms of healthcare outcomes, Elson et al., (2021) in their retrospective cohort study of the 2012-2016 National Inpatient Sample hospital discharge data revealed that uninsured patients residing in the most rural counties in the United States had a higher raw hospital mortality rate of 1.89% compared to 1.44% for those in the most urban counties, even after adjusting for various factors such as age, sex, comorbidities, and hospital characteristics.

The odds of hospital mortality remained significantly higher for individuals in rural areas (Elson et al., 2021).

Fielding-Miller et al., (2020) demonstrated that in urban areas, a lower percentage of the uninsured population correlates with fewer reported COVID-19 deaths, with 73.8 fewer deaths reported for every 1% decrease in the uninsured population. In contrast, in rural areas, an increase in uninsured individuals correlated with fewer COVID-19 deaths within and adjacent counties, a trend that may suggest underreporting or access gaps in testing and care for uninsured and particularly immigrant populations (Fielding-Miller et al., 2020). These findings emphasize the importance of having health insurance coverage to reduce COVID-19 health outcomes, particularly in urban areas.

2.2.2.6 Primary Care Physicians Rate. Primary care physicians play a crucial role in both urban and rural areas, influencing healthcare access and quality of care. In 2021, rural areas accounted for 61% of the primary care health professional shortage areas, with only 12% of physicians practicing in these communities (National Institute for Health Care Management, 2022). Research has shown that an increased number of primary care physicians is associated with improved population health (Basu et al., 2019) reduced health system costs (Bazemore et al., 2018), and decreased health disparities (Starfield et al., 2005). Their vital role lies in providing comprehensive, person-focused care with first contact access and coordination (Starfield & Shi, 2007). For instance, Basu et al., (2019) found that a 10 per 100,000 population increase in primary care physicians in the United States resulted in a significant 51.5-day increase in life expectancy (0.2% increase) and notable reductions in cause-specific mortality, including lower cardiovascular, cancer, and respiratory mortality rates. These findings highlight the importance of enhancing primary care physician supply to improve population health outcomes through preventive care, early detection, and effective management of various health conditions.

Ensuring an adequate supply of primary care physicians is crucial in addressing disparities in healthcare access, particularly in underserved populations. For example, individuals in rural areas with COPD face barriers to accessing care due to financial constraints (Gaffney et al., 2022). Moreover, racial and ethnic minorities in medically underserved areas may experience disease burdens and limited preventive care due to a shortage of primary care physicians (Poghosyan & Carthon, 2017). Rural hospital closures (181 since 2005), driven by factors like consolidation, provider shortages, and lower patient volumes, have been further intensified by the COVID-19 pandemic, resulting in increased travel distances for residents seeking healthcare services (National Institute for Health Care Management, 2022).

H5: Controlling for primary physician rates will attenuate the urban-rural disparity, as urban areas with higher primary physician rates will have a lower likelihood of COVID-19 mortality compared to rural areas.

This study also examines the three-way intersection among urbanicity, race, and crucial environmental and social factors, such as the food environment and income inequality. The rationale posits that COVID-19 mortality disparities are partially rooted in the urban-rural divide, with racial dynamics and socio-environmental contexts further complicating these patterns.

2.2.2.7 Food Environment Index. Access to a healthy food environment is essential for improving health outcomes, as it influences the socioeconomic disparities in food and beverage choices (Pechey & Monsivais, 2016). Fonge et al., (2020) demonstrated that limited access to healthy food retailers in certain areas increases the risk of requiring medication to manage gestational diabetes. Studies further explain this by showing that areas with unhealthy food options, also known as food swamps, are associated with adverse health outcomes such as cardiovascular disease and obesity compared to food deserts with limited access to healthy food (Cooksey-Stowers et al., 2017; Kelli et al., 2019). Furthermore, a healthier food environment, as assessed by measures such as food environment index, has been associated with lower heart failure mortality rates at the county level (Gondi et al., 2022). Wang et al., (2021) demonstrated a positive correlation between the Food Environment Index, which includes measures of food insecurity and the presence of food deserts, and COVID-19 incidence, suggesting that better access to healthy food may be associated with cluster transmission during shopping in crowded supermarkets. These studies suggest that enhanced access to nutritious food can potentially serve as a protective factor against various health challenges, including infectious diseases like COVID-19.

Richardson et al., (2012) highlight the complex relationships between socio-demographic factors and urbanicity on food resource distribution. They revealed that low-density urban areas with high poverty and minority populations experience significant disparities in accessing grocery stores and an abundance of fast-food outlets, while high-density urban areas display an overall increase in food resource availability irrespective of poverty levels, highlighting the complex links between poverty, race, and urban density in shaping the food environment landscape (Richardson et al., 2012).

In hypothesizing the compounded effects of race, urban residency, and access to a healthy food environment on COVID-19 mortality, this study investigates the potential protective benefits of a higher food environment index, which may be particularly crucial for racial minorities who otherwise face elevated risks of COVID-19 due to structural inequalities in urban settings. Thus, access to a quality food environment could provide a crucial buffer against COVID-19's most severe impacts.

H6: Controlling for access to a better food environment will attenuate the urban-rural disparity, as urban residents living in areas with better food environments will exhibit lower COVID-19 mortality compared to their rural counterparts.

H7: In urban areas, racial minorities, particularly Black and Hispanic, living in areas with better food environments, will have lower COVID-19 mortality compared to their rural counterparts in areas with lower food environments.

2.2.2.8 Income Inequality. Health inequalities, encompassing disparities in health outcomes among specific groups based on race, gender, and socio-economic status (SES), are influenced by income inequality, perpetuated by institutional policies fostering discrimination in employment and education (Fiscella & Williams, 2004). Income inequality, thus plays a vital role in shaping health disparities as it directly contributes to the creation of poverty, which in turn has a detrimental impact on the social structures that foster health and well-being (Raphael, 2000). Understanding the underlying causes of health problems and the prevalence of health inequalities among different racial and ethnic groups requires research studies on health services and the social and economic characteristics of specific urban areas (Illsley, 1990; Pickett & Wilkinson, 2015; D. R. Williams & Collins, 2001a).

Numerous studies have demonstrated a strong association between income inequality and population health (Braveman et al., 2011; Lynch et al., 2004; Wilkinson & Pickett, 2006). For instance, Matthew & Brodersen, (2018) found a positive association between income inequality and behavioral health outcomes such as obesity, as well as physical health outcomes like diabetes. They discovered that a one-point increase in the Gini coefficient, a measure of income inequality, corresponded to a 2.9 percentage-point increase in the probability of being obese. Similarly, for the lowest income group, the same increase in the Gini coefficient resulted in a 2.5 percentage point increase in the probability of being obese (Matthew & Brodersen, 2018). Research indicates that income inequality exacerbates health issues, as seen in Kim, (2016) study, which links high income inequality to increased instances of heart disease and suicide, by acting as a social stressor that influences psychological stress in economically unequal areas, thereby degrading essential health resources such as social support and cohesion (Avanceña et al., 2021; Pickett & Wilkinson, 2015).

Thiede et al., (2020)argue that income inequality, historically higher in rural counties, has converged with urban levels due to rising inequality within metropolitan areas, influenced by suburbanization and central-city gentrification. This shift has made cities focal points for income inequality, driven by changes in the labor market and economic development (VanHeuvelen, 2018). Over the past century, urban centers have faced significant economic disparities due to factors like gentrification, income polarization, and residential segregation (Nijman & Wei, 2020). Urban areas, characterized by higher population density, exhibit greater economic disparities, with rapidly urbanizing counties experiencing heightened levels of inequality (Moller et al., 2009).

Previous research has established a positive association between income inequality and COVID-19 impacts on health (Gaia & Baboukardos, 2023; Liao & De Maio, 2021). Specifically, Gaia & Baboukardos, (2023) highlighted the moderating role of income inequality in the relationship between ethnic minorities and COVID-19 excess mortality in a British urban context, underscoring the disproportionate impact of the pandemic on ethnic minority populations and the exacerbating effect of income inequality on health disparities.

H8: The relationship between income inequality and COVID-19 death is stronger in urban areas than in rural areas, particularly for individuals with pre-existing medical conditions compared to those without.

2.2.2.9 Particulate Matter ($PM_{2.5}$). Particulate matter $PM_{2.5}$, composed of fine inhalable particles smaller than 2.5 micrometers, is a significant air pollutant found in urban areas. It has both chronic and acute health effects (Kampa & Castanas, 2008; U.S. Environmental Protection Agency, 2019). Numerous studies have demonstrated the association between exposure to $PM_{2.5}$ and respiratory and cognitive health issues, highlighting its detrimental impact (Achilleos et al., 2019; Brook et al., 2010; Cheung et al., 2020; Cleary et al., 2018; Dedoussi et al., 2020; Ji et al., 2020; Pope III et al., 2019; Schwartz & Dockery, 1992; Stieb et al., 2012).

Negative physical environments, including pollutants from hazardous waste, air, and various biological and chemical sources, play a significant role in determining poor urban health outcomes for residents (Laumbach et al., 2015; Manisalidis et al., 2020; Satterthwaite, 1993). Moreover, the structural design of urban spaces, encompassing roads and transportation infrastructures, continuously shapes traffic conditions and contributes to other forms of pollution (Wang et al., 2021). Therefore, it is essential to examine the impact of air pollution, including $PM_{2.5}$, on public health, particularly its association with respiratory conditions like asthma (American Lung Association, 2022; Bowe et al., 2019; Cohen et al., 2017; Health Effects Institute, 2022; Kravitz-Wirtz et al., 2018; Y. Wu et al., 2021), as well as its adverse effects on other chronic diseases such as cardiovascular diseases and lung cancer (Al-Aly & Bowe, 2020; Bowe et al., 2019; Cohen et al., 2017). Notably, diseases such as cardiovascular, asthma diabetes, and chronic obstructive pulmonary disease (COPD) have been identified as comorbidities for COVID-19 (Rogliani et al., 2021).

Understanding the health impacts of air pollution, including $PM_{2.5}$, is crucial not only in urban areas, where more than 80% of the global population is exposed to this significant health risk through prevalent sources like transportation and industry but also in rural areas, considering the presence of air pollution resulting from wildfires (Attademo & Bernardini, 2017, 2020; J. C. Liu et al., 2017). By comprehending the role of $PM_{2.5}$ within the context of the urban-rural divide in COVID-19 health outcomes, we can expand our understanding of the relationships between the physical environment, health disparities, and disease outcomes.

This research investigates the associations between COVID-19 mortality and a range of factors, encompassing urban-rural divides, socioeconomic influences, healthcare accessibility, and environmental conditions. Hypothesis 1 suggests that COVID-19-related mortality rates are higher among urban residents, particularly within the Black community, compared to rural areas and Whites. Hypothesis 2 posits that urban residents with pre-existing conditions face higher COVID-19 mortality risks due to urban prevalence of pre-existing conditions potentially stemming from lifestyle, healthcare access, and environmental aspects. Likewise, Hypothesis 3 suggests that rural individuals over 60 face increased COVID-19 mortality risks, suggesting age-related vulnerability and limited healthcare access in rural areas. Hypothesis 4 proposes that urban regions with adequate primary care physicians exhibit lower COVID-19 mortality rates, founded on enhanced healthcare provisions and early detection potential. Driven by racial disparities in food accessibility and its impact on pre-existing health conditions, Hypothesis 5 probes higher COVID-19 mortality risks among urban residents with inadequate access to healthy foods, stemming from limited nutritious choices in these environments. Hypothesis 6 contends that Blacks who have limited access to healthy food environments face a higher risk of COVID-19 mortality. Finally, Hypothesis 7 suggests that in urban areas, income inequality intensifies COVID-19 death more in individuals with pre-existing conditions than in those without.

Previous studies (Karim & Chen, 2021; Paul et al., 2021) have examined the impact of COVID-19 on urban-rural disparities using county-level aggregate data or have confined their research to specific regional contexts (Denslow et al., 2022). However, there remains a significant research gap, particularly regarding individual-level data, and nationwide coverage. This study examines the influence of the urban-rural divide on COVID-19 mortality, while also accounting for the potential impacts of both physical and social environmental factors on individual-level COVID-19 patients with pre-existing medical conditions.

2.3 Data & Methodology

This study aims to explore the COVID-19 health disparities between urban and rural areas while considering underlying medical conditions, and other physical and social environmental factors. By analyzing measures such as income inequality, healthcare access, and the food environment, the study investigates their impact on COVID-19 mortality, shedding light on the urban-rural health divide, which is often differentiated by factors such as residence, socioeconomic status, and health-related measures associated with the physical and social environment.

2.3.1 Data

The analysis focuses on racial disparities in COVID-19 deaths across rural and urban (which also includes suburban) areas using multilevel models. I combined data from four existing datasets. The first dataset, CDC's COVID-19 Case Surveillance Restricted Access Detailed Data included both probable cause and laboratory-confirmed cases of COVID-19[7]. The

[7] While institutions like Johns Hopkins University have compiled detailed data, these datasets often lack individual-level information regarding pre-existing medical conditions.

data covered the period from January 1, 2020, which marked the earliest reported COVID-19 case, until April 15, 2021. The dataset may include individuals who had received emergency use vaccines starting in early December 2020 (U.S. Department of Health & Human Services, 2020). While the dataset lacks information on social and economic variables that are crucial in measuring the impact of SES, this is the best national-level dataset with individual-level information on pre-existing medical conditions that can best answer this study's research questions.

The dataset consists of 24,441,351 observations. The unanswered responses (blank) were redefined as NA values and considered "missing" data. These missing values were excluded from the final analysis. For instance, when examining the question regarding the existence of "pre-existing medical conditions?" with response options of "Yes," "No," or "Unknown," the "Unknown" values were eliminated after conducting initial descriptive statistics on the unknown responses. This data-cleaning process resulted in a final sample of 1,611,874 observations used for the analysis. The implications for the missingness on the CDC's Case Surveillance Restricted Access dataset are that it might lead to potential biases and limitations in the interpretation of the final analysis results, particularly when addressing questions related to "Unknown" responses (Neupane & Ruel, 2023). The Federal Information Processing Standard (FIPS) code for counties uniquely identifies each county in the Case Surveillance dataset and is assigned according to the individual's place of residence.

The second dataset originates from the Environmental Protection Agency's (EPA) new environmental justice (EJ) mapping and screening tool, EJscreen. This tool offers detailed environmental and demographic information for various locations across the United States. While it includes crucial environmental indicators such as $PM_{2.5}$, which help gauge the impact of the physical environment, it lacks other important variables like indoor air quality and drinking water quality, which are directly linked to population health outcomes. However, due to the nationally consistent dataset with census block group level granularity on various environmental indicators, EJscreen is the best dataset for the variable $PM_{2.5}$ for this study. The EJscreen dataset does not encompass other variables of environmental concerns, such as drinking water quality and indoor air quality which impact population health. EJscreen consolidates data from various sources, such as the EPA's Office of Air Quality Planning and Standards, the Office of Pollution Prevention and Toxics, and the Highway Performance Monitoring System. The $PM_{2.5}$ data is primarily at the block group level. For this study, I averaged the $PM_{2.5}$ data at the county level. By aggregating to the county level, EJscreen's limitations are addressed, consolidating data from multiple block groups in line with EPA recommendations, thus improving accuracy in smaller regions like single Census block groups (EPA, 2022a)

The third dataset is the County Health Rankings & Roadmaps (CHR&R), a program of the University of Wisconsin Population Health Institute. The CHR&R was utilized to incorporate factors such as the uninsured population, primary care physicians' rate, food environment index, and income inequality associated with social environments. The CHR&R national dataset is collected from entities including the National Center for Health Statistics, Bureau of Labor Statistics, U.S. Census Bureau, U.S. Department of Housing and Urban Development, and the American Community Survey, offering data at the county level.

The fourth dataset is from the National Center for Health Statistics (NCHS) 2013 and provides an urban-rural classification scheme. The NCHS urban-rural county classification scheme is the best for this study because the dataset was particularly designed to work with health data (National Center for Health Statistics, 2019).

This study recognizes that certain COVID-19 cases may not be documented if individuals do not engage with healthcare services. Predominantly, the data reflect cases severe enough to warrant medical care, potentially skewing the analysis toward more serious instances.

2.3.2 Constructs

The dependent variable in this study is COVID-19 mortality, measured as a binary individual-level variable called 'Death,' with 'Yes' coded as 1 and 'No' coded as 0. The variable ‘Death’ follows a binomial distribution.

2.3.2.1 Urban-Rural Residence. The focus of this study is on examining urban-rural residence as the key independent variable. To determine urban-rurality, the individual-level data containing county FIPS codes were categorized according to the 2013 National Center for Health Statistics (NCHS) classification scheme.

Urban-rurality was categorized into 'urban' for all metro areas, including 'large central', 'large fringe metro' with populations over 1 million, 'medium', and 'small metro' areas with populations from 250,000 to under 1 million, and 'rural' for 'micropolitan' and 'noncore' areas with populations below 50,000 (National Center for Health Statistics, 2019). These categories are defined by population size, density, and relative proximity to large urban centers. The NCHS Urban-Rural Classification Scheme is specifically designed for health disparity studies and is widely used in public health research (Guo et al., 2022; Matthews et al., 2017). Given this study’s focus on health disparities, the NCHS classification scheme is the best dataset as it is specifically designed for health disparity studies and captures the largest rural population (Long et al., 2021), potentially including a broader range of rural health environments, compared to other datasets such as Rural-Urban Continuum Code by the U.S. Department of Agriculture. All COVID-19 patients were assigned to 'urban' or 'rural' categories based on their residences.

2.3.2.2 Race and Pre-Existing Medical Conditions. The individual-level variable, race is classified into five groups—Whites, Blacks, Hispanics, Asians, and Others (which include American Indian Alaska Native, Asian, Multiple/Other, Native Hawaiian/Other Pacific Islander, and Hispanic/Latino). For pre-existing medical conditions in COVID-19-infected patients, the variable was dichotomized, with the presence of any pre-existing condition coded as '1' (Yes) and the absence as '0' (No).

2.3.2.3 Uninsured Population. As previously described in the third dataset, the percentage of the uninsured population, a continuous variable, in this study is derived from the Small Area Health Insurance Estimates (SAHIE) program by the US Census Bureau. This data is crucial for analyzing health insurance coverage trends and is included in the dataset provided by County Health Rankings & Roadmaps. The SAHIE provides detailed health insurance coverage estimates for the year 2020 at both state and county levels, leveraging data from diverse sources including the American Community Survey, population estimates, tax returns, SNAP participation records, County Business Patterns, and Medicaid and CHIP participation records (Census Bureau, 2023). SAHIE employs statistical modeling techniques utilizing one year of survey data to determine the uninsured rate, which represents the percentage of individuals under 65 without any health insurance coverage, excluding employer, union, insurance company, or government-assistance plans such as Medicare, Medicaid, TRICARE, Indian Health Services, VA, or other health coverage plans (Dalzell et al., 2015; Census Bureau, 2023).

2.3.2.4 Primary Care Physicians Rate. The Primary Care Physicians (PCP) rate represents the PCP per 100,000 population. The PCP rate is a continuous variable. The definition of Primary Care Physicians used by CHR&R includes both Doctors of Medicine (MDs) and Doctors of Osteopathic Medicine (DOs), with obstetrics/gynecology excluded as a primary care physician type. Counties with a population exceeding 2,000 and no primary care physicians have missing values. However, CHR&R notes that this measure has limitations, such as not accounting for non-physician primary care providers like nurse practitioners or physician assistants, and not considering the impact of care organization and coordination on health outcomes (County Health Rankings & Roadmaps, 2023c).

2.3.2.5 Food Environment Index. The Food Environment Index, a continuous measure, evaluates the factors contributing to access to a healthy food environment, ranging from 0 (worst) to 10 (best). The 2023 County Health Rankings used data from 2019 & 2020 for this measure, which takes into account proximity to healthy food options and income levels, including access to grocery stores and the impact of affordability (County Health Rankings & Roadmaps, 2023a). The index comprises two equally important indicators: limited access to healthy foods, which estimates the percentage of low-income individuals residing far from grocery stores, and food insecurity, which estimates the percentage of the population lacking consistent access to reliable food sources. According to CHR&R, the average value for counties in 2023 was 7.6, with the majority falling between 6.8 and 8.2. CHR&R notes that caution is advised when comparing estimates across state borders, as the food insecurity models may exaggerate differences in border counties.

2.3.2.6 Income Inequality. The study utilizes the ratio between the median household income at the 80th percentile and the 20th percentile in each county as an index for income inequality based on the ACS 2015-2019 estimate. In the continuous variable of income inequality, the 80th percentile represents the income level where 20% of households have higher incomes, while the 20th percentile represents the income level for the bottom 20% of the population. Higher index values indicate a larger income gap between individuals at the higher and lower ends of the income distribution.

2.3.2.7 Age and Gender. Age and gender are control variables. The CDC dataset contains individual-level data on sex and age, and the stratified ages are 10 years apart, starting from 0-9 years to 80+ years old. The ages were dichotomized by dividing into 60 and younger (0) and over 60 years old (1). The individual-level sex variable was dichotomized into males (0) and females (1).

2.3.2.8 Particulate Matter ($PM_{2.5}$). The continuous variable, particulate matter $PM_{2.5}$ was the control variable representing the physical environment, which could potentially have a confounding effect on COVID-19 mortality. The particulate matter $PM_{2.5}$ is an annual average concentration in micrograms per cubic meter. $PM_{2.5}$ is 2.5 microns or less in diameter and power plants, vehicular exhaust, and industrial facilities are the common sources of such air pollutants (Leffel et al., 2021). $PM_{2.5}$ data are based on 2019 estimates by EPA's Office of Research and Development. According to the EPA, different levels of $PM_{2.5}$ concentrations are found across the country, making residents vulnerable to varying degrees of inhalation. The block group-level $PM_{2.5}$ values were aggregated for a county-level analysis.

In addition, age, pre-existing medical conditions, gender, race, and time variables were used as control variables for this study.

I incorporated a vaccine availability variable in the analysis to distinguish the period before and after the availability of COVID-19 vaccines. This was represented as a dummy variable: 'vaccine availability' equals 1 for the period following vaccine rollout, and 0 for the period prior to vaccine availability. This vaccine availability control variable helps us understand how the impacts of COVID-19 evolved with the initiation of vaccination campaigns.

I also included a continuous time variable in my analysis, starting from 0, and calculated based on the number of months elapsed since the initial period, which begins on January 1st, 2020. This variable extends to April 15th, 2021, marking 15 months, which corresponds to the selected period for this study. Incorporating this time variable as a control is essential to model the temporal spread of COVID-19 across regions, enabling an understanding of the disease's changing impact over the course of the pandemic unconfounded by time. This approach aligns with the concept of 'period effects', referring to societal changes triggered by historical events or processes that uniformly affect people (Alwin & McCammon, 2003).

All the continuous variables such as uninsured population, food environment index, Primary care physicians rate, income inequality, and $PM_{2.5}$ were grand-mean-centered to facilitate the interpretation of the model parameters by setting the average level of the variables as the reference point across the dataset.

2.3.3 Statistical Analysis

A multilevel logistic regression analysis was conducted to examine the relationship between the urban-rural divide, socioeconomic and health variables, and COVID-19 mortality. The logistic regression model considers the hierarchical structure of the data, with individual-level observations nested within counties.

The analysis explores the associations between the main predictor variable, urban-rural residence, and other independent variables uninsured population, primary care physicians rate, food environment index, and income inequality. The model accounts for physical and social environment variables such as particulate matter ($PM_{2.5}$), and individual-level variables age, and gender as control factors.

For data analysis, *lme4* package in R was used. In this analysis, nAGQ = 1, the Laplace approximation for glmer models, was selected to balance model accuracy with computational efficiency. Given the large sample size of this study, the differences between nAGQ = 0 and higher values are minimal, making nAGQ = 1 an optimal choice to ensure precision without significantly increasing computational time (Gilbert, 2023; Q. Wu et al., 2019).

The random intercepts model:

$$Log\ (P_{ij} / (1-P_{ij})) = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_j + \gamma_{11}W_jX_{ij} + \mu_{0j} + r_{ij} \qquad \textbf{(1)}$$

where $\gamma_{00} \sim N(\beta_0, \sigma^2)$

where P_{ij} represents the probability of death occurring for individual i in county j, γ_{00} is the intercept, $\gamma_{10}X_{ij}$ represents the individual-level predictor variables, $\gamma_{01}W_j$ represents the county-level predictors and $\gamma_{11}W_jX_{ij}$ represents the cross-level race by urban-rurality interaction terms. Finally, there are two random terms in the model. The random term μ_{0j} is the unmodeled level-2 variability for each county j and r_{ij} allows for individual variation within county j.

The multilevel logistic regression analysis considers the nested structure of the data (individuals within counties) and examines both individual-level and county-level predictors. This approach allows for an understanding of how urban-rurality influences COVID-19 mortality.

To capture the non-linear progression of COVID-19 mortality over time, the wave variable, indicating months from the baseline, was squared in the hierarchical logistic regression models. This inclusion helps detect non-linear trends in mortality rates of the pandemic's temporal dynamics.

2.4 Results

Descriptive statistics for the analysis sample are provided in Table 1. The individual-level variables indicate that out of the total sample, 5% of the individuals are recorded as COVID-19 deaths. Females constitute slightly more than half of the sample at 54%, while men make up the rest at 46%. In terms of racial composition, Whites represent a majority at 64%, followed by Hispanics at 17%, Blacks at 11%, Asians at 3%, and other racial groups (including Multiple/Other, American Indian/Alaska Native, Native Hawaiian/Other Pacific Islander) at 4%. Those aged 60 and over comprise 24% of the sample, indicating a considerable portion of the population at higher risk due to age.

Table 6. Descriptive Statistics of Variables Included in Analyses

Individual level	***N***	**%**	**Range**
COVID-19 death	86,264	5	0-1
COVID-19 survival	1,525,610	95	
Women	862,701	54	0-1
Men	749,173	46	
White	1,028,557	64	0-1
Black	184,325	11	0-1
Hispanic	280,464	17	0-1
Asian	46,062	3	0-1
Other racial groups	72,466	4	0-1
Age 60 and over	388,940	24	60–80+
Under age 60	1,222,934	76	0-59
Pre-existing medical conditions	672,912	42	0-1
No pre-existing medical conditions	938,962	58	
Urban	440	43	0-1
Rural	588	57	
Vaccine availability	462,155	29	0-1
Vaccine unavailability	1,149,719	71	
Wave	16		0-15
***N*-individual**	1,611,874		
County level	**Mean**	**Standard deviation**	**Range**

Table 6. Descriptive Statistics of Variables Included in Analyses (continued)

$PM_{2.5}$	7.59	1.35	2.76 - 10.17
Percent Uninsured	9	3.48	2 - 28
Primary Physician Rate	76.16	34.56	0 - 576
Food Environment Index	8.1	0.78	2.7 - 9.9
Income Inequality Ratio	4.42	0.67	3 - 9.1
Number of People living in each county	594,696	696,696	1,284-5,275,541
N-county	1028		

A considerable sample size of 42% have pre-existing medical conditions. Urban residents constitute 43% (belonging to 440 urban counties) of the sample, while rural residents make up 57%. Regarding vaccine availability, 29% of the sample belongs to the period when the vaccine was available in December 2020, contrasting with 71% from the pre-vaccine availability period. This dataset covers the period of the pandemic in 16 waves, capturing the monthly trends of the spread of COVID-19.

At the county level, the mean concentration of particulate matter air pollution or $PM_{2.5}$, a control variable, is 7.59 micrograms per cubic meter, with some variability (standard deviation of 1.35) and a range of 2.76 to 10.17. The average percent of uninsured individuals in a county is 9, with a standard deviation of 3.48 and a range from 2 to 28, indicating differences in healthcare coverage accessibility. The average rate of primary care physicians is 76.16 per 100,000 population, with substantial variability (standard deviation of 34.56) and a range from 0 to 576, reflecting healthcare resource distribution. The Food Environment Index has an average score of 8.1, indicating generally favorable conditions for accessing healthy foods. The index ranges from 2.7 to nearly 10, with the lower end representing less favorable conditions and the higher end representing the best. Income inequality, with a mean ratio of 4.42, highlights economic disparities within counties, with a range from 3 to 9. The average population size of the counties included in the sample is approximately 594,696, with a range from as few as 1,284 to as many as 5,275,541 individuals, highlighting the vast differences in county sizes. A total of 1,028 counties are represented in the analysis.

To systematically address the three research questions, results are presented in two focused tables. Table 7 starts by modeling COVID-19 deaths over time and period effects to ensure these temporal effects do not confound urban-rural differences or racial disparities in COVID-19. Then I introduce urban differences, and demographic variables, such as age and race. Table 8 explores the roles of social and physical environments in shaping COVID-19 mortality, offering insights into how these factors diverge across urban and rural contexts while directly addressing the interactions between urbanicity, race, and critical social and environmental factors, notably food environment and income inequality, to investigate how these combined factors moderate COVID-19 mortality disparities.

In Table 7, Model 1 assesses if COVID-19 mortality changes over time as measured linearly. The wave variable indicates that as months of COVID-19 progressed, COVID-19 mortality decreased by 12%. In Model 2 I add a quadratic effect of time and period effect dummy variable for vaccine availability. Both variables are statistically significant, and Model 2 is a better fitting model compared to Model 1 based on all three measures of model fit (AIC, BIC, -2LL). While the linear effect of time suggests that COVID-19 mortality is decreasing over time, the quadratic effect tells us it is decreasing at slower rate over time. With an odds ratio of 1.54 (CI: 1.48 – 1.60), vaccine availability, indicates that individuals, in the period after vaccine availability began saw a 54% increase in the odds of mortality[8].

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[8] The observed increase in mortality odds post-vaccine availability is not indicative of vaccines causing higher mortality, but rather reflects a limited analysis period and may account for unaccounted factors.

In Model 3, the inclusion of the urban variable shifts the understanding of COVID-19 mortality. With an odds ratio of 1.98 (CI: 1.68 – 2.34), residing in urban areas nearly doubles the risk of COVID-19 mortality compared to rural areas, after accounting for other variables in the model.

Table 7. COVID-19 Mortality by Demographics and Urban-Rural Factors

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Predictors	*OR*	*CI*	*OR*	*CI*	*OR*	*CI*	*OR*	*CI*
Wave	0.88*	0.88 – 0.89	0.69*	0.68 – 0.70	0.69*	0.68 – 0.70	0.71*	0.70 – 0.72
Wave squared			1.01*	1.01 – 1.01	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01
Vaccine availability			1.54*	1.48 – 1.60	1.54*	1.48 – 1.60	1.33*	1.28 – 1.38
Urban					1.98*	1.68 – 2.34	2.23*	1.84 – 2.71
Sex [Male]							1.45*	1.42 – 1.47
Black							1.03*	1.01 – 1.06
Hispanic							0.70*	0.68 – 0.72
Asian							0.92*	0.87 – 0.97
Other race							1.39*	1.20 – 1.61
Over 60							25.83*	25.19 – 26.48

Random Effects				
σ^2	3.29	3.29	3.29	3.29
τ_{00}	4.03 county	3.94 county	3.81 county	3.00 county
ICC	0.55	0.54	0.54	0.48
N	1028 county	1028 county	1028 county	1028 county
Obs	1,611,874	1,611,874	1,611,874	1,611,874
Marginal R^2 / Conditional R^2	0.023 / 0.561	0.028 / 0.558	0.042 / 0.556	0.278 / 0.623
AIC	472254.5	469155.1	469130.2	356605.2
BIC	472291.4	469216.6	469204	356752.7
-2LL	472248.5	469145.1	469118.2	356581.2

Note: reference category is rural, White, women, under age 60

In Model 4, the analysis expands to include demographic variables such as gender and race alongside age, over 60. The odds ratio for individuals over 60 is remarkably high at 25.83 (CI: 25.19 – 26.48), indicating a sharp increase in the risk of COVID-19 mortality for this age group. Gender also emerges as a significant factor, with males having higher odds of mortality (OR: 1.45, CI: 1.42 – 1.47) compared to females. The findings indicate racial disparities in COVID-19 mortality: Blacks have a slightly increased risk of death, indicating a 3% higher odds, (CI: 1.01 – 1.06), whereas Hispanics and Asians show reduced odds of mortality by 30% (CI: 0.68 – 0.72) and 8% (CI: 0.87 – 0.97), respectively, compared to Whites. Other race category showed a 39% increased risk of COVID-19 mortality, compared to Whites in this model.
The urban variable maintains its significance in Model 4, with urban residents facing 2.23 times the odds (CI: 1.84 – 2.71) of mortality compared to rural residents, which is a slight increase from Model 3. This increase may reflect the additional demographic controls in Model 4. The model shows the consistent significance of other variables such as wave and vaccine availability. Each model in Table 7 improves model fit.

In addition to demographic variables, Model 5 adds an interaction term between race and urban variables. The results reveal that the odds ratio of 0.85 (CI: 0.79 – 0.92) signifies that the increased risk of COVID-19 mortality associated with being over 60 years old is less pronounced in urban areas than in rural areas. In addition, the odds ratio of 0.88 (CI: 0.80 – 0.97) indicates that the higher risk of COVID-19 mortality for Black individuals is slightly mitigated in urban settings compared to rural ones. No statistical significance is observed between Hispanics living in urban areas and COVID-19 mortality.

Model 6 adds a number of explanatory variables such as pre-existing medical conditions, and other county level factors such as percent uninsured, primary care physicians, particulate matter, income inequality, and food environment index. Net of the time and period effect variables and the explanatory variables, the effect of urban on COVID-19 mortality has attenuated from 2.58 times to 63% more likely to die. Notably, when accounting for social and environmental factors, there is a discernible shift in the impact of demographic variables on COVID-19 mortality outcomes. Specifically, the data indicate that Black individuals in urban areas experience a 15% reduced risk of COVID-19 mortality, with an odds ratio of 0.85 (CI: 0.77 – 0.94). Although Hispanic individuals generally exhibit a decreased risk of COVID-19 mortality with an odds ratio of 0.79, the interaction term for Hispanics in urban areas, compared to rural ones, shows no significant association with COVID-19 mortality, evidenced by an odds ratio of 0.90 (CI: 0.79 – 1.03). In contrast, Asian individuals show no significant association, whereas individuals of Other races are still associated with an increased risk of COVID-19 mortality. The model also underscores the profound influence of pre-existing medical conditions, which heighten the risk of mortality by 11.56 times (CI: 11.10 – 12.04), and elevated $PM_{2.5}$ levels correspond with a 36% increase in mortality risk (CI: 1.25 – 1.48). However, variables such as the food environment index, percentage of uninsured individuals, and primary care physician rates, do not demonstrate a significant association with COVID-19 mortality in this analysis. Income inequality was 2.12 times associated with COVID-19 mortality. This model is the best fitting model so far.

Table 8. Race, Urbanicity, and Social/Environmental Factors and COVID-19 Mortality

	Model 5		**Model 6**		**Model 7**		**Model 8**	
Predictors	*OR*	*CI*	*OR*	*CI*	*OR*	*CI*	*OR*	*CI*
Wave	0.71*	0.70 – 0.72	0.76*	0.75 – 0.77	0.76*	0.75 – 0.77	0.76*	0.75 – 0.78
Wave squared	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01	1.01*	1.01 – 1.01
Vaccine availability	1.33*	1.28 – 1.38	1.25*	1.20 – 1.30	1.25*	1.20 – 1.30	1.25*	1.20 – 1.30
Urban	2.58*	2.06 – 3.23	1.63*	1.31 – 2.03	1.54*	1.21 – 1.97	1.67*	1.34 – 2.09
Sex [Male]	1.45*	1.42 – 1.47	1.45*	1.42 – 1.47	1.45*	1.42 – 1.47	1.45*	1.42 – 1.48
Black	1.17*	1.06 – 1.28	1.11*	1.01 – 1.22	1.11*	1.01 – 1.22	1.19*	1.01 – 1.40
Hispanic	0.68*	0.60 – 0.77	0.79*	0.69 – 0.90	0.79*	0.69 – 0.89	0.71*	0.61 – 0.82
Asian	0.92*	0.87 – 0.97	0.95	0.90 – 1.00	0.95	0.90 – 1.01	0.94*	0.89 – 0.99
Other race	1.40*	1.22 – 1.62	1.31*	1.14 – 1.51	1.31*	1.13 – 1.51	1.32*	1.15 – 1.52
Over 60	29.81*	27.71 – 32.06	16.65*	15.45 – 17.93	17.17*	15.94 – 18.50	17.15*	15.92 – 18.47
Urban × Over 60	0.85*	0.79 – 0.92	0.90*	0.83 – 0.98	0.87*	0.80 – 0.94	0.87*	0.81 – 0.95
Urban × Black	0.88*	0.80 – 0.97	0.85*	0.77 – 0.94	0.84*	0.77 – 0.93	0.79*	0.67 – 0.93
Urban × Hispanic	1.03	0.91 – 1.16	0.90	0.79 – 1.03	0.90	0.79 – 1.03	1.05	0.90 – 1.21
Pre-existing condition			11.56*	11.10 – 12.04	8.98*	8.22 – 9.80	8.95*	8.18 – 9.79
Uninsured			0.91	0.75 – 1.12	0.95	0.76 – 1.17	0.95	0.78 – 1.16
Primary Care Physician			1.02	0.97 – 1.07	0.98	0.91 – 1.05	0.98	0.92 – 1.05
Income inequality			2.12*	1.10 – 4.09	1.36	0.90 – 2.06	1.45	0.92 – 2.30
Particulate Matter ($PM_{2.5}$)			1.36*	1.25 – 1.48	1.35*	1.24 – 1.47	1.35*	1.24 – 1.47
Food Environment			1.04	0.90 – 1.19	0.86	0.73 – 1.02	0.86	0.74 – 1.01
Urban × pre existing					1.36*	1.23 – 1.50	1.23*	1.11 – 1.36
Urban × Primary Care Physician					1.08	0.98 – 1.19	1.08	0.98 – 1.19
Urban × income inequality					1.96*	1.21 – 3.16	0.33*	0.20 – 0.54
Urban × food env					1.54*	1.21 – 1.96	1.58*	1.28 – 1.95
Black × Food Environment							1.06	0.93 – 1.22
Hispanic × Food Environment							0.79*	0.68 – 0.92
Pre-existing condition × income inequality							0.94	0.70 – 1.26
(Urban × Black) × Food Environment							0.85*	0.74 – 0.98
(Urban × Hispanic) × Food Environment							1.07	0.91 – 1.25
(Urban × pre existing) × income inequality							6.73*	4.94 – 9.17
Random Effects								
σ^2	3.29		3.29		3.29		3.29	
τ_{00}	3.00 county		2.49 county		2.43 county		2.42 county	
ICC	0.48		0.43		0.42		0.42	

Table 8. Race, Urbanicity, and Social/Environmental Factors and COVID-19 Mortality (continued)

N	1028 county	1028 county	1028 county	1028 county
Observations	1,611,874	1,611,874	1,611,874	1,611,874
Marginal R^2 / Conditional R^2	0.282 / 0.625	0.460 / 0.693	0.466 / 0.693	0.456 / 0.687
AIC	356588.8	333205.4	333168.1	332859.5
BIC	356773.2	333463.6	333475.4	333240.6
Neg2LL	356558.8	333163.4	333118.1	332797.5

Note: reference category is rural, White, women, under age 60

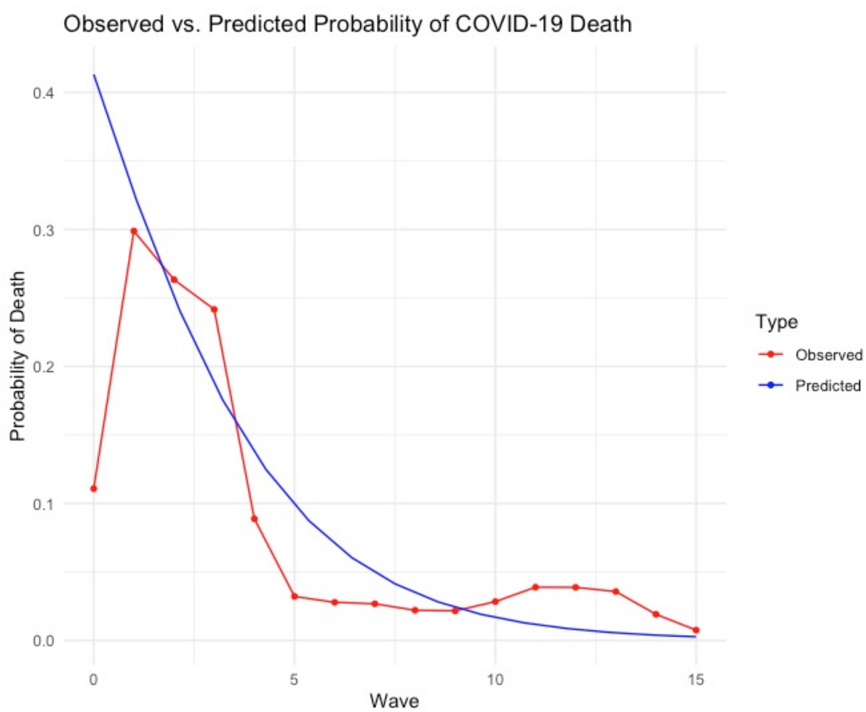
In Table 8, Model 7 explores the interactions of race, urbanicity, and environmental factors, uncovering patterns in COVID-19 mortality disparities. Consistently across models, the wave, vaccine availability, urban status, sex, those over 60, $PM_{2.5}$ levels, and pre-existing medical conditions remain significant predictors. In urban areas, however, the risk associated with COVID-19 mortality among Black individuals is significantly altered. The interaction term for Blacks in urban settings indicates a reduced mortality risk by 16% compared to their rural counterparts, with an odds ratio of 0.84 (CI: 0.77 – 0.93). This finding suggests that the heightened risk observed among Black individuals in rural areas is notably less pronounced in urban environments, highlighting the impact of geographic context on health outcomes. Hispanics consistently exhibit a lower overall mortality risk; however, no significant associations are observed in urban areas. Older individuals in urban areas have a 13% reduced mortality risk compared to those in rural settings (CI: 0.80 – 0.94).

The interaction between urbanicity and pre-existing conditions significantly increases the risk of COVID-19 mortality, with an odds ratio of 1.36 (CI: 1.23 – 1.50), suggesting that individuals with pre-existing health conditions in urban areas are at a higher risk compared to those in rural areas, likely due to greater exposure or other urban-specific risk factors. The interactions between urban residency and both income inequality and food environment significantly affect COVID-19 mortality. For income inequality, an odds ratio of 1.96 (CI: 1.21 – 3.16) suggests that higher levels of inequality in urban areas significantly increase the risk of death, highlighting the impact of socioeconomic disparities on health outcomes. Conversely, a better food environment in urban settings, indicated by an odds ratio of 1.54 (CI: 1.21 – 1.96), suggests that urban areas with improved access to quality food significantly increased COVID-19 mortality risk. There was no significant association between urban areas and the primary care physicians rate.

Despite the lack of significant main effects for variables such as income inequality and the food environment, their interaction significantly increased COVID-19 mortality risk when combined with urbanicity and pre-existing conditions (see Models 7 and 8). This underscores the importance of studying how various factors interact to enhance our understanding of complex, context-dependent effects on outcomes (Hardy, 1993). Lorah, (2020) supports interpreting main effects as conditional, particularly when significant interactions provide a clearer understanding of relationships within the data.

Model 8 emerged as the most appropriate for detailed analysis due to presenting the lowest values for both AIC and BIC suggesting it is the best-fitting and most parsimonious model among those considered. The results from Model 8 substantiate several of the hypotheses put forward regarding factors influencing COVID-19 mortality.

Figure 8. Comparison of Observed and Predicted COVID-19 Mortality over Time



In Model 8, the time variables—wave and wave squared—alongside vaccine availability, are pivotal for understanding the changing risk of COVID-19 mortality throughout the pandemic. The wave variable, with an odds ratio of 0.76 (CI: 0.75 – 0.78), reflects a consistent decrease in mortality risk over successive waves, confirmed visually by the corresponding plot from Model 3 (see Figure 7). This decline is moderated by the wave-squared term, which shows an odds ratio of 1.01 (CI: 1.01 – 1.01), hinting at minor risk escalations that could correspond to infection rebounds or variations in wave intensity. Figure 7 graphically represents these findings, illustrating both the observed and predicted probabilities of death, thereby validating the model's ability to accurately reflect temporal trends.

Hypothesis 1 posited that urban residency would correlate with higher COVID-19 mortality rates. This hypothesis is strongly supported, with an odds ratio of 1.67 (OR: 1.67, CI:

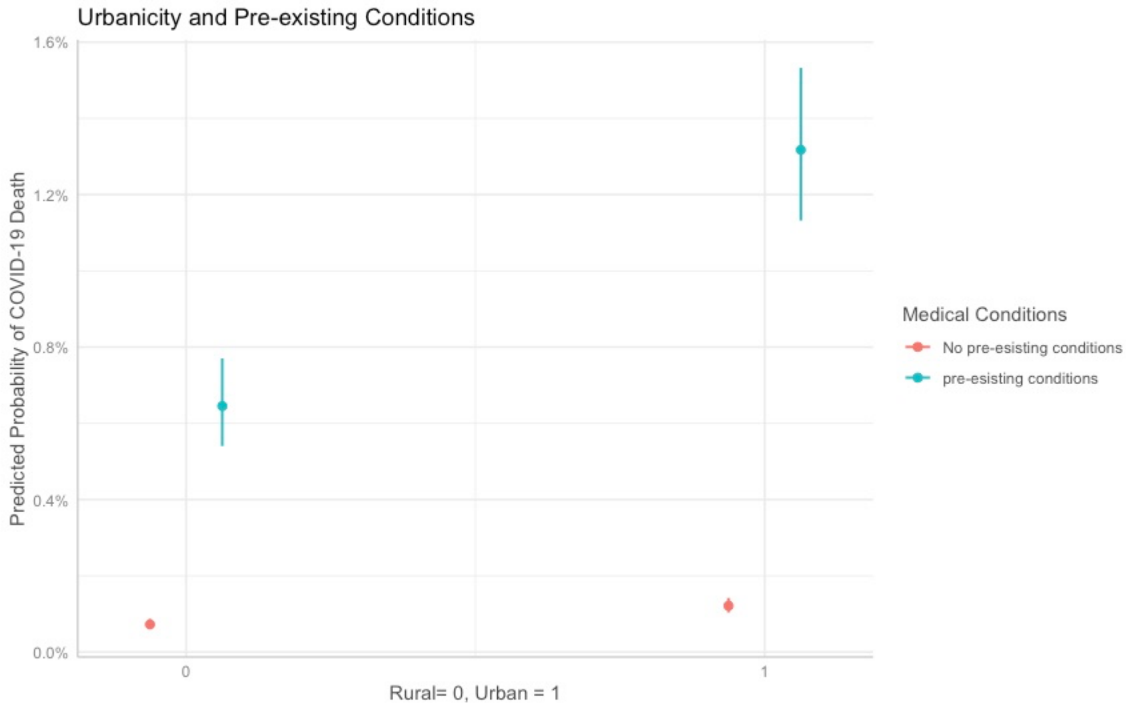
1.34 – 2.09) for urban areas, indicating a 67% increased risk of mortality compared to rural settings.

Hypothesis 2 was partially supported; Black individuals generally experienced an increased risk of mortality (OR: 1.19, CI: 1.01 – 1.40), but those in urban areas actually showed a 21% reduced risk (OR: 0.79, CI: 0.67 – 0.93). For Hispanics, the reduced mortality risk was confirmed (OR: 0.71, CI: 0.61 – 0.82), but no significant urban-specific effect was observed, as their urban interaction term was not statistically significant (OR: 1.05, CI: 0.90 – 1.21).

Hypothesis 3, concerning the increased mortality risk among urban residents with pre-existing conditions, was strongly confirmed (OR: 1.23, CI: 1.11 – 1.36). This finding indicates that living in urban areas with pre-existing medical conditions is associated with a 23% higher risk of COVID-19 mortality, highlighting a substantially elevated risk. This is consistent with the general findings that pre-existing conditions alone pose nearly a 9-fold increase in mortality risk (OR: 8.95, CI: 8.18 – 9.79).

Figures 9 and 10 illustrate the marginal effects of selected independent variables on the probability of COVID-19 mortality in Model 8. These plots were produced using the ggpredict() function from the ggeffects R package, which computes the average predicted probabilities across observed values for a specific predictor, taking into account the distribution of other covariates in the model (Lüdecke, 2018). Figure 9 plot illustrates the predicted COVID-19 mortality based on (Model 8) a two-way interaction between urbanicity and pre-existing conditions, showing significantly higher risks for urban individuals with such conditions.

Figure 9. Two-Way Interaction: Urbanicity and Pre-Existing Conditions



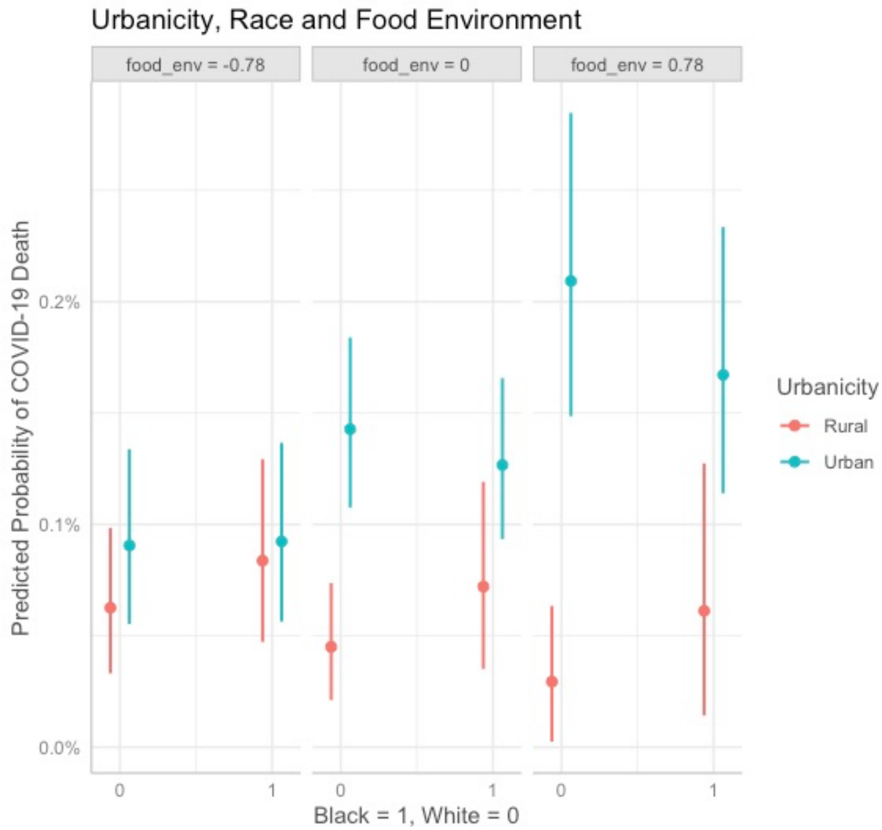
Hypothesis 4 proposed that older individuals in urban areas would exhibit lower mortality odds compared to their rural counterparts. This was confirmed by the findings, which demonstrated a 13% reduced mortality risk for individuals over 60 residing in urban settings (OR: 0.87, CI: 0.81 – 0.95).

Hypothesis 5, which suggested that higher rates of primary care physicians in urban areas would correlate with lower COVID-19 mortality, did not find support; the effect of primary care physician density was not statistically significant (OR: 0.98, CI: 0.91 – 1.05). The interaction between urban residency and the density of primary care physicians also does not reach statistical significance, suggesting that while access to primary healthcare is crucial, its direct impact on COVID-19 mortality in urban settings might be less pronounced or confounded by other factors not captured in the model. Likewise, Hypothesis 6 predicted that superior food environments in urban areas would lead to reduced COVID-19 mortality; however, the result indicated a 58% increased risk (OR: 1.58, CI: 1.28 – 1.95), which directly contradicts the expected outcome.

Hypothesis 7 asserted that urban minorities, specifically Blacks and Hispanics, would experience reduced mortality with better food environments. This hypothesis was only partially corroborated for Blacks, indicating a beneficial effect with a 16% decrease in mortality risk (OR: 0.85, CI: 0.74 – 0.98) in the context of urban settings with favorable food environments, whereas no significant effect was evident for Hispanics. However, the result showed that Hispanics in general living in better food environments showed a 21% lower likelihood of dying of COVID-19 (OR: 0.79, CI: 0.68 – 0.92). There was, however, no statistical significance between Black and food environment.

Figure 10 illustrates the three-way interaction between urbanicity, race, and food environment on the predicted probability of COVID-19 death. In urban areas, Black individuals with average and above-average food environments exhibit a lower predicted probability of COVID-19 death compared to White individuals in the same food environments. In rural areas, however, the predicted probability of COVID-19 death is generally lower overall, yet Black individuals appear to have higher predicted mortality than Whites in areas with above-average food environments. The plot also shows that Blacks in both urban and rural areas with below-average food environments have slightly higher predicted mortality compared to their White counterparts. This pattern suggests that an improved food environment mitigates the risk of COVID-19 mortality more effectively for Black individuals in urban settings than for their White counterparts.

Figure 10. Three-Way Interaction of Urbanicity, Race, and Food Environment



Finally, Hypothesis 8 concerns increased COVID-19 mortality risks among individuals with pre-existing conditions living in areas of high income inequality in urban areas. This three-way interaction (urbanicity, pre-existing medical conditions, and income inequality) was confirmed, revealing a nearly seven-fold increase in risk associated with income inequality (OR: 6.73, CI: 4.94 – 9.17). However, without pre-existing conditions, the results showed that urban areas with higher income inequality actually had a significant reduction in COVID-19 mortality risk (OR: 0.33, CI: 0.20 – 0.54). Figure 11 illustrates the three-way interaction between urbanicity, income inequality, and the presence of pre-existing conditions on the predicted probability of COVID-19 death. The plot shows that in urban settings, regardless of the level of income inequality—below average, average, or above average—individuals with pre-existing conditions consistently experience the highest risks of COVID-19 mortality. This highlights the pronounced impact of compounded socioeconomic and health vulnerabilities in urban environments.

Figure 11. Three-Way Interaction: Urbanicity, Income Inequality, and Pre-Existing Conditions

Other notable findings on demographic variables from Model 8 show that men are 45% more likely to die of COVID-19 than women (OR: 1.45, CI: 1.42 – 1.48). Asians (OR: 0.94, CI: 0.89 – 0.99) showed a 6% reduced likelihood of COVID-19 mortality, while individuals in the "other race" category (OR: 1.32, CI: 1.15 – 1.52) were 32% more likely to die than Whites. Age continued to be a strong predictor of COVID-19 mortality, with individuals over 60 (OR: 17.15, CI: 15.92 – 18.47) showing over a 17-fold increased risk compared to those below 60 years old. As in other models, particulate matter pollution ($PM_{2.5}$) was a significant predictor of COVID-19 mortality, with a 35% increased risk in areas with higher $PM_{2.5}$ levels. No statistical significance was observed among county-level factor of the uninsured population and COVID-19 mortality.

These findings confirm that urban residency, race, and pre-existing conditions are significant predictors of COVID-19 mortality, with complex interactions between these factors revealing the COVID-19 pandemic's impacts across communities in urban and rural settings.

2.4.1 Sensitivity Analysis

Several sensitivity analyses were performed to assess the robustness of the findings. As shown in Table 10, different approaches to handling "unknown" data on the outcome death variable as well as a random subsample of fifty thousand observations were run to examine the consistency of the results.

Table 9. Sensitivity Analyses

Predictors	Multiple imputations, model S1	Unknown as death, model S2	Unknown as survival, model S3	Random selection analysis, model S4	Model 8 Comparison
Wave	0.69*	1	0.70*	0.81*	0.76*
Wave squared	1.02*	1	1.01*	1.01*	1.01*
Vaccine availability	1.11	1.09*	1.05*	1.28*	1.25*
Urban	2.01*	1.05	1.54*	6.20*	1.67*
Sex [Male]	1.27*	1.13*	1.44*	1.49*	1.45*
Black	1.12	0.94	1.13	2.37	1.19*
Hispanic	0.67*	0.80*	0.63*	1.24	0.71*
Asian	1.00	0.92*	0.89*	1.13	0.94*
Other race	1.07	0.92*	1.07	1.09	1.32*
Over 60	15.93*	1.77*	17.47*	28.83*	17.15*
Pre-existing condition	6.97*	1.91*	8.64*	19.47*	8.95*
Uninsured	1.01	0.52*	1.07	0.87	0.95
Primary Care Physician	0.96*	0.82*	1	0.98	0.98
Income inequality	2.21	1.37	0.81	6.69	1.45
Particulate Matter ($PM_{2.5}$)	1.12*	1.57*	1.09*	1.19*	1.35*
Food Environment	0.95	0.87	0.89*	0.74*	0.86

Table 9. Sensitivity Analyses (continued)

Urban × Over 60	0.66*	1.38*	0.75*	0.55*	0.87*
Urban × Black	0.77*	1.05	0.79*	0.48	0.79*
Urban × Hispanic	1.21	1.15*	1.17	0.72	1.05
Urban × pre existing	1.02	1.30*	1.16*	0.55	1.23*
Urban × Primary Care Physician	1.03	1.26*	1.02	1.03	1.08
Urban × income inequality	3.11*	0.04*	4.71*	0.30	0.33*
Urban × food env	1.33*	1.03	1.39*	1.70*	1.58*
Black × Food Environment	1.05	0.97	1.05	2.41	1.06
Hispanic × Food Environment	0.78*	0.93*	0.78*	1.51	0.79*
Pre-existing condition × income inequality	0.76	2.57*	0.94	0.25	0.94
(Urban × Black) × Food Environment	0.88	0.99	0.84*	0.47	0.85*
(Urban × Hispanic) × Food Environment	1.09	0.89*	1.11	0.65	1.07
(Urban × pre existing) × income inequality	1.52	16.67*	0.97	37.17	6.73*
N	2,129,138	2,129,138	2,129,138	50,000	1,611,874

Model S1, employing multiple imputations using the 'mice' package in R, treats missing outcomes as randomly distributed, creating five separate imputed datasets. This method helps to capture the variability in potential outcomes. Although there are some variations in the strength of associations, the results from Model S1 are very consistent with those from Model 8 comparison, which was selected for the final analysis. The variations between the multiple imputations model and Model 8, particularly in the interaction of urban residency with pre-existing conditions and income inequality (OR: 1.52 vs. 6.73), may reflect the multiple imputations model's conservative estimates due to addressing missing data, which could result in less pronounced effects. Additionally, the interaction between urban residency and income inequality contrasts sharply (OR: 3.11 vs. 0.33), suggesting that the multiple imputations model might underestimate the protective effects observed in Model 8, or that Model 8 could overestimate these effects.

The treatment of missing data as deaths in Model S2 results in lower odds ratios, such as 1.91 for pre-existing conditions, compared to 8.95 in Model 8. This indicates Model S2 may underestimate risks by assuming a worst-case scenario, unlike the more nuanced approach in Model 8. Similarly, Model S2 underestimates COVID-19 mortality risks for 'Over 60', compared to Model 8.

Closely aligning with Model 8, Model S3 presents an odds ratio of 8.64 for pre-existing medical conditions, suggesting that when missing data is considered as survivors, the risk estimate for pre-existing conditions is more reflective of the observed data trends. The age category 'Over 60' consistently presents a higher risk across all models, although with varying odds ratios. Notably, Model S3 reports an odds ratio of 17.47 for individuals over 60, closely paralleling Model 8. This similarity suggests that failing to account for missing data could result in an underestimation of the risk associated with this age group. Despite some deviations, the results from Model S3, mostly match those of Model 8, implying that the missing cases likely had milder symptoms or went unreported to medical institutions.

Model S4, analyzing a random subsample of fifty thousand cases, generally supports the main findings of Model 8, with some exceptions. Notably, this model did not find a statistically significant relationship between race and COVID-19, underscoring the need for careful interpretation. These models collectively highlight the significance of methodological choices in socio-epidemiological data analysis and the potential biases from handling missing data.

2.5 Discussion

The study's findings highlight the nature of disparities in COVID-19 mortality, indicating that a mix of demographic factors, social and physical environments, and individual health factors like pre-existing conditions—coupled with the urban-rural context—play a crucial role in mortality outcomes. This study shows answers to the research questions and supports or challenges the related hypotheses presented.

Hypothesis 1 posits that urban residents are at higher risk of COVID-19-related death compared to rural residents pertaining to the first research question as to whether demographic factors explain urban-rural disparities. This hypothesis is supported by an odds ratio of 1.67 for urban residency, which indicates a 67% increased risk of mortality in urban settings, affirming that demographic factors, notably urbanicity, are critical in explaining COVID-19 mortality disparities. It particularly illuminates the impact of the urban-rural divide, revealing that urban areas, characterized by high population densities potentially conducive to virus transmission, exhibit higher mortality compared to rural areas (Huang et al., 2021). This observation aligns with previously documented patterns of increased incidence and mortality rates in urban areas during the pandemic's peak periods (Cuadros et al., 2021; Karim & Chen, 2021). Additionally, this study showed that urban Black individuals have a lower risk of mortality (OR: 0.79), contrary to the higher risk seen generally among Blacks, indicating that other urban-specific factors may mitigate this risk.

In addressing the first research question regarding the role of demographic factors in urban-rural COVID-19 mortality disparities, the study's findings specifically support Hypothesis 4, which posited that individuals over 60 in urban areas are less likely to die from COVID-19 than their rural counterparts, as evidenced by the significant associations that those individuals who are over 60 years old and reside in urban areas are 13% less likely to die of COVID-19, compared to those in rural areas. This could be related to the more significant disease burden typically experienced by rural older adults, who also tend to have higher medication needs (Goeres et al., 2016). In addition to a higher percentage of elderly residents, adults in rural communities often face greater health challenges compared to their urban counterparts, including lower rates of physical activity, and a greater prevalence of multiple chronic health conditions (Barton et al., 2021). Rural-urban health disparities, thus necessitate a nuanced understanding of how socioeconomic status impacts rural-urban status on health outcomes, with economic factors playing a crucial role in shaping these disparities (Cohen et al., 2017).

Addressing the second research question on the role of social and physical environments in COVID-19 mortality, the study provides varied outcomes. Hypothesis 5, which predicts an association between the rates of primary care physicians and COVID-19 mortality in urban settings, is not confirmed by the findings. Conversely, the absence of a significant association in this study between the availability of primary care physicians and COVID-19 mortality in urban areas challenges assumptions about the role of healthcare access in the pandemic response. This unexpected finding may highlight the limitations of healthcare infrastructure in managing the COVID-19 case surge in densely populated urban areas, while also reflecting the complexity of capturing the full impact of healthcare accessibility at a county level, where variability within regions can be considerable. While urban areas typically have more healthcare resources (Barton et al., 2021), this study's finding suggests that the differential impact of COVID-19 extends beyond primary care availability, mitigating COVID-19's impact requires not just primary care but also enhanced specialized healthcare infrastructure and capacity, particularly in ICUs and staffing, to reduce mortality and bolster preparedness (Janke et al., 2021).

Similarly, county-level variables such as the uninsured rate and food environment index do not show a significant direct relationship with mortality caused by COVID-19. However, the study does reveal that areas with higher $PM_{2.5}$ pollution levels see a 35% increased risk of COVID-19 mortality. Urban areas, which generally face higher levels of $PM_{2.5}$ (Garcia et al., 2016), may consequently see an increased risk of such comorbidities (Basith et al., 2022; Bowe et al., 2019).

Investigating the third research question on the combined effects of race, urbanicity, and environmental factors on COVID-19 mortality disparities, the results challenge Hypothesis 6 by revealing a 58% higher mortality risk for urban residents in areas with superior food environments. This outcome suggests that, although urban settings generally correlate with increased mortality risk, particular components such as the food environment may exert diverse effects across different racial groups.

Hypothesis 2 and Hypothesis 7 both consider the racial dimension within urban settings. Partially supporting Hypothesis 2, the finding shows that while Blacks have an increased risk of COVID-19 mortality overall, the finding reveals that urban Blacks have a reduced mortality risk, suggesting that urban living may provide some protective benefits. The study found that while urban settings generally correlate with increased mortality, specific components such as the food environment may exert diverse effects across different racial groups. For Blacks, better food environments in urban areas are associated with a 15% decrease in mortality risk, suggesting that improved access to quality food can significantly impact health outcomes. This finding is in line with the observations by Corona et al., (2021), who highlight the positive influence of enhancing neighborhood food environments on dietary behaviors and cardiometabolic health, in predominantly Black urban women. Conversely, for Hispanics, despite generally benefiting from better food environments, the interaction with urban settings did not show a statistically significant effect, indicating that other factors may play a more dominant role in influencing their COVID-19 mortality risk in urban areas.

Exploring Hypothesis 3, this study finds strong evidence that urban residents with pre-existing conditions face a higher risk of COVID-19 mortality, a 23% increase, affirming the critical link between health status and urbanicity. This finding corroborates existing studies that highlight individuals with comorbidities—such as cardiovascular diseases, diabetes, chronic respiratory conditions, and cancer—as particularly susceptible to severe outcomes and mortality from COVID-19 (Clark et al., 2020; Ejaz et al., 2020; Kompaniyets et al., 2021; Ssentongo et al., 2020).

One focus of the third research question is to explore the three-way interaction effects among demographic, urban-rural, and physical and social environmental factors. Hypothesis 8 investigates the impact of income inequality and pre-existing medical conditions in urban environments on COVID-19 mortality. The findings show a significant interaction effect, indicating nearly a seven-fold increase in COVID-19 mortality risk for urban residents with pre-existing conditions in areas of higher income inequality. This underscores the exacerbating role of income inequality on mortality rates among urban dwellers with health vulnerabilities, potentially intensified over time by urban developments like suburbanization and gentrification (Thiede et al., 2020). The higher vulnerability of individuals with pre-existing health issues in urban settings, particularly amid socioeconomic disparities, could be attributed to differential access to essential resources, underscoring a need for public health policies to address socioeconomic inequality as a crucial element in mitigating health disparities (Braveman et al., 2011; Lynch et al., 2004; Wilkinson & Pickett, 2006).

This study's overarching narrative shows a pronounced urban-rural divide in COVID-19 mortality, shaped by demographics, pre-existing health conditions, and their interactions with socio-environmental factors. The findings suggest that policy interventions to reduce health outcome inequalities must be focused on addressing these complex interrelations, with an understanding of how urban or rural environments differentially impact various population groups.

2.5.1 Limitations of County-Level Measures

The use of county-level variables in both Chapters 1 and 2 introduces limitations that may impact the study's ability to accurately capture the effects of urban physical and social environments on racial disparities in COVID-19 mortality. Primary variables such as air pollution levels ($PM_{2.5}$ and hazardous air pollutants), Social Vulnerability Index (SVI), crime, and food environment index aggregate data at the county level, potentially masking intra-county disparities. For example, county-level averages of factors like $PM_{2.5}$, HAP, SVI, and food environment index can obscure localized hotspots of high pollution or vulnerability that disproportionately affect specific neighborhoods or demographic groups.

Ecological studies using counties or smaller units like census tracts to examine area effects on health have been employed to investigate mortality rates (Diez Roux, 2001). Given the scarcity of individual-level data with smaller geographic units during the COVID-19 pandemic, county-level data is the best-suited approach. However, this approach is subject to the Modifiable Areal Unit Problem (MAUP), potentially introducing biases due to the use of spatially aggregated data. Conclusions drawn from county-level data may not accurately reflect individual-level associations, contributing to ecological fallacy. For instance, assuming all individuals in a county with high SVI are equally vulnerable ignores substantial variability within the county.

Data from sources like the EPA's EJscreen and the CDC's SVI datasets may not capture rapid changes in environmental or social conditions affecting COVID-19 mortality rates. Additionally, county-level data often represent snapshots in time and may not capture temporal changes effectively. Counties also vary widely in population density, urbanization, resource distribution, and COVID-19 regulations or restrictions, further complicating comparisons and obscuring the effects of urban-specific factors.

These limitations necessitate caution in interpreting the results and highlight the need for more granular data collection methods in future research.

Chapter III: Racialized Differential Effects of COVID-19 on Mental Distress Due to Social and Economic Factors

3.1 Introduction

The COVID-19 pandemic, which started in early 2020, has claimed millions of lives globally and infected hundreds of millions of people. In the US alone, over 1 million deaths were reported (The New York Times, 2022). States with high COVID-19 death rates also saw a greater overall mortality increase, including diabetes and respiratory diseases, beyond what can be attributed solely to COVID-19, possibly due to healthcare disruptions, financial hardships, and interactions with other diseases (Luck et al., 2023). The virus also led to significant economic impact, with millions of job losses, totaling 23 million in May 2020 (Georgetown University, Center on Education and the Workforce, 2022). The severe financial loss led to potential economic distress, and anxiety, resulting in mental health issues (Cao et al., 2020; de Miquel et al., 2022; Tull et al., 2020). Emerging evidence highlights the disproportionate impact of COVID-19 on racial minorities, leading to higher infection rates (Webb Hooper et al., 2020), and mortality (Aschmann et al., 2022; Lundberg et al., 2022; Tai et al., 2021) compared to White individuals. Studies have shown that pandemics like COVID-19 can induce mental distress in the population (Pfefferbaum & North, 2020; Zhao et al., 2020). These disparities raise the critical question of whether this unequal burden has a more pronounced impact on the mental health of racial minorities.

In this chapter, I use the differential effect pathway to examine the impact of COVID-19 on racialized mental health disparities. The concept of differential effect suggests that even when potential risks, such as those associated with COVID-19, are distributed evenly across social groups, their impact on health may vary due to underlying differences in each groups vulnerability (Diderichsen et al., 2001). These differences in vulnerability, often linked to factors like socioeconomic status (SES), play a crucial role in health disparities across racial subgroups (Grzywacz et al., 2004; Ulbrich et al., 1989).

Studies show that fears of COVID-19 infection and mortality, along with other potential factors such as job losses, social isolation, and fear of infection, led to a 25% global increase in anxiety and depression during the first year of the pandemic (Ibarra-Mejia et al., 2022; Torales et al., 2020; World Health Organization, 2022). A Kaiser Health report showed that 4 in 10 adults reported negative impacts on their mental health due to COVID-19, a sharp increase from June 2019, months before the COVID-19 pandemic started (Panchal et al., 2021). During the early phase of the COVID-19 pandemic, depression rates among young adults aged 18 to 24 increased by 90% within the first few months, reaching this elevated level by July 2020, and over one-third of high school students, particularly females and those identifying as LGBQ, experienced poor mental health during the same period (Center for Disease Control and Prevention, 2022; Giuntella et al., 2021). The psychological distress among the general public, however, subsided after peaking in the initial phase of the pandemic in April 2020 (Daly & Robinson, 2021). These fluctuations in mental health emphasize the need to understand the evolving mental health landscape across a more extended period, covering the full scope of the pandemic.

Amidst stressors like job loss and concerns about COVID-19's health impact, individuals and families faced what Diderichsen et al., (2001) refer to as 'social consequences' stemming from certain health events. In light of this, the study addresses two primary research questions: Firstly, it examines the magnitude of mental health disparities among racialized populations during the COVID-19 pandemic in relation to the varying COVID-19 mortality rates across states in the United States. Secondly, it seeks to understand how individual socioeconomic status

(SES) factors may impact this disparity. I use a multilevel logistic regression model focusing on outcome variables such as anxiety and depression, with explanatory variables including COVID-19 death rates, SES, job loss, and other pertinent social and demographic factors to answer these research questions.

Building on the current literature, this research investigates the differential impact of COVID-19 on the mental health of racialized populations, emphasizing regions with higher COVID-19 mortality rates. By incorporating socioeconomic measures --such as income, education, and employment-- and factoring in pandemic-induced challenges such as job loss, this study aims to provide a deeper understanding of the factors affecting mental anxiety and depression during the pandemic.

3.2 Literature Review

COVID-19, caused by the highly infectious SARS-CoV-2 virus, is a zoonotic respiratory disease transmissible between humans and animals (Feng et al., 2023; Hui et al., 2020; Zhou et al., 2020). COVID-19 spreads through respiratory droplets and primarily impacts the respiratory system resulting in a fatal infection (CDC, 2020b). The COVID-19 pandemic has already passed historical pandemics like HIV/AIDS and the 1918 "Spanish flu" in terms of global fatalities (Sampath et al., 2021). Ongoing mutations in SARS-CoV-2 result in various variants, including Delta and Omicron, which were initially classified as variants of concern due to their heightened transmissibility and disease severity (CDC, 2020b; Hebbani et al., 2021). Various vaccines against COVID-19 have been developed that have significantly mitigated global infections, some demonstrating efficacy rates exceeding 90% in reducing documented cases (Ioannidis, 2021). Over 5 billion individuals across the world have received at least a single COVID-19 vaccine dose (Holder, 2023).

3.2.1 COVID-19 Disparities

This study examines racialized disparities in mental health during the COVID-19 pandemic, focusing on how COVID-19 mortality rates and various socioeconomic factors influence these disparities. The analysis also considers gender disparities (Carethers, 2021; Chaturvedi et al., 2022; Danielsen et al., 2022), noting that men have a 14% higher risk of COVID-19 mortality on average (Danielsen et al., 2022). However, women are more vulnerable also due to their overrepresentation as frontline healthcare workers (Su et al., 2022), accounting for 73% of healthcare personnel during the early pandemic (CDC COVID-19 Response Team, 2020).

Research indicates that racial minorities experienced disproportionate impacts from COVID-19, which can be attributed to the systemic challenges they often face, resulting in higher rates of infection, hospitalization, and mortality compared to White individuals (Aschmann et al., 2022; Lundberg et al., 2022; Magesh et al., 2021; McLaren, 2020; Millett et al., 2020; Shortreed et al., 2023; Sze et al., 2020). For instance, Black individuals had a 20% higher risk of COVID-19-related mortality than White individuals, and Hispanics faced a 51% higher risk (Isath et al., 2023). Similarly, Native Americans and Native Alaskans also experienced elevated COVID-19 mortality rates (Bassett et al., 2020). Furthermore, disparities in COVID-19 vaccination rates were evident among racial groups. Approximately 44% of Black individuals are fully vaccinated, in contrast to 64% of Asians, 50% of White individuals, 56% of Hispanics, and 63% of Native Indian and Hawaiian/Pacific Islanders (USAFacts, 2023).

3.2.2 Mortality Fears and Other Factors as Drivers of Mental Health

Studies have consistently shown that COVID-19 infection and fear contribute to heightened psychological distress (Catania et al., 2020; Khubchandani et al., 2022), with the pandemic leading to widespread mental distress, especially among vulnerable populations, such as women, the elderly, and those with pre-existing medical conditions (Mistry et al., 2021; Rahman et al., 2020). The fear of COVID-19 infection was linked to a range of issues, including personal health anxiety, food insecurity, and loneliness, leading to the development of mental distress such as anxiety and depression (Fitzpatrick et al., 2020; Ganson et al., 2021; Hoffart et al., 2021; Mertens et al., 2020; Posel et al., 2021). These findings highlight the connection between COVID-19 infection and the psychological distress that arises from the fears associated with the pandemic and its resulting consequences.

In a study in Italy, Carrà et al., (2022) found no significant associations between regional COVID-19 mortality ratios and depression or psychological distress; however, they did observe significantly elevated anxiety levels in individuals residing in areas with the highest mortality rates, highlighting the influence of local mortality rates as a factor contributing to heightened anxiety among the general population. In another study involving Turkish adults, Koçak et al., (2021) revealed a significant positive relationship between fear of COVID-19 and both depression and anxiety, highlighting the considerable mental health consequences of the pandemic. Conversely, Demirbas & Kutlu (2022) shows that individuals with lower income or education levels exhibited reduced fear of COVID-19, suggesting a potential lack of awareness regarding the gravity of the ongoing pandemic.

Moreover, studies also showed that individuals with a history of COVID-19 infections showed increased mental health challenges (Khubchandani et al., 2022; Saeed et al., 2023). Survivors of COVID-19 infection, when compared to those without a history of infection, demonstrate a notably increased likelihood of reporting anxiety (OR: 2.93), depression (OR:

1.83), or both, underlining a significant link between COVID-19 infection and psychological distress (Khubchandani et al., 2022).

While this study primarily centers on broader populations and does not distinctly assess the mental health impacts on essential workers such as healthcare workers, it is important to note that frontline healthcare workers too faced increased mental distress during the pandemic (Alnazly et al., 2021; Z.-Q. Dong et al., 2020; Lai et al., 2020; Murat et al., 2021; Talevi et al., 2020). Dong et al., (2020) showed that 24.2% of healthcare personnel experienced severe psychological issues, including anxiety and depression, with exposure to COVID-19 cases among friends or relatives. During the early COVID-19 pandemic, one in five healthcare workers reported anxiety and depression (Pappa et al., 2020).

The lockdowns and isolation measures put in place to contain the spread of COVID-19 potentially impacted the emotional and mental health of the population by limiting opportunities for social engagement. For instance, Mitra et al., (2021), noted that social engagement played an important role in reducing anxiety and distress and that maintaining physical activities was crucial for people's subjective well-being (Mitra et al., 2021). The lockdowns had a negative impact on loneliness and social isolation, which are associated with mental health symptoms such as depression (Adegboye et al., 2021; S. Wu et al., 2021; Yamamoto et al., 2022). These studies collectively suggest the fear of COVID-19 infection risks has had a significant impact on the mental health of various populations.

Studies have highlighted that excessive fear or worry about diseases, such as health anxiety, can have a significant impact on individuals' quality of life and daily functioning (Janzen Claude et al., 2014; Jones et al., 2014; Lebel et al., 2020; Norbye et al., 2022). For example, Norbye et al., (2022) found that individuals with current chronic diseases like cancer had health anxiety scores twice as high as a healthy reference group, while those with current cardiovascular disease and diabetes or kidney disease saw a 50% and 60% increase in health anxiety scores, respectively, underscoring the profound influence of these health conditions on heightened health anxiety levels. Likewise, Janzen Claude et al., (2014) show that health anxiety is associated with higher levels of anxiety about diabetes complications. These studies provide evidence that fear of health or mortality associated with diseases helps increase anxiety.

3.2.2.1 Socioeconomic Status (SES). While this study examines the effect of state-level COVID-19 mortality rates on racialized differences in anxiety and depression among individuals, it is important to acknowledge SES as a known determinant of mental health outcomes. SES serves as a crucial determinant of mental health outcomes, with various studies underscoring its association with conditions such as depression and anxiety (Janzen Claude et al., 2014; Jones et al., 2014; Lebel et al., 2020; Norbye et al., 2022). Lorant et al., (2003) show a consistent negative link, highlighting a depression odds ratio of 1.81 among individuals in lower SES groups in comparison to those in higher SES categories. Chidobem et al., (2022) further investigated this relationship by utilizing employment, health insurance coverage, and education as indicators of SES. They discovered that unemployed individuals (compared to employed) had significantly higher odds ratios for psychological distress in cancer survivors, with an odds ratio for severe distress of 11.67, while those with graduate degrees (compared to those with high-school degrees or lower) exhibited the lowest distress odds, with a severe odds ratio of 0.26. While my study primarily concentrates on individual-level socioeconomic status (SES), it is also worth noting that research has confirmed the connection between mental health and SES at the neighborhood or area level (Sallis et al., 2009; Stulberg et al., 2021), highlighting the significance of this factor in understanding mental health outcomes.

During past infectious epidemics, such as Severe Acute Respiratory Syndrome (SARS), SES has been linked to mental health, with individuals of lower household incomes showing increased depressive symptoms (Hawryluck et al., 2004). Additionally, those with lower levels of education, employment, and economic stability are at a higher risk of experiencing stress-related health problems (Pearlin et al., 2005). In a review of the literature, Khanijahani et al., (2021) show that 19 out of 28 studies indicated that individuals with lower SES, encompassing factors such as poverty, poor housing conditions, household size, and lower education levels, were at a heightened risk of contracting COVID-19.

Education and income, measures of SES, are associated with health behaviors by increasing resource access. However, Assari, (2018) argues the "diminished return theory" for Blacks, indicating that despite high SES, they may experience disparities in certain health outcomes (Assari et al., 2017, 2018). For instance, Assari, (2018) showed that high SES has a greater impact on lowering BMIs in White youth compared to Black youth, highlighting unequal distribution of SES-related health benefits, possibly due to societal barriers and life conditions. In another study, Assari et al., (2017) observed that the effects of higher education and income varied across health outcomes, with education being less protective for Black men and income not providing protection against high BMI for both White and Black men. However, both education and income universally protected all racial and gender groups against sustained depressive symptoms (Assari et al., 2017).

3.2.2.2 Income. Income has a strong association with mental distress, as studies have established that a higher income is associated with lower levels of psychological distress (Holingue et al., 2020; Jaspal & Breakwell, 2022; Pieh et al., 2021). Family economic hardship, including financial deprivation and cash-flow problems, is associated with a greater risk of mental health problems, especially among adults (Kiely et al., 2015; Wickrama et al., 2012). This supports the idea that higher household income is associated with better mental health outcomes (Assari et al., 2018). These findings suggest the importance of financial stability in maintaining good mental health. Adegboye et al., (2021) explored COVID-19's impact on children's mental health, especially in vulnerable groups, revealing significant increases in child mental health issues. Their study, however, emphasized the link between financial stress and parental mental health, with a particular focus on how parental mental health influences a child's mental well-being.

3.2.2.3 Household Job Loss. The shift in the labor market caused by the pandemic resulted in widespread layoffs and an increase in work-from-home arrangements, leading to an increased risk of poor mental health outcomes (Brooks et al., 2020; Courtet et al., 2020). The impacts were especially severe for women, low-wage workers, and people of color who were worst hit by unemployment (Cortes & Forsythe, 2022; Keeter, 2020; Panchal et al., 2021; Saenz & Sparks, 2020).

Loss of jobs in the households makes a deep impact on everyday economic activities, putting the family into financial shocks. According to the Brookings Institute, 40 million unemployment benefit claims were filed during the early period of the COVID-19 pandemic (Despard et al., 2020). Although the US government's April 2020 economic stimulus checks brought some measures of financial relief, stress levels spiked among the general population, especially at the beginning of the pandemic (Daly & Robinson, 2021).

This economically challenging period made it extremely difficult for families to make ends meet and avoid financial hardships. Holingue et al., (2020) in their study conducted during the early period of the COVID-19 pandemic show that having a job was protective against mental distress. The financial loss resulting from quarantine also contributed to economic distress, and such factors were found to be associated with symptoms of psychological disorders and long-lasting anxiety (Brooks et al., 2020). The quarantine regulations also forced many to work from home, making it advantageous for only a subset of higher-income individuals. Compared to those who worked from home, a study showed that those who lost jobs due to various reasons associated with the COVID-19 pandemic have higher symptoms of depression, anxiety, and stress (McDowell et al., 2021). The COVID-19 pandemic has underscored the significant relationship between financial stability and mental health, highlighting the pivotal role that income can play in mental health outcomes.

3.2.2.4 Education. Education level significantly influences one's SES and health outcomes, as research demonstrates that lower educational attainment is correlated with heightened mental distress (Bjelland et al., 2008; Burch et al., 2021; Islam, 2019; Kaya et al., 2021; Niemeyer et al., 2019). Niemeyer et al., (2019) show that lower educational levels were significantly associated with higher odds (OR = 1.78) of depressive symptoms, and such a relationship was partially mediated by psychosocial factors such as cultural activity and daily hassles, among others. No educational gradient was found for positive mental health, indicating that higher education did not necessarily result in greater positive mental health levels (Niemeyer et al., 2019). This suggests that unexamined factors play a role in influencing positive mental health. Moreover, another study establishes such associations. For instance, in a longitudinal study, Bjelland et al., (2008) found that participants who had less than 13 years of education, were 1.83 times more likely to have depression compared to those with higher levels of education. Moreover, Chazelle et al., (2011) identified a strong connection between educational level and depression and anxiety in both genders, with factors such as the absence of private health insurance and employment playing a prominent role in explaining these disparities.

Studies conducted during the initial phase of the COVID-19 pandemic have indeed revealed connections between education and mental health (S. A. Lee, 2020; Rudenstine et al., 2021; Wang et al., 2020). However, these studies, confined to the early period of the pandemic, have limited scope. For example, Rudenstine et al., (2021) found a 54% prevalence of significant depression in individuals with lower education levels compared to 42% in those with higher education. Nevertheless, Rudenstine et al., (2021)'s study was constrained to the early stages of the pandemic in Spring 2020. My research aims to provide a comprehensive year-long analysis of COVID-19's impact on mental health in a more diverse sample.

3.2.2.5 Marital Status. Marital status's impact on mental well-being has shown significant research attention, revealing both positive and negative outcomes, contingent on marital attributes (Girme et al., 2022; Pan et al., 2022; Waite, 2009). Waite, (2009) contends that marriage generally enhances mental health, but divorce disproportionately affects women, with increased depressive symptoms. Moreover, Williams et al., (2010) argue that marriage impacts short-term well-being, but divorce initially impairs mental health, underscoring the significance of weighing both rewards and challenges when assessing mental health outcomes.

Research has consistently indicated reduced well-being among single adults in comparison to those in relationships (Girme et al., 2022; Kessler et al., 2003). For instance, Kessler et al., (2003) show significantly higher major depressive disorder (MDD) prevalence among unmarried individuals (12-month MDD prevalence 2.3 times higher) compared to married or divorced individuals. Furthermore, Pan et al., (2022) demonstrate a 39% higher likelihood of depressive symptoms among individuals separated, divorced, widowed, or never-married compared to the married population. While household size's impact remains inconclusive, Okabe-Miyamoto et al., (2021) highlight the crucial role of romantic relationships in mitigating the negative impact of the COVID-19 pandemic on individuals' social connections, with living with a partner being the strongest predictor of positive social connection changes during times of social isolation.

3.2.2.6 Household Size. Household size plays a crucial role in shaping mental health outcomes. Grinde & Tambs, (2016) revealed that larger households with more siblings and older adults, particularly slightly older siblings, were associated with reduced signs of poor mental health in children. Children in households with six or more individuals displayed potential decreases in depression symptoms with a mean score of -0.10 (95% CI: -0.26, 0.07), suggesting a potential decrease in depression symptoms compared to those in households with 2 people, possibly due to increased companionship and emotional support from family members Grinde & Tambs, (2016).

Conversely, Kim & Lee, (2022) established a strong connection between household size and depression prevalence. Single-person households exhibited a higher prevalence of depression (odds ratios 3.1 to 6.3) compared to multi-person households, highlighting the detrimental effects of diminished social interaction and economic vulnerability, resulting in elevated depression rates and poorer mental health (Kim & Lee, 2022). Additionally, the influence of household size on mental health extends to economically deprived communities. For instance, larger family sizes were associated with higher levels of anxiety symptoms among rural Mexican adolescents (Ozer et al., 2008) and increased odds of psychiatric morbidity among children in Indian slum communities (Patil et al., 2013), underscoring associations between household composition, socio-economic factors, and mental health outcomes.

3.2.2.7 Health Insurance Coverage. The economic well-being of individuals is closely linked to their access to health insurance coverage, which, in turn, has significant implications for their ability to access healthcare services and, consequently, contributes to health disparities. Studies have shown how financial challenges create barriers to accessing necessary medical care or services (Bundorf et al., 2021; Gaffney et al., 2022). The cost of mental health care is a major barrier to treatment, and the lack of insurance coverage has led to disparities in mental health treatment in the United States (Mojtabai et al., 2014). The pandemic-induced income loss among low-income individuals has amplified healthcare access barriers, potentially increasing their vulnerability to mental health issues (Burgette et al., 2021; Jaspal & Breakwell, 2022). There is a link between mental health outcomes, income, and access to health care. Data from the 2009-2013 National Health Interview Survey showed that 30.4% of adults aged 18-64 with serious psychological distress were more likely to be uninsured than 20.5% of those without psychological distress (Weissman et al., 2015). A total of 8.7% of adults with income below the federal poverty level had serious psychological distress, as compared to 1.2% of adults whose incomes were at or above 400% of the poverty level (Weissman et al., 2015). The cost of mental health care is a major barrier to treatment, and the lack of insurance coverage has led to disparities in mental health treatment in the United States (Mojtabai et al., 2014). These findings are consistent with previous research on the association between mental health and socioeconomic deprivation (Assari et al., 2018; Kiely et al., 2015; Weissman et al., 2015).

During the early stages of the COVID-19 pandemic, health insurance coverage, including all types such as employer-sponsored or government-subsidized Affordable Care Act, and

Medicaid[9], saw a significant decline, with a prominent increase in uninsurance of 1.4 percentage points, resulting in over 2.7 million individuals newly becoming uninsured over a 12-week period, especially observed in the spring and summer of 2020 (Bundorf et al., 2021). The immediate aftermath of COVID-19 also saw disparities in coverage changes across population subgroups. For instance, early in the pandemic, rising uninsurance was concentrated among men, people aged 27 to 50 years, people of Hispanic ethnicity, and people in families with relatively low pre-pandemic income (Bundorf et al., 2021). Vaccination likelihood was also linked to health insurance status, as individuals with public insurance like Medicaid had 1.31 times higher odds of getting vaccinated than the uninsured, and those with private insurance had 1.6 times higher odds (Ku, 2022). These findings highlight the increased vulnerability of those lacking health insurance coverage to COVID-19 morbidity.

3.2.3 Comparisons with Other COVID-19 Studies

While Carrà et al., (2022) did identify significantly increased anxiety levels in individuals living in regions with the highest COVID-19 mortality rates; however, it is important to note that their cross-sectional study was conducted between March and May 2020, potentially missing the impact of the longer period of the pandemic on mental health. Similarly, previous research has shed light on the associations between measures of SES, which is considered an important factor in driving mental anxiety, and mental health using various indicators such as financial instability (Zheng et al., 2021), income, employment, and education treated individually as proxies for SES (Chidobem et al., 2022; Lorant et al., 2003a; Maffly-Kipp et al., 2021; Nagasu et al., 2021), several gaps in the current literature warrant further investigation. For instance, Zheng et al.,

[9] Medicaid, a joint federal and state program, provides health coverage to jobless individuals in 36 states (including DC) with low incomes, but in 15 non-expansion states like Florida and Texas, adults without dependent children are ineligible for Medicaid (Gangopadhyaya & Garrett, 2020).

(2021) identified a link between COVID-19 pandemic-related stressors such as financial insecurity and higher depressive symptoms but their study predominantly focused on higher-income White participants, limiting the generalizability of their findings to diverse or marginalized groups.

To contribute to the existing body of literature, in addition to incorporating the potential impact of state-level COVID-19 mortality rates as a driving factor of mental anxiety among the general population, my study includes income, education, and employment as measures of SES, replicating previous research (Chidobem et al., 2022; Maffly-Kipp et al., 2021; Nagasu et al., 2021). Furthermore, the study also includes key covariates such as job loss and pandemic-induced factors like difficulty with expenses, providing a more comprehensive understanding of the multifaceted dimensions of financial instability that can impact mental health. This approach aims to offer valuable insights into the complex link between socioeconomic factors and mental well-being, especially during times of significant societal stressors such as the COVID-19 pandemic.

Differences in mental distress among racial groups can be attributed to a variety of socio-economic and systemic factors. Alegría et al., (2015) outline mechanisms such as differences in SES, family structure, and neighborhood-level influences that lead to racial and ethnic disparities in mental health. Systemic issues such as discrimination and lack of access to quality mental health care disproportionately affect minority groups, leading to higher levels of mental distress (Zvolensky et al., 2017). For instance, Black children are more likely to live in disorganized neighborhoods, which increases mental distress, and, along with higher adverse childhood experiences, contributes to long-term mental health disparities among minority children (Glassgow et al., 2019; Slopen et al., 2016).

The literature review highlights the significance of factors such as household job loss, income, education, and mechanisms influencing racial disparities in mental health outcomes, which are crucial in understanding the effects of COVID-19 on mental health. I have proposed hypotheses to examine the social and economic factors that could influence mental distress among different racial groups during the COVID-19 pandemic.

H1: Individuals residing in states with higher COVID-19 mortality rates are at a greater risk of experiencing anxiety or depression compared to those in states with lower mortality rates.

H2: Racial minorities are likely to have greater depression and anxiety during the COVID-19 pandemic compared to whites.

In Hypothesis 3, I propose that including SES in the analysis will attenuate racial COVID-19-related mental health disparities. This is because research shows that SES is a significant determinant of mental health outcomes (Alegría et al., 2015; Villatoro et al., 2018). Lower SES is linked to increased mental distress (H. Lee & Singh, 2021; Lorant et al., 2003b). By accounting for SES, we can better isolate the impact of race on anxiety or depression, reducing the confounding effects of socio-economic factors on racial disparities in mental health during the COVID-19 pandemic.

H3: Controlling for SES should attenuate some of the racial COVID-19-related mental health disparities.

In Hypothesis 4, I suggest that even within the high SES group, Blacks may experience higher levels of anxiety or depression compared to Whites, potentially due to structural factors such as systemic racism (Asonye et al., 2020). While high SES is generally linked to better mental health outcomes, the "diminished return theory" indicates that Blacks with high SES may not benefit as much in terms of self-rated health (Farmer & Ferraro, 2005) and mental health as Whites with high SES (Assari, 2018). This interaction highlights the complex nature of how SES and race intersect to impact mental health outcomes.

> *H4: Blacks with high SES are more likely to experience anxiety or depression due to COVID-19 than whites with high SES.*

3.3 Methodology

To measure if the *differential effect* of COVID-19 due to social and economic factors could explain mental health gaps among racial groups, this study uses mental distress—anxiety, and depression—as response variables while treating variables such as socioeconomic status (SES), job losses due to COVID-19, difficulty with expenses, health insurance coverage, household size, race, gender, and age as predictors.

3.3.1 Data

I used the Household Pulse Survey (HPS), a cross-sectional dataset for this study. In collaboration with the National Center for Health Statistics (NCHS) and other federal agencies, the Census Bureau conducts the HPS, an experimental data system survey designed specifically to capture the impact of COVID-19 on society. The HPS collects and continues to gather data every two weeks on various aspects of households, including demographic characteristics, education, employment, and mental health, specifically in relation to the COVID-19 pandemic. HPS started data collection on April 23, 2020, employing a two-week on, two-week off data collection and dissemination approach. During each data collection period, HPS selected independent samples, and each selected household unit (HU) underwent a single interview. This contrasts with Phase 1, which was longitudinal and involved weekly data collection with three rounds of interviews for the same households (Fields et al., 2020).

For this study, I used the dataset covering the weeks from January 6, 2021, to January 10, 2022 (weeks 21 to 41), corresponding to Phase 3 to Phase 3.3 of the HPS, which consists of bi-weekly cross-sectional datasets. The choice of this one-year timeframe allows for an analysis of trends over the course of a year, including the period when HPS began inquiring about COVID-19 infections and after the COVID-19 vaccine became available to the public. The data is publicly available on the Census Bureau's web portal. (Census Bureau, 2022). The dataset comprises 1, 403, 424 respondents from 21 different data collection periods, with varying response rates. For example, of the 1,037,606 sample size on Week 21, only 69,944 responded (Fields et al., 2020). Non-response rates ranged from 5.8% to 7.2% for weeks 40 and 41, respectively (Fields et al., 2020). Following the removal of responses labeled as "Question seen but category not selected" and "Missing/Did not report," a final analysis dataset with 877,645 observations, which represents 63% of the original sample, was employed for the analysis.

The HPS employs a systematic sampling method based on the Census Bureau's Master Address File (MAF), a comprehensive list of addresses used for statistical purposes. The Census Bureau randomly selects addresses rather than individuals for participation, and only those with selected addresses are invited to complete the survey. The MAF contains contact information such as email addresses and cellphone numbers, enabling the HPS to employ email and SMS invitations for communication with selected households. The HPS focuses on producing estimates at various geographical levels, including state and Metropolitan Statistical Areas (MSAs). The sampling rates are determined at the state level, with adjustments made to account for nonresponse and demographic characteristics.

According to the Census Bureau, approximately 145 million housing units are represented in the MAF and 73 percent of valid addresses are associated with at least one email, and 75 percent of valid addresses with at least one cell phone number (Fields et al., 2020). The survey is conducted using the Qualtrics online data collection platform. It is important to consider that online surveys like the HPS may underrepresent older and very low-income individuals who lack internet access or familiarity with its use. The MAF ensures confidentiality protections for respondents (Fields et al., 2020).

Regarding eligibility, the respondent in the household must be at least 18 years old. The survey provides information about the number of adults and children in the household, which is crucial for understanding financial dynamics. However, it does not specify whether the household is a two-parent or single-parent arrangement. The survey also does not exclusively state if everyone in the household is of the same race or citizenship status.

The COVID-19 state-level death rates data were obtained from the CDC's openly accessible data portal (Center for Disease Control and Prevention, 2023). Since the onset of the pandemic, the CDC has collected data, verifying information from state and local jurisdictions to ensure accurate case and death counts. While the CDC collected daily state-level data up until October 20, 2022, that data is now archived (Center for Disease Control and Prevention, 2023). For this study, however, we selected the non-cumulative weekly COVID-19 death data from January 6, 2021, to January 10, 2022, to align with the timeframe of the HPS dataset.

3.3.2 Constructs

To investigate the potential impact of the COVID-19 differential effect resulting from social and economic factors on mental health disparities among racial groups, this study utilizes anxiety and/or depression as proxies for mental health (response variables). It examines variables including socioeconomic status, COVID-19-related job losses, COVID-19 infection history, difficulty with expenses, health insurance coverage, and demographic variables such as race, age, sex, marital status, and household size to explain the effect on mental health.

3.3.2.1 Dependent Variable. The dependent variables are anxiety and depression for this study. For anxiety, Generalized Anxiety Disorder (GAD-2) is a two-item self-report scale that identifies the generalized anxiety disorder based on the Diagnostic and Statistical Manual of Mental Disorders-IV (DSM-IV) (Newman et al., 2002; Spitzer et al., 2006). Unlike the traditional GAD-7, GAD-2 uses the first two questions, "Over the last 2 weeks, how often have you been bothered by feeling nervous, anxious, or on edge?" and "Over the last 2 weeks, how often have you been bothered by not being able to stop or control worrying?" The two items GAD-2 are scored on a four-point Likert scale ordered as "Not at all" (0), "Several days" (1), "More than half the days" (2), and "Nearly every day" (3). A total score, ranging from 0 to 6 points, was obtained by adding each item. The cutoff point of 3 or higher was found to be acceptable for identifying GAD (Plummer et al., 2016). GAD-2 scale screening for anxiety disorder is considered a well-performing tool (Kroenke et al., 2007). A study (Plummer et al., 2016) showed that a cutoff score of 3 demonstrates an optimal equilibrium between sensitivity and specificity in utilizing the GAD-2 questionnaire for the identification of generalized anxiety disorder.

The anxiety variable will be dichotomized due to its highly skewed distribution. Moreover, this study's primary focus is on investigating the presence or absence of a disorder rather than capturing the spectrum of anxiety symptoms. A sum less than 3 will be considered normal (0) and a GAD-2 score equal to or greater than 3 will be considered as a respondent with anxiety (1). I also ran a hierarchical logistic regression, incorporating random state effects, and an ICC value of 0 indicated no autocorrelation, supporting the use of a binary anxiety variable as the most suitable method for this analysis.

The Patient Health Questionnaire (PHQ)–2, a two-item self-report scale, evaluates depressive disorders based on DSM-IV criteria by utilizing PHQ-9's first two items, and it is suggested as an initial screening tool before administering the full PHQ-9 assessment (Levis et al., 2020; Maurer et al., 2018). The PHQ-2 are responses to “Over the last 2 weeks, how often have you been bothered by having little interest or pleasure in doing things?” and “Over the last 2 weeks, how often have you been bothered by feeling down, depressed, or hopeless?” Each item provides response options such as "not at all," "several days," "more than half the days," and "nearly every day," which correspond to numeric values of 0, 1, 2, and 3, respectively. The PHQ-2 score also ranges from 0 to 6. A cutoff point of 3 or higher indicates major depressive disorder is likely (Kroenke et al., 2003; Passos et al., 2020).

The depression variable was also dichotomized for the logistic regression analysis, with a Generalized Anxiety Disorder 2-item (GAD-2) score of less than 3 denoting absence and a score of 3 or greater indicating the presence of symptoms indicative of anxiety. This threshold aligns with established criteria, as scores of 3 or above on the GAD-2 are strongly associated with the likelihood of major depressive disorder (Kroenke et al., 2003; Passos et al., 2020), enabling a clear distinction for the modeling process.

Kroenke et al., (2003) offer evidence supporting the validity of the PHQ-2 as a concise tool for screening depression, intended as an initial step rather than a definitive diagnostic measure for the disorder. I constructed the depression variable consistent with prior studies (Kroenke et al., 2003; Plummer et al., 2016) before generating dummy variables.

3.3.2.2 Independent Variables. The state-level COVID-19 mortality rate was the main independent variable in predicting anxiety and depression during this one-year period. The HPS encompasses geographic units such as regions, states, and metropolitan statistical areas. To effectively capture the individual-level health outcomes, the state-level COVID-19 mortality rate was chosen as the most appropriate unit, as it provides a more comprehensive and inclusive measure than MSAs, which are limited to large metropolitan areas and may not represent the broader population's experience with the pandemic. The state-wide ACS 2021 population estimate was used to calculate the death rates, following the formula of the number of deaths per 100,000 resident population (CDC, 2023c). Furthermore, the COVID-19 mortality rates dataset was merged with the main dataset for further analysis.

This study measures the effect of socioeconomic status (SES) on anxiety and depression among the racialized population. The SES was measured by education, household income, and employment. Household income is categorized into eight ordered ranks, ranging from low to high: 1) Less than $25,000, 2) $25,000 - $34,999, 3) $35,000 - $49,999, 4) $50,000 - $74,999, 5) $75,000 - $99,999, 6) $100,000 - $149,999, 7) $150,000 - $199,999, and 8) $200,000 and above. Similarly, the education variable, which measures the level of educational attainment of the adults who participated in the survey, has seven ranked levels in increasing orders from low to high, 1) Less than high school, 2) Some high school, 3) High school graduate or equivalent (for example GED), 4) Some college, but degree not received or is in progress, 5) Associate’s degree, 6) Bachelor's degree, and 7) Graduate degree (for example master's, professional, doctorate). Lastly, employment status was transformed into a dichotomous variable. A value of (1) indicates individuals who engaged in paid or profit-driven work during the past week, while a value of (0) denotes those who did not, corresponding to "yes" and "no" respectively.

Two variables were used to assess household characteristics: household size and marital status. Household size is a continuous variable representing the total number of individuals residing in the household. Marital status, on the other hand, encompasses five categories: "Now married," "widowed," "divorced," "separated," and "never married." The marital status was recategorized into three dummy-coded groups: "married," "unmarried," and "others," the latter category encompassing individuals who are widowed, divorced, or separated. The "married" category was the reference group.

Other independent variables that are related to household financial situations used in this study are recent household job loss and difficulty with expenses. The recent household job loss measures if the individuals who lived in the household had experienced job loss in the past four weeks. Job loss is a binary category, which was dummy-coded with yes (1) and no (0). Likewise, difficulty with the expenses variable measures the precarious financial situation. The respondents are asked if the household faced any difficult situations with the payment of the usual household expenses such as food, rent or mortgage, car payment, medical expenses, student loans or so on in the past seven days. The responses have four categories-- “Not at all difficult,” “a little difficult,” “somewhat difficult,” and “very difficult.” The responses were dichotomized into -- “Not at all difficult,” and “difficult” (by combining “a little difficult,” “somewhat difficult,” and “very difficult”). “difficult” and “Not at all difficult” were coded (1) and (0) respectively.

Another independent variable used in the study is a binary variable of COVID-19 infection. The survey asks, “has a doctor or other health care provider ever told you that you have COVID-19?” with responses “yes”, “no” and “not sure.” The responses are dichotomized, yes (1) and no (0), while “not sure” were excluded. The survey does not inquire about any health-related outcomes pertaining to COVID-19 experienced by either individuals or their family members.

Additionally, another predictor, health insurance coverage, was a binomial. The respondents were asked in three different questions if they were currently covered by any health insurance through a current or former employer or union, private insurance purchased from a company, or Medicare. Those responding “no” on all of them were coded 0 and responded “yes” on any of those categories, 1.

In the HPS, race is recorded as White, Black, Asian, and others, and Hispanic or Latino as ethnicity. I created dummy variables for race (which also includes ethnicity) that indicate the presence (1) of that category and (0) indicates its absence. White (not Hispanic or Latino) were the reference category.

3.3.2.3 Control Variables. Gender and age serve as control variables. Similarly, in the dataset each respondent has birth year, which were converted to create age as a continuous variable. Age is a continuous variable. I included a continuous time variable, starting at 0, which were calculated based on the number of weeks from the initial period, January 6th to January 18th, 2021 (corresponding to week 22 in HPS). I subtracted each week's start date from this baseline and add 1 to account for the baseline week. For example, week 41 has a value of 44, indicating it is 44 weeks away from the baseline week 22.

The gender variable was transformed into a binomial format, specifically categorized as "female" (coded as 0) and "male" (coded as 1). The total number of individuals listed as transgender (1,148) and "None of these" (3,382) were excluded from the sample, representing approximately 0.52% of the total observations. This exclusion was justified because the small numbers in these categories could lead to statistical instability and potential bias in the analysis.

The primary focus of the study was on the binary gender categories due to their larger representation in the dataset, which allows for more robust and reliable statistical conclusions.

Understanding how mental health changed throughout the pandemic is essential because studies (Ruel & Campbell, 2006; Spurk & Straub, 2020) have highlighted the significance of "period effects," which are societal changes stemming from historical events or processes that impact people from all cohorts uniformly (Alwin & McCammon, 2003).

3.3.3 Statistical Analysis

A logistic regression model was run to observe the relationship between the outcome variables anxiety and depression, and explanatory such as SES, and job loss, among other social and demographic variables. Studies have consistently demonstrated a high prevalence of co-occurring anxiety and depression as comorbid conditions within individuals (Kaufman & Charney, 2000; Ruscio & Khazanov, 2017). Therefore, this study aims to investigate the effects of predictors on anxiety and depression simultaneously by employing separate logistic regression models, treating both as dependent variables.

The logit model also obtains an odds ratio, which is used to model the relationship between the dependent and independent variables. For the purpose of logistic regression analysis, the responses are treated as binary. The logistic regression uses the maximum likelihood estimation to estimate the coefficients. The regression models were run using the statistical tool, R. The following model was run:

$$\text{Log } (P/1\text{-}P) = \alpha + \beta_1 X + \beta_2 Z + \beta_3 X \times Z + \epsilon$$

Where:

$\log(P/1\text{-}P)$ is the log-odds of the probability P

P is the probability of the outcome (e.g., experiencing anxiety or depression)

α is the intercept

β_1, β_2, and β_3 are the coefficients for the independent variables X and Z, and interaction terms respectively, and

ε represents the error term

3.4 Results

The descriptive statistics presented in Table 1 offer an overview of the variables considered in the analysis. The race distribution within the sample shows Whites at 76%, followed by Hispanic (9%), Black (7%), Asian (5%), and other races (4%). Males comprise 60% of the sample, with females accounting for 40%. A majority of the sample, 59% includes individuals who are currently married. Unmarried individuals comprise 19% of the sample, while those who were previously married, including those who are widowed, divorced, or separated, make up 22%.

A majority (88%) of respondents have an education level above high school, while 12% have a high school education or below.

Table 10. Descriptive Statistics of Variables Included in the Analysis

Race	**Frequency**	**Percentage**	**Range**
White	670858	76	0-1
Black	58639	7	
Asian	41294	5	
Hispanic	75912	9	
Other race	30942	4	
Gender			
Male	521467	59	0-1
Female	356178	41	
Unmarried	168504	19	
Married	514983	59	
Divorced/widowed	194158	22	
Education			

Table 10. Descriptive Statistics of Variables Included in the Analysis (continued)

High School or below	102200	12	0-1
Above High School	775445	88	
Income			
Low (< $35,000)	163347	19	Low-High
Medium ($35,000 - $99,999)	243920	28	
High (>= $100,000)	470378	54	
Anxiety			
No	360225	41	0-1
Yes	518526	59	
Depression			
No	417514	48	0-1
Yes	460131	52	
COVID-19 Infection			
No	765398	87	
Yes	107643	12	
Not sure	4604	1	
Employment			
Yes	541709	62	0-1
No	335936	38	
Job loss			
Yes	178041	20	0-1
No	699604	80	
Health Insurance			
Yes	835534	95	
No	42111	5	
	Mean	**SD**	**Range**
Age	56	15	20-91
Household Size	3	1	1-10
Death rate	328	92	138-567
Wave			0-44
Observations	877,645		

Income levels show a skew towards the higher end, with 53% of the sample earning $100,000 or more, 28% earning between $35,000 and $99,999, and 19% earning below $35,000. When it comes to the main dependent variables anxiety and depression symptoms are fairly evenly distributed among the participants, with 59% reporting anxiety and 53% reporting depression.

Regarding COVID-19 infection, the vast majority of respondents (87%) have not been infected, 12% have been, and 1% are not sure. Employment figures show that 62% of the respondents are employed while 38% identified as not employed. Recent household job loss experienced by respondents stands at 20%, suggesting economic repercussions for a decent portion of the sample.

The mean age of the sample is 55 years, with a standard deviation (SD) of 15 years, ranging from 20 to 91 years. The household size averages 3, with a range from 1 to 10, suggesting a variety of household living arrangements. The COVID-19 death rate per 100,000 people stands at a mean of 328, with an SD of 92, and a range from 138 to 567, reflecting state-wide variations in the COVID-19 pandemic's impact.

Figure 12. Temporal Trends in Average Anxiety and Depression Scores

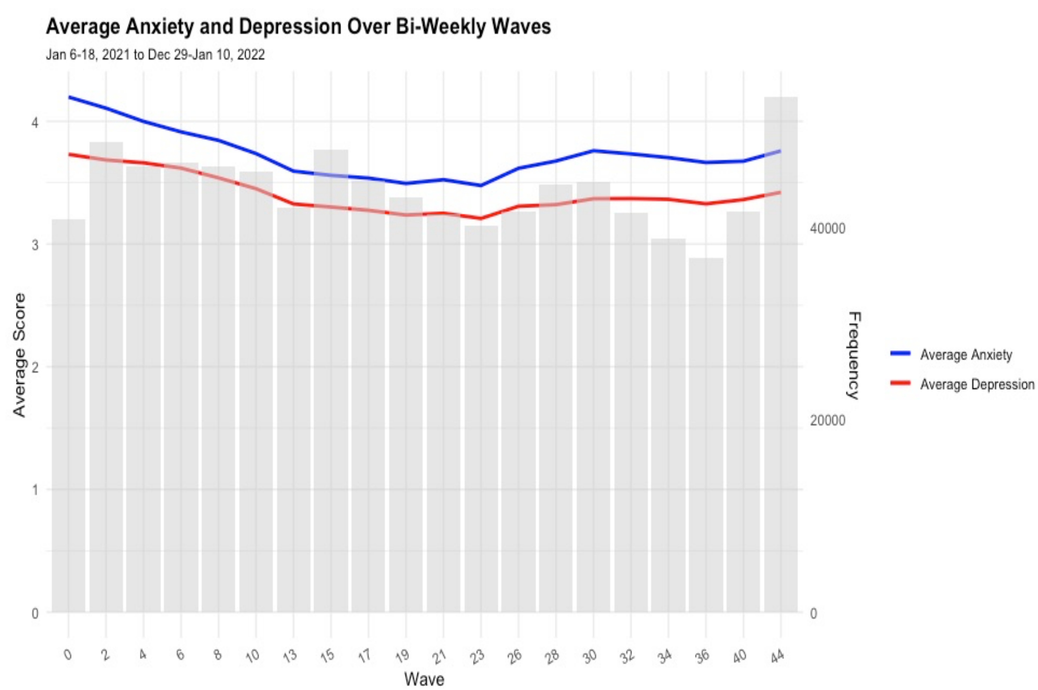


Figure 12 illustrates the average anxiety and depression scores among participants across specific survey weeks throughout the study period. The wave variable, indicating the bi-weekly survey wave number, ranges from 0 to 44, corresponding to the time frame from January 6, 2021, to January 10, 2022. The bars represent the total number of observations for each survey period.

Table 11. Regressing Anxiety on Social and Economic Factors

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Predictors	**OR**	CI	**OR**	CI	**OR**	CI	**OR**	CI	**OR**	CI
Wave	0.99*	0.99-0.99	0.99*	0.99-0.99	0.99*	0.99-0.99	1	1-1	1	1-1
Black			1.13*	1.11-1.15	0.92*	0.91-0.94	0.82*	0.8-0.83	0.71*	0.66-0.78
Hispanic			1.47*	1.44-1.49	1.17*	1.15-1.19	1.03*	1.01-1.05	1.03*	1.01-1.05
Asian			0.87*	0.86-0.89	0.77*	0.75-0.78	0.75*	0.73-0.76	0.75*	0.73-0.76
Other race			1.54*	1.51-1.58	1.25*	1.22-1.28	1.11*	1.08-1.14	1.11*	1.08-1.13
Male					0.57*	0.56-0.57	0.57*	0.57-0.58	0.57*	0.56-0.58
Age					0.97*	0.97-0.97	0.97*	0.97-0.97	0.97*	0.97-0.97
Unmarried					1.39*	1.37-1.41	1.14*	1.13-1.16	1.14*	1.13-1.16
Previously married					1.51*	1.49-1.52	1.23*	1.21-1.25	1.23*	1.21-1.24
Household					1.03*	1.03-1.03	1.01*	1.01-1.01	1.01*	1.01-1.01
COVID-19 death rate							1	1-1	1	1-1
Employment							0.90*	0.89-0.91	0.90*	0.89-0.91
Job loss							0.39*	0.39-0.4	0.39*	0.39-0.4
Income Medium ($35,000 - $99,999)							0.74*	0.73-0.75	0.72*	0.71-0.73
Income High (>= $100,000)							0.56*	0.55-0.56	0.54*	0.53-0.55
COVID-19 infected Yes							0.95*	0.94-0.96	0.95*	0.94-0.96
COVID-19 infected Not sure							1.29*	1.2-1.38	1.29*	1.2-1.38
Education							1.31*	1.29-1.33	1.31*	1.29-1.33
Health insurance							1.01	0.98-1.03	1.01	0.98-1.04
Black x Income Medium ($35,000 - $99,999)									1.22*	1.16-1.28
Black x Income High (>= $100,000)									1.30*	1.24-1.37
Black x education									0.99	0.94-1.05
Black x health insurance									0.97	0.9-1.05
AIC	1186268		1182476		1110917		1077754		1077632	
BIC	1186291		1182546		1111046		1077988		1077912	

Table 11. Regressing Anxiety on Social and Economic Factors (continued)

-2LL	1186264	1182464	1110895	1077714	1077584
N	877,645	877,645	877,645	877,645	877,645

Table 11 and Table 12 reveal the sequential progression of models, providing insight into how the addition of different variables impacts the relationships between predictors and the mental health outcomes of anxiety and depression, respectively. Throughout the models, the predictors for both anxiety and depression remain consistent, and the results display a comparable pattern across these mental health conditions.

Table 12. Regressing Depression on Social and Economic Factors

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Predictors	**OR**	**CI**	**OR**	**CI**	**OR**	**CI**	**OR**	**CI**	**OR**	**CI**
Wave	0.99*	0.99-0.99	0.99*	0.99-0.99	0.99*	0.99-0.99	1	1-1	1	1-1
Black			1.21*	1.19-1.24	1.01	0.99-1.03	0.88*	0.86-0.9	0.74*	0.68-0.8
Hispanic			1.46*	1.44-1.48	1.23*	1.21-1.25	1.05*	1.03-1.06	1.04*	1.03-1.06
Asian			0.96*	0.94-0.98	0.88*	0.87-0.9	0.89*	0.87-0.91	0.89*	0.87-0.91
Other race			1.55*	1.52-1.59	1.30*	1.27-1.33	1.14*	1.11-1.17	1.14*	1.11-1.17
Male					0.77*	0.76-0.77	0.79*	0.78-0.8	0.79*	0.78-0.8
Age					0.98*	0.98-0.98	0.98*	0.97-0.98	0.98*	0.97-0.98
Unmarried					1.71*	1.69-1.73	1.36*	1.34-1.37	1.36*	1.34-1.38
Previously married					1.78*	1.76-1.8	1.41*	1.39-1.42	1.40*	1.39-1.42
Household					1.01*	1.01-1.01	0.99*	0.98-0.99	0.99*	0.98-0.99
COVID-19 death rate							1	1-1	1	1-1
Employment							0.82*	0.81-0.83	0.82*	0.81-0.83
Job loss							0.44*	0.44-0.45	0.44*	0.44-0.45
Income Medium ($35,000 - $99,999)							0.73*	0.72-0.74	0.72*	0.71-0.73
Income High (>= $100,000)							0.51*	0.51-0.52	0.50*	0.5-0.51
COVID-19 infected Yes							0.99	0.98-1	0.99	0.98-1
COVID-19 infected Not sure							1.26*	1.18-1.34	1.26*	1.18-1.34
Education							1.09*	1.07-1.11	1.09*	1.07-1.1
Health insurance							0.90*	0.88-0.93	0.90*	0.88-0.92
Black x Income Medium ($35,000 - $99,999)									1.19*	1.13-1.25

Table 12. Regressing Depression on Social and Economic Factors (continued)

Black x Income High (>= $100,000)					1.24*	1.18-1.3
Black x education					1.01	0.95-1.06
Black x health insurance					1.03	0.96-1.11
AIC	1212270	1208338	1162277	1125066	1124973	
BIC	1212293	1208408	1162405	1125299	1125253	
-2LL	1212266	1208326	1162255	1125026	1124925	
N	877,645	877,645	877,645	877,645	877,645	

Model 1 only includes the wave variable as a predictor, suggesting that there is a very slight decrease in the odds of reporting anxiety or depression with each subsequent wave, but this change is very small. Moving to Model 2, which includes race, the odds ratios for Black, Hispanic, and other race individuals (OR: 1.13, 1.47, and 1.54, respectively), indicate that racial groups are more likely to report anxiety compared to Whites. In contrast, for Asians (OR: 0.87), anxiety appears less. Simultaneously, Model 2 for depression reveals a similar tendency, with these racial groups more prone to report depression as well, except for Asians who appear less likely in both cases.

Model 3 adds other demographic variables such as gender and age to the previous model. The associations for racial groups change notably in this model. For anxiety, the odds ratio for Black individuals drops to 0.92, suggesting that the racial disparity in anxiety between Black and White individuals as observed in Model 2 is largely explained by other demographic variables such as gender, age, marital status, and household size. For depression, Model 3 illustrates a reduction in the odds ratio across all racial categories except for Blacks, where no significant association is found. The odds ratios for Hispanics, Asians, and other race categories see slight changes but remain statistically significant, suggesting that while gender, age, marital status and household size account for some disparity, Hispanics and other race still have higher odds of experiencing anxiety. Similar results were found for Hispanics and other race groups on depression.

The model also shows that males have 43% lower odds (OR 0.57) of reporting anxiety and 23% lower (OR: 0.77) for depression, compared to females. The odds ratio for age (0.97) shows that slight decrease in the odds of reporting anxiety with each additional year of age, suggesting younger individuals may experience more vulnerability to anxiety. The heightened likelihood for unmarried individuals to experience anxiety (39% more likely) or depression (71% more likely) and for previously married individuals (51% more likely for anxiety and 78% more likely for depression) remains consistent, reinforcing that marital status is a predictor of mental health across the board.

In Model 4, where socioeconomic factors such as employment and education are included, partial support for Hypothesis 3 is observed. This hypothesis suggests that controlling for SES would reduce the racial disparities in anxiety or depression. For anxiety, the addition of SES factors results in a notable decrease in the odds ratio for Black individuals from 1.13 to 0.82. Similarly, for depression, the odds ratio for Black individuals decreases from 1.21 to 0.88 when SES is accounted for. These results indicate that, especially for Black individuals, controlling for SES attenuates some of the racial disparities in mental health outcomes during the COVID-19 pandemic. For Hispanic individuals, the increased risk compared to Whites persists, suggesting that SES does not fully explain the increased likelihood of anxiety or depression in this group.

The results show individuals who are employed have slightly lower odds of reporting anxiety (OR: 0.90) or depression (OR: 0.82), suggesting the potential role of financial stability in mitigating anxiety. Contrary to expectations, the association between recent job loss within the household and reported anxiety levels is inverse; individuals from households that have experienced job loss are shown to have a lower likelihood of reporting anxiety (OR: 0.39) and depression (OR: 0.44). This finding appears counterintuitive, suggesting that other factors not captured in the model may be influencing this relationship. However, the results show that higher income levels are associated with lower odds of reporting anxiety (OR: 0.56) or depression (OR: 0.51).

Compared to those who reported that they did not have COVID-19 infections, individuals who reported being infected had 5% lower odds of reporting anxiety, which may suggest resilience or a relief of uncertainty following recovery. This is further corroborated by the evidence that those unsure about their infection status were 29% more likely to report anxiety (26% more likely for depression).

The results show that those above high school education are associated with increased odds of reporting anxiety (OR = 1.31) (OR: 1.09 for depression), which might reflect increased awareness or reporting of mental health symptoms among those with more education.

The progression of models from Model 1 to Model 5 shows an increasingly comprehensive assessment of the predictors that can explain anxiety or depression. The stability of the wave variable across all five models suggests that the time progression of the pandemic has a consistent effect on anxiety levels. Consistent across models, being male or older is associated with lower odds of reporting anxiety. The results show that COVID-19 death rates at the state level may not be directly influencing individual anxiety, thus Hypothesis 1, which suggests individuals living in States with higher COVID-19 death rates are at greater risk of having anxiety or depression, is not supported.

Model 5 adds interaction terms for race and SES to see how they together influence anxiety and depression risks. This model tests Hypotheses 4, proposing that higher socioeconomic status (SES) does not shield Black individuals from increased odds of anxiety or depression when compared to Whites of similar SES. The results support this hypothesis: Black individuals with a medium income range ($35,000 - $99,999) show higher odds of anxiety (OR: 1.22) and depression (OR: 1.19), while those in the high-income bracket (>= $100,000) exhibit even higher odds (anxiety OR: 1.30, depression OR: 1.24). The finding highlights the notion that higher SES does not seem to mitigate the risks for anxiety or depression among Black individuals as effectively as it does for Whites, suggesting the presence of other structural factors that disproportionately affect Black communities, regardless of income or educational attainment.

The results in Model 5 also show that when controlling for SES and the interaction terms, the associations for racial groups remain consistently significant, indicating that race continues to be an important factor even after accounting for SES. This shows partial support for Hypothesis 2, which posits that compared to Whites, racial minorities are likely to have greater depression or anxiety. The results in the anxiety model show that Hispanics are 3% more likely to report having anxiety, compared to Whites. Similarly, other race category showed an 11% increased risk of having anxiety. For Blacks, associations with anxiety showed a 29% decrease in risk. Very close to similar results were observed for depression.

The findings indicate that, in comparison to married individuals, unmarried or previously married people—including those who are widowed, divorced, or separated—are at a higher risk for anxiety or depression. Specifically, unmarried individuals are 14% more likely to report anxiety, while those who were previously married are 23% more likely. In addition, the likelihood of depression is 36% higher for unmarried individuals and 40% higher for those previously married, compared to married individuals, suggesting that marital status significantly influences mental health outcomes.

Model 5 in both anxiety and depression models shows no associations between Black and education and Black and health insurance, indicating that the effect of education and having health insurance on anxiety or depression does not differ significantly between Black and White individuals. Unlike in anxiety, individuals having health insurance see a reduction in odds of depression by 10%. Model 5 in both anxiety and depression is selected for further analysis as AIC and BIC are slightly lower than other models, indicating a better fit despite the more complex model.

3.4.1 Sensitivity Analysis

Table 4 shows various sensitivity analyses, exploring different scenarios to examine the robustness of this study's findings of the final model for anxiety. The sensitivity analyses focus solely on the anxiety model due to consistent estimates between anxiety and depression as shown in Tables 2 and 3.

Table 13. Sensitivity Analyses

	Multiple imputation on missing anxiety	**Treating missing anxiety as 1**	**Treating missing anxiety as 0**	**Random subsample**	**Selected anxiety Model 5 (Table 12)**
Wave	1	1	1	1	1
Black	0.71*	0.71*	0.71*	0.65*	0.71*
Hispanic	1.04*	1.04*	1.04*	1	1.03*
Asian	0.75*	0.75*	0.75*	0.72*	0.75*
Other race	1.12*	1.12*	1.11*	1.19*	1.11*
Male	0.57*	0.57*	0.57*	0.57*	0.57*
Age	0.97*	0.97*	0.97*	0.97*	0.97*

Table 13. Sensitivity Analyses (continued)

Unmarried	1.14*	1.14*	1.14*	1.18*	1.14*
Previously married	1.21*	1.21*	1.21*	1.23*	1.23*
Household	1.01*	1.01*	1.01*	1.02*	1.01*
COVID-19 death rate	1	1	1	1	1
Employment	0.90*	0.90*	0.90*	0.93*	0.90*
Job loss	0.40*	0.40*	0.40*	0.41*	0.39*
Income Medium ($35,000 - $99,999)	0.72*	0.72*	0.72*	0.75*	0.72*
Income High (>= $100,000)	0.54*	0.54*	0.54*	0.54*	0.54*
COVID-19 infected Yes	0.96*	0.96*	0.96*	0.93*	0.95*
COVID-19 infected Not sure	1.26*	1.27*	1.25*	1.27	1.29*
Education	1.30*	1.30*	1.30*	1.36*	1.31*
Health insurance	1.01	1.01	1.01	0.92	1.01
Black x Income Medium ($35,000 - $99,999)	1.20*	1.21*	1.20*	1.29*	1.22*
Black x Income High (>= $100,000)	1.28*	1.28*	1.28*	1.73*	1.30*
Black x education	1	1	1.01	0.88	0.99
Black x health insurance	0.97	0.97	0.98	1.04	0.97
N	1,403,424	1,403,424	1,403,424	50,000	877,645

The first model utilizes multiple imputation through the MICE package in R to handle missing data presumed to be missing at random. After imputing the 'anxiety' variable five times, creating a series of datasets, the derived odds ratios align closely with those of the selected anxiety Model 5 from Table 12 for most predictors. These include factors such as race, gender, age, employment status, education, and income levels. This alignment indicates that the imputation process has not meaningfully changed the association between these variables and anxiety, affirming the robustness of the model's results.

In a model where missing anxiety values are presumed to be 1, reflecting a 'worst-case scenario' assumption, the odds ratios remain largely in line with those from the final selected model. This suggests robustness in the primary findings; even if all unreported cases were due to anxiety, the identified relationships persist. However, it is plausible that in reality, missing data could represent individuals reluctant to disclose anxiety, possibly due to stigma.

In the model where missing anxiety cases are considered absent of anxiety, the results also mirror those of the main model selected for in-depth analysis, further affirming the stability of the findings across different assumptions for missing data.

Finally, the sensitivity analysis utilizing a random subset of fifty thousand individuals reveals largely stable estimates compared to the full sample Model 5. Notably, variables such as Black and COVID-19 infection status lose statistical significance in this smaller dataset, hinting at potential sample size effects. However, other variables such as gender, age, income, and education maintain similar odds ratios, supporting the consistency of the associations observed in the larger analysis.

Overall, these analyses affirm the reliability of the final model's conclusions, demonstrating that the core findings remain robust across various sample compositions and assumptions regarding missing 'anxiety' data.

3.5 Discussion

This study's findings highlight the differential effect pathways across racialized communities, illustrating that despite widespread exposure to the highly infectious SARS-CoV-2 virus, the pandemic’s mental health impacts vary significantly among racial groups, with socioeconomic factors playing a critical role in these disparities. While the results indicate that COVID-19 death rates at the state level do not impact individual levels of anxiety or depression, contrary to the hypothesis, this absence of direct association suggests that individual-level factors, such as personal health traits or SES, may exert a stronger influence on mental health outcomes than broader state-level mortality statistics.

The findings suggest a complex relationship among race, SES, and anxiety or depression during the COVID-19 pandemic. Before considering SES, gender, age, and marital status, Blacks exhibited a 13% higher risk for anxiety, underscoring significant disparities. Before accounting for factors like age, gender, marital status, and socioeconomic status, Hispanics and other racial groups were 47% and 54% more likely, respectively, to face a higher risk of anxiety compared to Whites, while Asians were 23% less likely to experience anxiety than Whites.

Before considering socioeconomic status, gender, age, and marital status, significant variations in depression prevalence were observed across racial lines, with Blacks, Hispanics, and other races experiencing increased instances of depression by 21%, 46%, and 55% respectively, compared to Whites, partially confirming Hypothesis 2 and indicating a higher risk of depression among racial minorities, while Asians consistently showed a decreased likelihood of depression relative to Whites, regardless of other factors.

Incorporating demographic and SES factors, including their interactions, into the analysis notably reduced the disparity in anxiety and depression rates among Black individuals. The odds ratio of reporting anxiety decreased from 1.13 to 0.71, and for depression from 1.21 to 0.74. This outcome aligns with Hypothesis 3, indicating SES considerations attenuate racial disparities in mental health during the pandemic. Consequently, the observed lower likelihood of anxiety and depression among Blacks in this study—29% and 26% respectively—echoes the findings of Owens & Saw, (2021), which noted a significant reduction in probable anxiety and depression among Blacks compared to non-Black population[10]. By detailing the mitigating role of SES, this study, thus expands Owens & Saw, (2021) insights, highlighting the attenuating effect of SES factors on racial disparities in mental health outcomes amid the COVID-19 pandemic. Moreover,

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[10]Owens & Saw (2021) study's non-Black population included Whites, Hispanics, Asians, and other race

despite these adjustments, the higher risk remained for Hispanics, suggesting that factors beyond SES contribute to their increased susceptibility to anxiety and depression.

Another significant insight from this study supports the hypothesis that higher socioeconomic status (SES) does not shield Black individuals from anxiety or depression in the same way it does for Whites. Analysis revealed that Black individuals, even with higher incomes, are more likely to experience anxiety—30% more for those in high-income brackets and 22% more for those in medium-income brackets, compared to their White counterparts. The pattern is similar for depression, where high and medium-income Black individuals are 24% and 19% more likely to report depression, respectively, compared to Whites. These findings, suggesting mental health inequalities extend beyond financial stability for Black individuals, reflect the broader concept of differential health returns previously observed in chronic health outcomes (Boen, 2016; Ciciurkaite, 2021). Specifically, higher income does not necessarily lead to better health benefits for Blacks, paralleling the "diminished return theory" described by Assari et al., (2017, 2018, 2020), which suggests that the advantages typically associated with high SES do not uniformly translate into equitable mental health outcomes for Black individuals.

The study demonstrated consistent trends related to gender and age across all models, with men being 43% less likely than women to report anxiety and 21% less likely to report depression. Furthermore, an increase in age was associated with a 3% lower likelihood of reporting anxiety and a 2% lower likelihood of reporting depression. This aligns with initial observations during the pandemic that older age is correlated with reduced reporting of anxiety, echoing findings from other research emphasizing the influence of gender and age on mental health during the pandemic (Center for Disease Control and Prevention, 2022; Giuntella et al., 2021).

This research indicates that higher income or employment status is associated with reduced symptoms of anxiety and depression, underscoring the relationship between financial stability and improved mental health outcomes. This connection is supported by evidence showing that higher income levels correlate with lower mental distress (Holingue et al., 2020; Jaspal & Breakwell, 2022; Pieh et al., 2021). In particular, individuals earning ≥ $100,000 annually reported 46% less anxiety and 50% less depression than their lower-income peers. Conversely, recent job loss in the household is linked with a 61% reduction in anxiety (56% lower in depression), an unexpected finding but the outcome is possibly influenced by factors like decreased exposure to job-related COVID-19 risks or other unaccounted stressors.

This study's findings underscore the heightened risks of anxiety and depression among unmarried and previously married individuals—including those who are widowed, divorced, or separated—compared to their married counterparts, echoing the broader consensus within mental health and marital status research. Specifically, the results reveal a 14% increased likelihood of anxiety among unmarried individuals and a 23% increase for those previously married, alongside a 36% and 40% higher risk of depression, respectively. These outcomes resonate with the protective mental health benefits of marriage (Waite, 2009) and the challenges highlighted by Kessler et al., (2003) individuals not in marital unions. In addition, the patterns of depressive symptoms among previously married such as divorced, separated, and widowed, as noted by Pan et al., (2022), reinforce the findings of this study, demonstrating the significant role of marital status in determining mental health outcomes.

In the context of the pandemic, the role of infection status in mental health is noteworthy. Those who had COVID-19 showed marginally lower levels of anxiety (but no association with depression), suggesting psychological resilience or potential reduction in uncertainty in the post-recovery. Conversely, compared to those without COVID-19 infections, individuals unsure of their infection status exhibited notable increases in anxiety (29%) and depression (26%), reflecting the mental stress from uncertain infections.

Health insurance emerged as a mitigating factor for health concerns related to depression, with coverage associated with a 10% reduction in depression levels, likely due to enhanced access to healthcare services. This finding aligns with earlier studies indicating disparities in mental health care due to a lack of insurance coverage in the United States (Mojtabai et al., 2014). Nevertheless, this study did not find a significant direct correlation between health insurance possession and reduced anxiety levels.

This study underscores the impacts of socioeconomic factors on mental health disparities among racialized populations during the COVID-19 pandemic. The findings showed that while SES appears to generally attenuate racial disparities, its protective effects are not uniformly experienced across all racial groups. Notably, for Blacks, higher SES does not afford the same degree of mental health protection as observed in White counterparts. Future research, thus, should consider race, socioeconomic status, and other potential systemic factors alongside economic ones to explain racialized mental health disparities.

3.5.1 Limitations

Several limitations exist in this study. The Household Pulse Survey is an online survey response collected from individuals across the country. There is a possibility that the survey has underrepresented the population sample because it is a self-administered response and those who have technological advantages could only participate in the survey. Low-income people or people with less education and limited resources may have not been equally represented in the sample. Furthermore, while examining the connections between an individual respondent's SES and anxiety or depression, this study uses household income and individual education and employment status, potentially neglecting the SES dynamics in households with multiple earners, where changes in one individual's income or employment status may be offset by others. Only those whose addresses have been selected to participate can complete the survey. A limited number of addresses across the country have been invited to answer the HPS. The GAD-2 and PHQ-2 only included the two questions for depression and anxiety symptoms, thus limiting the assessment of other variables that could potentially be associated with the independent variables. The HPS lacks variables indicating pre-existing mental health problems. The dataset also has a large amount of missing data. To address these limitations, sensitivity analyses were conducted to assess the impact of missing data and potential biases. These analyses help us better understand the extent to which the limitations might affect our findings.

Chapter IV: Conclusion

This dissertation extends the theoretical paradigms of differential exposure and differential effects to examine the uneven impacts of the COVID-19 pandemic across diverse demographic groups, with a particular focus on racialized populations. The investigation is methodologically partitioned into two distinct yet interrelated components. The first component, encompassed by Chapters 1 and 2, analyzes the 'risk' dimensions of differential exposure. It systematically examines whether variations in physical and social environmental conditions can account for the observed disparities in COVID-19 mortality among racialized populations. The second component, articulated in Chapter 3, shifts the analytical focus to the 'consequences' of differential effects, exploring how differential socioeconomic contexts influence mental health outcomes amidst the COVID-19 pandemic. This dual approach provides a comprehensive analysis of the pandemic's disparate impacts and enhances our understanding of how societal structures affect health outcomes among racialized populations. Chapter 1 focuses on the urban context, where racial minorities face heightened risks due to poor environmental and social conditions, while Chapter 2 broadens this view to compare urban and rural disparities, where similar themes of systemic inequalities emerge, although manifested differently across geographic landscapes.

In Chapter 1, the examination of racial disparities in COVID-19 mortality within urban settings highlights how various environmental and social factors exacerbate the risk of differential exposure among racial minorities. The study notably uncovers that environmental hazards, specifically urban air pollution, have a disproportionate impact on racial communities such as Blacks and Hispanics. This research expands our understanding by highlighting hazardous air pollutants (HAPs), also known as urban air toxics, as significant environmental risk factors. Originating from industrial facilities and vehicles, these pollutants are linked to serious health issues such as cancer and respiratory diseases (EPA, 2018). Although residing in areas with average levels of HAPs and Social Vulnerability Index (SVI) markers might correspond to lower COVID-19 mortality rates among racial minorities, including Black and Hispanic communities, this study reveals that their mortality risk escalates with each incremental increase in exposure to air pollutants like HAPs, exacerbating health disparities and disproportionately impacting these groups. For instance, this study revealed that, controlling for all other factors, Black individuals living in areas with above-average levels of HAPs have a more than 4-fold increase in COVID-19 mortality risk, while Hispanics face a nearly 19-fold increase. This argument consolidates the notion that the interaction between environmental conditions and racial demographics plays a crucial role in the differential health outcomes observed during the pandemic. These findings align with previous research suggesting that poor environmental conditions are a significant determinant of health disparities (Laumbach et al., 2015; Manisalidis et al., 2020). In addition, social factors like severe housing conditions, and income inequality compound these risks, with the study confirming that systemic discrimination plays a pivotal role in this enhanced exposure (Mohai et al., 2009).

Chapter 2 extends the narrative of differential exposure by dissecting the urban-rural divide. The study reveals stark contrasts in COVID-19 mortality driven by underlying health conditions and environmental and social factors. Urban settings, characterized by dense populations and diverse socioeconomic compositions, contrast with rural areas where access to healthcare is often limited, and residents typically exhibit a higher burden of chronic health conditions. The differential exposure is evident in the varied health outcomes where urban areas show increased mortality potentially due to factors such as environmental conditions, including higher pollution levels, as highlighted in the study. For instance, this study demonstrated that compared to individuals in rural areas, those with underlying conditions in urban areas face a 23% increased risk of COVID-19 mortality. Furthermore, while Blacks generally face a 19% higher risk of COVID-19 mortality, Blacks in urban areas with better food environments actually experience a 15% lower risk, potentially suggesting that improved access to healthy food options might mitigate some of the health disparities experienced by Blacks in urban settings.

Chapters 1 and 2 effectively merge multiple datasets to analyze the impact of physical and social environmental factors on COVID-19 mortality, including individual-level traits like underlying medical conditions, providing a multidimensional perspective on differential effects and exposures. They highlight the disproportionate impact of COVID-19 on racial minorities, offering valuable insights into addressing systemic health inequities. However, the CDC Case Surveillance dataset has limitations such as large amounts of unknown values, and missing individual-level socioeconomic data. The use of county-level variables in Chapters 1 and 2 introduces limitations, as county averages can mask localized disparities. County-level data is subject to the Modifiable Areal Unit Problem (MAUP) and may introduce biases, underscoring the need for more granular data to avoid ecological fallacy and improve accuracy. In addition, the focus on urban areas in Chapter 1, also limits generalizability to rural settings. Nevertheless, this research underscores the necessity for public health strategies to adopt a multidimensional approach, addressing both structural and individual factors to effectively mitigate COVID-19 mortality disparities. The research also prompts deeper investigation into the mechanisms through which environmental and social factors contribute to racial disparities in health outcomes and explores how individual behaviors interact with these factors to influence health outcomes.

Transitioning from risk to consequences, Chapter 3 investigates the differential effects of COVID-19 on mental health across racial lines within the context of varying social and economic conditions. This chapter emphasizes that while exposure to the virus was widespread, the consequent mental health impacts were disproportionately distributed, with racial minorities experiencing varying effects. The research reveals that despite higher socioeconomic status, racial minorities, particularly Blacks, do not benefit equally in terms of mental health outcomes when compared to Whites. For instance, this study revealed that Blacks with high incomes (greater than or equal to $100,000) reported a 30% increase in anxiety and a 24% increase in depression compared to Whites of similar income. This finding resonates with the concept of diminished returns, where increased SES does not necessarily translate into better mental health for racialized groups, particularly Black (Assari et al., 2017, 2018, 2020).

Chapter 3 investigates the racialized differential effects of COVID-19 on mental distress due to social and economic factors. This chapter's strength lies in its comprehensive examination of how COVID-19 exacerbated mental health disparities among racial minorities through socioeconomic pathways from the Household Pulse Survey. It reveals significant findings that higher SES does not shield Black individuals from anxiety or depression as effectively as it does for Whites. However, the study's weaknesses include reliance on self-reported data, which may introduce bias, and the potential underrepresentation of low-income and less-educated populations due to the survey's online nature. In addition, the study’s cross-sectional design limits causal inferences. Nevertheless, this research prompts critical questions: What underlying mechanisms prevent higher SES from providing the same mental health benefits to Black individuals as it does to Whites? How do systemic and structural factors contribute to these disparities? How can public health interventions be tailored to address these unique challenges and ensure that mental health support systems are effective across different racial and socioeconomic groups? Future research should address these questions to develop comprehensive strategies that address the intersectionality of race, SES, and mental health.

The synthesis of these findings in this study within the differential exposure and effects frameworks underscores a multifaceted public health crisis. Racial minorities face increased risks due to systemic factors that lead to higher environmental and social vulnerabilities. These same populations then bear the brunt of the consequences in the form of mental health disparities, despite variations in socioeconomic status. This analysis reveals how multidimensional factors of the physical and social environments and individual biological characteristics of pre-existing health conditions shape the health outcomes of racialized populations during the COVID-19 pandemic.

This study draws parallels between how systemic structural factors shape health outcomes in chronic conditions and infectious diseases like COVID-19. The insights gained from studying the COVID-19 pandemic have broader applications for chronic diseases as well. Understanding how systemic inequalities impact health outcomes can inform public health strategies for future health emergencies and mitigate health disparities among racialized populations. Lessons from the COVID-19 pandemic underscore the importance of addressing environmental and social determinants of health to build equity in health systems, preparing us better for future public health challenges, including both pandemics and chronic diseases.

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Vita

Suresh Nath Neupane earned his Ph.D. in Urban Studies with a focus on social epidemiology from Georgia State University, where he investigated health disparities across racial communities. His research examines the impact of environmental and socio-structural factors such as air pollution and social vulnerability on health outcomes in both urban and rural settings. He emphasizes how these factors influence outcomes related to both chronic and infectious diseases, including COVID-19. Mr. Neupane has published his findings in reputable journals and collaborated with the Centers for Disease Control and Prevention (CDC) on a study concerning the Minority Health Social Vulnerability Index (MHSVI) and its impact on COVID19 mortality outcomes. He draws parallels between chronic diseases and infectious diseases, demonstrating how similar structural factors shape health outcomes across different types of diseases. He possesses a strong quantitative background, using machine learning techniques and various statistical tools to analyze large datasets. His work aims to inform public health strategies and interventions tailored to the needs of racially and economically diverse populations. Mr. Neupane holds an MS degree in Geosciences (Geography) from Georgia State University, an MA in Sociology from the University of West Georgia, and a BA in Sociology from Georgia College & State University. He can be contacted at sureshnathneupane@gmail.com.