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# What Is Contributing To Covid-19 Mortality In Harris County, Texas?

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WHAT IS CONTRIBUTING TO COVID-19 MORTALITY

IN HARRIS COUNTY, TEXAS?

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by

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WHAT IS CONTRIBUTING TO COVID-19 MORTALITY IN HARRIS COUNTY, TEXAS?

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The COVID-19 pandemic exposed long-standing inequities that have been present in the United States since its origin. While the entire country has been devastated by this pandemic, low-income and minority communities were hardest hit. Race alone does not predict poor health outcomes. Rather, the historic strategies implemented in the United States, such as redlining, placed racial and ethnic minorities in neighborhoods where cycles of disinvestment in education, transportation infrastructure, flooding infrastructure, healthy food, and clean air and water have created low socioeconomic status and poor health outcomes. This public health research aims to understand how historical processes have created and maintained social, economic, and environmental conditions that give rise to poor health during pandemics. We investigated whether exposure to air pollution, pre-existing chronic disease, and various factors that determine socioeconomic status are contributing to increased mortality following COVID-19. A multivariable logistic regression analysis was done on a population of COVID-19 cases that had been reported to Harris County Public Health between March 2020 and March 2022. In this study, we found that the odds of COVID-19 mortality were 37% higher in Hispanic and 20% higher in Black individuals

compared to non-Hispanic White individuals after adjusting for age, race, gender, and $PM_{2.5}$ exposure. After adjusting for age, race, gender, pre-existing chronic disease, and social vulnerability, a 1μg/$m^3$ increase in the 14-day average $PM_{2.5}$ exposure increases the odds of mortality by 6%. Additionally, the odds of COVID-19 mortality in those reporting obesity were 11.09 times the odds of mortality in those who did not report obesity and obesity had the highest risk of all reported pre-existing chronic conditions. Finally, after adjusting for, age, race, gender, pre-existing chronic disease, and $PM_{2.5}$ exposure, the odds of COVID-19 mortality are 77% higher in those living in census tracts with the highest SVI score (0.75 – 1) compared to those living in census tracts with the lowest SVI score (0 - 0.25).

The findings evidenced in this research indicate that modifiable factors such as air pollution exposure, pre-existing chronic disease, and social vulnerability may be contributing to an increased risk of mortality following COVID-19 illness. Thus, offices and divisions within local health departments that are responsible for targeting public health interventions such as chronic disease prevention and pollution control services may consider making an effort to continue these essential services and, in some cases, even strengthen these services during public health emergencies like the COVID-19 pandemic. Additionally, local health departments may consider incorporating the lessons identified in this research in their Infectious Disease Response Plan, Continuity of Operations Plan, and standard operating guides pertaining to vulnerable populations during public health emergencies.

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## BACKGROUND

### Literature Review

#### *COVID-19 Impacts in Harris County*

In 2019, the severe acute respiratory syndrome- coronavirus 2 (SARS-CoV-2), a positive strand RNA virus that scientists believe mutated from a wild animal source into a variant that could be actively transmitted from human to human (Obukhov et al., 2020). SARS-CoV-2 causes the disease known as Coronavirus Disease 2019 (COVID-19) which is responsible for the current global pandemic. SARS-CoV-2 is a novel virus; therefore, an important public health objective is to identify key modifiable environmental factors that may contribute to the severity of the health outcomes (e.g., ICU hospitalization and death) among individuals with COVID-19 (Wu et al., 2020a). Additionally, researchers have noted challenges in determining or exploring these risk factors because individual-level data on COVID-19 health outcomes for large, representative populations are not publicly available or accessible to the scientific community (Wu et al., 2020b). For example, the ecologic studies that have been done are unable to adjust for individual-level risk factors and therefore are unable to make conclusions about associations at the individual level.

The impacts of COVID-19 are not homogenous and differs by racial/ethnic group. As of September 2022, over 1 million Harris County residents have tested positive for SARS-CoV-2 by PCR molecular confirmatory test. As of March 2022, the time period which this research covers, over 3,000 residents have passed away due to COVID-19 in Harris County. In the current dataset in the period from March 2020 – March 2022, Harris County Public Health jurisdiction reports Hispanics make up 35% of deaths and represent 31% of the population, non-Hispanic Blacks make up 14% of deaths and 12% of the population and Non-Hispanic Whites make up

38% of deaths and 22% of the population. Reports at the national level for individuals with COVID-19 states that Black non-Hispanic individuals are 1.9 times more likely to die than non-Hispanic Whites and Hispanic individuals are 2.3 times more likely to die than non-Hispanic Whites (CDC, n.d.-a).

There are several neighborhood-level factors that could be contributing to the occurrence of these Hispanic and Black population's vulnerability (Oluyomi et al., 2021). Social, economic, and environmental factors all play a role as to why Hispanic and Black people experience more health disparities than non-Hispanic Whites (Moise & Moise, 2020). Focusing solely on race/ethnicity without examining the sociodemographic and environmental factors however can attribute too much emphasis on the "biological" concept of race rather than exploring the contextual relationships that could better explain these disparities (Isaacs & Schroeder, 2004). Over 70% of Harris County's population identifies as Hispanic, Black, or Asian, and therefore, it is critical that local researchers explore other contextual relationships that may be contributing to health disparities during the COVID-19 pandemic, such as air quality, chronic disease, or social vulnerability (George, 2020) . More evidence of these relationships will help local health authorities and leaders make more informed targeted interventions for their communities. First this research will look at the association between $PM_{2.5}$ pollution and COVID-19 mortality and will be explained in the following section.

***$PM_{2.5}$ and its Impacts in Harris County***

The pollutant of interest in this research is particulate matter, which is a mixture of solid particles such as dust, dirt, soot, or smoke and liquid droplets found in the air. These particles have two widely accepted sizes, 10 microns and smaller ($PM_{10}$) and 2.5 microns and smaller

($PM_{2.5}$). According to the Environmental Protection Agency, most of these particles form in the atmosphere as a result of complex reactions of chemicals such as sulfur dioxide and nitrogen oxides, which are pollutants emitted from power plants, industries and automobiles (Epa & of Air, 2014). This research is interested in $PM_{2.5}$ specifically because these fine particles pose the greatest risk to human health due the small size and ability to reach multiple organs. There are long-term and short-term impacts of $PM_{2.5}$ pollution on the human respiratory and cardiovascular organ systems. Fine particles inhaled into the respiratory tract are foreign to the human body and cause inflammatory immune responses. Pro-inflammatory cells such as macrophages or neutrophils that respond to these foreign particles can cause inflammation of the lung and respiratory organs leading to impaired lung function over time (Xing et al., 2016). In addition, the impact of $PM_{2.5}$ on the cardiovascular system has been documented in animal models (Du et al., 2016). The health impacts on the cardiovascular system manifest in endothelial dysfunction and vasoconstriction, increased blood pressure (BP), prothrombotic and coagulant changes, systemic inflammatory and oxidative stress responses, autonomic imbalance and arrhythmias, and premature atherosclerosis (Brook et al., 2010). Exposure to $PM_{2.5}$ air pollution was estimated by the Global Burden of Disease study to be responsible for 4.2 million deaths and 108 million disability-adjusted life years in 2015 (Forouzanfar et al., 2016).

The air quality in Harris County is influenced by multiple sources of $PM_{2.5}$ air pollutants which includes extensive road traffic, proximity to one of the largest petrochemical industry complexes in the United States, and port activities in the Houston Ship Channel. Harris County has communities which have been in non-attainment for several years, meaning their air quality is worse than the National Ambient Air Quality Standards, and has documented issues with poor air quality due to the aforementioned factors (Bethel et al., 2006). It is also important to note that environmental risks are not always uniformly distributed in urban areas like Harris County and individuals classified with low socioeconomic status (SES) can become overburdened by environmental exposures. For example, a study conducted in 2017 found evidence of exposure to heavy metals (cadmium (Cd), arsenic (As), Pb, and Ni) among economically disadvantaged pregnant women in Houston, Harris County, TX (Rammah et al., 2019).

The current EPA standard for $PM_{2.5}$ pollution is 12 micrograms per meter cubed [$\mu g/m^3$]; however, most scientists agree that the new EPA standard should be between 8-10$\mu g/m^3$ due to the negative health impacts seen at levels lower than 12μg/m3 (Di et al., 2017; Pinault et al., 2017). Many studies supporting a standard of 12$\mu g/m^3$ consisted of populations whose socioeconomic status is higher than the national average and who reside in well monitored areas. To fill this gap, a large nationwide cohort study of Medicaid beneficiaries from 2000 – 2012 with 460 million person-years of follow up found that exposure to $PM_{2.5}$ of less than 12$\mu g/m^3$ (the current EPA standard) was associated with a 13.6% increased risk of death (95% CI, 13.1 to 14.1) (Di et al., 2017).

Although vulnerable populations have more difficulty overcoming the health impacts from air pollution due to their access to care, or pre-existing health conditions, fine particle pollution such as $PM_{2.5}$ affects the health of nearly all Houstonians (Roy, n.d.-b). An analysis done by the environmental defense fund found that almost all Houstonians are exposed to a yearly average of 10$\mu g/m^3$ of fine particle pollution ($PM_{2.5}$) and in some cases even above 12$\mu g/m^3$ (Roy, n.d.-b). It is also important to note that even though the COVID-19 pandemic resulted in a stay-at-home order, air pollution from industries continued and air pollution still affected Houston/Harris County residents. A study from Texas A&M University found that pre and post pandemic stay-at-home order air pollution levels were not significantly different in areas where pollution has historically been influenced by industry such as Deer Park, Aldine, and Clinton Park. In fact, $PM_{2.5}$ levels slightly increased after March 20, 2020 at the Aldine site by 14%, at the Clinton Dr. site 12%, and at the Deer Park site 52% (Schade, 2020a).

***Air Quality and COVID-19***

Prior to the COVD-19 pandemic, literature supporting air quality as a contributing factor to respiratory illness mortality is an ecologic analysis of the 2003 severe acute respiratory syndrome coronavirus 1 (SARS-CoV-1) that reported infected patients who lived in moderate air pollution levels were approximately 84% more likely to die than those in regions with lower air pollution (Cui et al., 2003). Several studies have shown a relationship between COVID-19 severity and air quality on an ecologic scale (Cole et al., 2020; Hendryx & Luo, 2020; Konstantinoudis et al., 2021; Petroni et al., 2020; Sasidharan et al., 2020a; Wu et al., 2020a). One pollutant of interest in the literature is fine particulate matter ($PM_{2.5}$), which is associated with increased risk of severe outcomes in patients with certain infectious respiratory diseases, including influenza, pneumonia, and SARS (Wu et al., 2020a). Additionally, long-term exposure to $PM_{2.5}$ is linked to many of the comorbidities that have been associated with poor prognosis and death in COVID-19 patients, including cardiovascular disease, lung disease, emergency room visits, hospitalization, and mortality; therefore, those with COVID-19 exposed to unsafe levels of $PM_{2.5}$ pollution could be more at risk for poor outcomes (Sasidharan et al., 2020). When exploring the relationship between $PM_{2.5}$ exposure and mortality in COVID-19 patients, the relationship between $PM_{2.5}$ exposure and cardiovascular disease should also be considered.

Several studies have linked long term $PM_{2.5}$ exposure with cardiovascular disease (Atkinson et al., 2013; Cesaroni, 2013; Madrigano et al., 2013). It will be important to explore both relationships of fine particle pollution and history of CVD in deceased COVID-19 patients.

More recently, a census tract level ecologic study from the Colorado Department of Public Health found that a 1μg/m$^3$ increase in long term $PM_{2.5}$ exposure is associated with a statistically significant 25% increase in the relative risk of hospitalizations (RR: 1.25, 95% CI: 1.06 - 1.46) and a 35% increase (RR: 1.35, 95% CI: 1.05 - 1.74) in mortality in patients with COVID-19 (Berg et al., 2021b).

***Cardiovascular Disease, Hypertension, Obesity, Diabetes and COVID-19***

It is still largely unclear why certain racial and ethnic groups are disproportionality affected by COVID-19 and this could be related to the prevalence of certain chronic diseases in these racial groups. For example, the CDC reports Non-Hispanic Black adults (49.6%) have the highest age-adjusted prevalence of obesity, followed by Hispanic adults (44.8%), non-Hispanic White adults (42.2%) and non-Hispanic Asian adults (17.4%) (*Adult Obesity Facts | Overweight & Obesity | CDC*, n.d.). The CDC's National Diabetes Statistics reported that non-Hispanic Blacks have the highest prevalence of diabetes (13.3% [11.9 – 14.9]), followed by non-Hispanic Asians (11.2% [9.5 – 13.3]), Hispanics (10.3% [8.1 – 13.1]), and non-Hispanic Whites (9.4% [8.4 – 10.5])(CDC, 2020). Although hypertension and cardiovascular disease affect all racial/ethnic groups nearly the same, heart disease is the leading cause of death in the United States and therefore it is important to understand it's burden on patients with COVID-19 (Heart Disease Facts | Cdc.Gov, n.d.).

Cardiovascular disease

The current literature suggests that mortality from coronavirus disease 2019 (COVID-19) is strongly associated with cardiovascular disease (CVD), diabetes, and hypertension (Hanff et al., 2020). A meta-analysis investigating cardiovascular disease and poor COVID-19 outcomes found that pre-existing conditions such as cardiovascular disease were associated with an increased mortality rate from COVID-19 (RR 2.25 [1.53,3.29], $p<0.001$; $I^2$: 33%) and severe COVID-19 (RR 2.25 [1.51,3.36], $p<0.001$; $I^2$: 76%). The association was not influenced by gender, age, hypertension, diabetes, and other respiratory comorbidities (Pranata, Huang, et al., 2020). Further evidence for investigating heart disease specifically is the mechanism of angiotensin-converting enzyme 2 (ACE2) proteins. ACE2 has been identified as a functional receptor for SARS-CoV-1 and SARS-CoV-2 and infection is initiated following binding of the spike protein of the virus to ACE2, which is highly expressed in the heart's cells (Turner et al., 2004). Although SARS-CoV-2 mainly invades alveolar epithelial cells, resulting in respiratory symptoms, these symptoms are more severe in patients with CVD. The increased severity in patients with CVD might be associated with increased secretion of ACE2 in these patients compared with healthy individuals. Given that ACE2 is a functional receptor for SARS-CoV-2, antihypertension therapies using ACE inhibitors in patients with COVID-19 should be considered (Zheng et al., 2020).

Hypertension

Hypertension is the most commonly reported pre-existing condition associated with COVID-19. There are reports in animal models and humans suggesting that the expression of

ACE2 may be increased after treatment with an ACEI or ARB, which might augment patients' susceptibility to viral host cell entry and propagation(Gao et al., 2020). Meta-analysis also shows that hypertension was associated with an increased composite poor outcome (RR 2.11 (1.85, 2.40), p <0.001; $I^2$ 44%, p = 0.006), increased mortality (RR 2.21 (1.74, 2.81), p < 0.001; $I^2$ 66%, p = 0.001), severe COVID-19 (RR 2.04 (1.69, 2.47), p < 0.001; $I^2$ 31%, p = 0.14), and ARDS (RR 1.64 (1.11, 2.43), p = 0.01; $I^2$ 0%, p = 0.35) (Pranata, Lim, et al., 2020).

Obesity

Obesity has been identified as one of the key factors associated with severe COVID-19 outcomes (Phe, 2020; Williamson et al., 2020). A cohort study out of the UK found that a higher BMI, waist circumference, waist-to-hip ratio and waist-to-height ratio were each associated with a greater risk of death from COVID-19, influenza/pneumonia and CHD in both sexes. More specifically a 1-SD higher BMI was associated with a stronger risk of COVID-19 mortality (HR: 1.20 [1.00 – 1.43]) and influenza/pneumonia mortality (HR: 1.19 [1.01 – 1.48] (Peters et al., 2021). Another study found a strong negative correlation between age and BMI in 265 patients admitted to an intensive care unit (ICU), suggesting that obesity can shift severe forms of COVID-19 to a younger age group (Kass et al., 2020). This could be related to a number of different factors including the fat deposition around upper airways, higher prevalence of obstructive sleep apnea in obese individuals, and a heavier thorax all resulting in poor outcomes following intubation. To note, the relationship between obesity and COVID-19 mortality rates may be explained by the propensity of those with obesity to also have diabetes. This research will adjust for diabetes when assessing obesity as an exposure.

Diabetes

Diabetes mellitus (DM) is one of the most prevalent chronic conditions facing Americans (Saeedi et al., 2019). A meta-analysis showed that DM was associated with a composite poor outcome (i.e. COVID-19 mortality, severe COVID-19, ARDS, need for ICU care, and increased disease progression rates) (RR 2.38 [1.88, 3.03], $p < 0.001$; $I^2$: 62%) and its subgroup which comprised of mortality (RR 2.12 [1.44, 3.11], $p < 0.001$; $I^2$: 72%), severe COVID-19 (RR 2.45 [1.79, 3.35], $p < 0.001$; $I^2$: 45%), ARDS (RR 4.64 [1.86, 11.58], $p = 0.001$; $I^2$: 9%), and disease progression rate (RR 3.31 [1.08, 10.14], $p = 0.04$; $I^2$: 0%). Meta-regression showed that the association with composite poor outcome was influenced by age ($p = 0.003$) and hypertension ($p < 0.001$)(Huang et al., 2020). Both age and hypertension will be included in the models used in this research.

In addition, a large representative (nearly the entire English population) individual level multivariable logistic regression analysis out of NHS England found that after adjusting for age, sex, index of multiple deprivation, ethnicity, and region, the odds for death (related to COVID-19) in people with type 1 diabetes was 3.51 (95% CI 3.16–3.90) and for people with type 2 diabetes it was 2.03 (1.97–2.09) compared with the population without known diabetes (Bakhai et al., 2020). In addition to showing the adjusted association, other analyses suggest that the effect of diabetes on risk of death with COVID-19 is independent of age, ethnicity, deprivation, or cardiovascular comorbidities, and is observed across all types of diabetes(Bakhai et al., 2020).

### ***Social Vulnerability Index and COVID-19***

Due to their lack of adequate medical care, transportation, and nutrition, socially vulnerable populations are more at-risk during disasters (Rufat et al., 2015). To further examine social vulnerability, the CDC in partnership with the Agency for Toxic Substances and Disease Registry (ATSDR) created the Social Vulnerability Index (SVI). The index includes themes that represent socioeconomic status, household composition, race/ethnicity and language, and housing and transportation. During the COVID-19 pandemic, socially vulnerable communities suffered disproportionately(Karaye & Horney, 2020a). For example, analyses showed an increased odds of in hospital death with COVID-19 for older people; men; people of Black, Asian, or mixed ethnicities; and those who live in areas of high socioeconomic deprivation (Bakhai et al., 2020). This can be explained by the systemic inequities that these communities face such as income, environment, education, nutrition, etc. For example, African Americans are more likely to live in environmentally polluted neighborhoods than non-Hispanic Whites (Bell & Ebisu, 2012; Karaye & Horney, 2020a; Perez et al., 2015). This air pollution whether it be volatile organic compounds, $PM_{2.5}$, or other hazardous air pollutants can cause health issues that lead to increased COVID-19 morbidity and mortality such as asthma and cardiovascular disease (*Asthma and African Americans - The Office of Minority Health*, n.d.). Poor housing and crowded spaces (SVI theme 4) also made it difficult for socially vulnerable communities to remain socially distanced. In addition to increased exposure due to their living spaces, these individuals are more likely to be exposed in the workplace (Rufat et al., 2015). Essential workers and public transit riders are disproportionally composed of racial minorities, which may increase their risk of exposure to and subsequent infection with COVID-19 (Biggs et al., 2021). The socially vulnerable also have fewer opportunities to improve their physical health and diet, resulting in chronic diseases such as heart disease and diabetes. These comorbidities are associated with poor prognosis in those with COVID-19 (Kruglikov et al., 2020). A recent study found that of the theme-specific SVI measuring minority status and language (Theme 1) was found to have the strongest relationships with COVID-19 incidence (aRR: 1.36, 95% CI: 1.12-1.49) after adjusting for the other SVI subthemes and population density. For each percentile increase in overall SVI, the COVID-19 incidence increased by a multiplicative factor of 1.52 (95% CI: 1.41-1.65) after adjusting for population density (Biggs et al., 2021). For COVID-19 mortality, a recent study by Khazanchi et al. found that there is a 1.73-fold greater risk for COVID-19 related death in counties with highest composite vulnerability (Johnson et al., 2021).

**Knowledge Gaps**

There is limited availability on individual level COVID-19 data. Researchers around the world have noted that one key challenge in understanding the current COVID-19 pandemic is the lack of access to individual-level data on COVID-19 health outcomes for large representative populations (Wu et al., 2020c). In addition, a study on the impact of social vulnerability on COVID-19 in the U.S notes that there is an insufficiency of race-stratified data and few primary studies on social vulnerability to COVID-19 have been undertaken (Karaye & Horney, 2020a). According to the United States Census, Harris County, TX is the third most populous county in the United States, where racial minorities represent over 50% of its residents. This makes Harris County a great example of a “large representative population” where social vulnerability can be assessed. Studies on COVID-19 and neighborhood level factors have been done in Harris County, TX at the zip code level and interpolated to the census tract; however, there is still a gap in research on individual level COVID-19 data. This is important because other relevant studies suffer from course spatial resolution by relying on county or even zip code level data. Harris County is a large geographical area that is home to one of the most diverse populations in the country. Research at the zip code and county levels could produce erroneous results because there is large variability between communities living in one zip code. By analyzing COVID-19 data at the individual level, health departments are able to identify jurisdictional differences, avoid ecologic fallacy and apply the findings to individuals, and focus their efforts on populations that need resources most.

This research aims to fill this gap by analyzing the risk factors of air pollution, social vulnerability, and pre-existing comorbidities such as obesity, diabetes, hypertension, and cardiovascular disease to COVID-19 mortality using individual level COVID-19 data from Harris County Public Health residents. The data that is publicly available on COVID-19 provides wide variations in results and is not necessarily applicable to determining risk factors for COVID-19. Given the potential heterogeneity of vulnerable regions within the county, this individual level analysis can provide the missing information on risk factors for COVID-19 for Harris County officials.

**Public Health Significance**

Climate change is one of the largest public health threats the world faces today. The U.S. Global Change Research Program's Fourth National Climate Assessment warns that unless the nation acts to improve air quality, climate change will worsen existing air pollution levels. This increase in air pollution would have several adverse consequences including increased occurrences of negative respiratory and cardiovascular health effects. More specifically, climate change is predicted to increase formation of ozone pollution, increase frequency and severity of wildfires, thereby increasing particulate pollution such as $PM_{2.5}$ and $PM_{10}$ that can be spread for miles (Ridlington et al., 2018). Exposure to fine particle air pollution in 2015 was responsible for 5,213 premature deaths and over $49 billion in associated economic damages in Houston, TX (Roy, n.d.-a). Not only will climate change affect the air we breathe but it will also affect the potential for more zoonotic and vector borne diseases to arise. The seasonality, distribution, and prevalence of vector-borne diseases are influenced significantly by climate, primarily high and low temperature extremes and precipitation patterns (Frumkin et al., 2008). This lends the question of who is most vulnerable or “sensitive” to these detrimental effects of climate change. The current COVID-19 pandemic, although detrimental in nature, has provided an ideal opportunity for researchers to understand the impacts of the pandemic in real time. Therefore, it is important that public health leaders take this opportunity to identify the modifiable factors that cause communities to be more vulnerable than others during infectious disease outbreaks. The evidence-based findings from this research will add to the current body of literature for future investigators. With additional information and further evaluations, elected officials and public health leaders can make more informed decisions about allocating resources and putting more emphasis on surveillance of these modifiable factors in specific geographic areas. For example, health departments will be responsible for outreach and public health intervention for residents with long-term impacts from contracting SARS-CoV-2. This research will help identify those at most at risk for developing adverse outcomes and may inform those at risk regarding long term impacts.

Additionally, it is evident that chronic disease burden in the United States is high whether that be in monetary cost burden or loss of life burden (Boersma et al., 2020). Understanding whether or not certain chronic diseases are associated with COVID-19 can help local health departments target interventions for these diseases to prevent loss of life and cost burden to the county.

**Hypothesis, Research Question, Specific Aims or Objectives**

This research aims to answer the question: What is contributing to COVID-19 Mortality in Harris County Public Health jurisdiction residents? This research examines the risk factors *i.e.,* $PM_{2.5}$ exposure, pre-existing chronic conditions (hypertension, obesity, diabetes, and cardiovascular disease), and social vulnerability that may be contributing to COVID-19 mortality in Harris County, TX from March 1, 2020 – March 31, 2022 using a retrospective observational design to assess the association in a sample of COVID-19 cases reported in Harris County Public Health. This dissertation will answer the research question with the following aim:

*Aim 1: Determine if census tract $PM_{2.5}$ exposure is associated with COVID-19 mortality among Harris County Public Health jurisdiction residents using a retrospective observational study design comparing those who died after testing positive for COVID-19 and those who survived after testing positive for COVID-19 between March 1, 2020 to March 31, 2022.*

(Q1): Is $PM_{2.5}$ exposure associated with COVID-19 mortality in COVID-19 cases reported to Harris County Public Health Jurisdiction?

(H1): A 1µg/$m^3$ increase in census tract $PM_{2.5}$ exposure will be associated with a significant increase in the odds of COVID-19 mortality in Harris County Public Health jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022.

*Aim 2: Determine if pre-existing diabetes, cardiovascular disease, hypertension, or obesity are significantly associated with COVID-19 mortality using a cross-sectional study design comparing those who died after testing positive for COVID-19 and those who survived after testing positive for COVID-19 in Harris County Public Health Jurisdiction between March 1, 2020 to March 31, 2022.*

(Q1): Are individuals with pre-existing diabetes, CVD, hypertension, or obesity significantly at risk for COVID-19 mortality in Harris County Jurisdiction who tested positive for COVID-19 between March 1, 2020 – September 31, 2021?

(H1): There is an increased odds of mortality in individuals with COVID-19 who have a history of cardiovascular disease compared to those who do not have a history of cardiovascular disease controlling for relevant factors.

(H2): There is an increased odds of mortality in individuals with COVID-19 who have a history of obesity compared to those who do not have a history of obesity controlling for relevant factors.

(H3): There is an increased odds of mortality in individuals with COVID-19 who have a history of diabetes compared to those who do not have a history of diabetes controlling for relevant factors.

(H4): There is an increased odds of mortality in individuals with COVID-19 who have a history of hypertension compared to those who do not have a history of hypertension controlling for relevant factors.

*Aim 3: Determine the magnitude of association between census tract Social Vulnerability Index (SVI) themes and COVID-19 mortality among Harris County jurisdiction residents using a* *retrospective observational study design comparing those died after testing positive for COVID-19 and those who survived after testing positive for COVID-19 in Harris County Public Health Jurisdiction between March 1, 2020 to March 31, 2022.*

(Q1): Is there an association between SVI and COVID-19 mortality in Harris County census tracts?

(Q2): Which SVI subtheme is most strongly associated with COVID-19 mortality?

(H1): There is an increased odds of mortality in those in the highest quantile SVI category (most vulnerable) compared to the lowest quantile SVI category (least vulnerable).

(H2): Subtheme 3, minority status and language has the strongest association with COVID-19 mortality

## METHODS

### Study Design

This research is a secondary data analysis of primary COVID-19 data which includes Harris County Public Health (HCPH) jurisdiction residents (Ages 0 – 19 were removed from the dataset) who had a confirmatory SARS-CoV-2 positive test result reported to HCPH during March 1, 2020 – March 31, 2022 from the Texas Department of State Health Services (DSHS), clinics, hospitals, labs, and local and federal testing sites. Information on comorbidities, symptoms, etc. are collected through a standard questionnaire provided by DSHS and developed by the Centers for Disease Control (CDC) and The Council of State and Territorial Epidemiologists (CSTE). HCPH staff utilized this questionnaire through epidemiology investigation, contact tracing, and extracting information from medical records to import into the COVID-19 Reporting Program (CRP) where all data is housed. The questionnaire includes data on demographics, medical history, occupation, social habits, and exposure history. The investigation was initiated within 14 days of a lab result received by Harris County Public Health. COVID-19 deaths were reported to HCPH via hospitals and the medical examiner's office. This process is detailed in the outcome measures section.

### Study Population

The source population in this research is a database of Harris County Public Health Jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022. The study population eligibility includes residents that reside within HCPH jurisdiction, tested positive for COVID-19 through confirmatory PCR test between March 1, 2020 – March

31, 2022, have address information, age 19 +, and underwent an epidemiological investigation either through medical record review or interviewing the case for self-reported information.

## Data Collection and Data Types

### *Unit of analysis*

Individual level outcome assessment: The unit of analysis for this study is the individual. The outcome of COVID-19 mortality is based on the individual. An individual tested positive for COVID-19 between March 1, 2020 and March 31, 2022 and either survived or did not. In analysis, the exposure variables are at the census tract level, were merged to the individual's census tract, and then census tracts were removed from the dataset. For further clarification, the census tract level measures such as $PM_{2.5}$ and Social Vulnerability Index are assigned to individuals that reside in those tracts.

Census tract level exposure assessment: To maintain the confidentiality of residents within Harris County, the dataset used in this analysis has the census tract removed. The individual level COVID-19 dataset with census tract, pre-existing conditions, and demographics will be merged to the census tract level datasets for $PM_{2.5}$ air pollution and SVI. The final dataset consists of individual level and each individual is assigned to the $PM_{2.5}$ and SVI scores that align with the census tract that they live in. Air pollution and vulnerability vary within larger geographic units like zip code within Harris County and therefore census tracts are more appropriate for exposure measures (Karaye & Horney, 2020b). Further detailed explanation of these exposure datasets will be explained in the independent variable section.

### *Outcome Measures*

**Primary outcome- COVID-19 Mortality:**

Medical examiner's office (ME), the Institute of Forensic Science (IFS), hospitals, and relatives of deceased residents report deaths due to COVID-19 to their local health department. Investigators are instructed not to toggle a deceased COVID-19 case because only lead epidemiologists are allowed to do so after consulting the Local Health Authority. The purpose of this is to ensure that cases are truly deceased due to COVID-19 and not some other reason such as trauma or another illness, and that records were provided to confirm this. This process increased the validity of our deaths related to COVID-19. Only confirmed cases are included in the analysis. A case meets confirmatory laboratory evidence if there is detection of SARS-CoV-2 RNA in a clinical or autopsy specimen using a molecular amplification test. Only confirmed cases containing complete address information will be included in analysis. Hospitals provide medical records, admission, and discharge notes for HCPH jurisdiction residents. Epidemiologists and case investigators extract relevant case information such as hospital admission date, discharge date, ICU stay, pre-existing conditions, symptoms, etc. from medical records or by calling hospitals for patients who have been reported to us by Electronic Lab Report (ELR).

**Table 1**: Variables in Dissertation Dataset

| | ***Data Type*** | |
|---|---|---|
| ***Variable name in dataset*** | ***Individual/Census Tract*** | ***Source*** |
| **Outcome Measures** | | |
| Deceased COVID-19 | Individual, dichotomous | CRP (Harris County Public Health) |
| Hospital admission | Individual, dichotomous | CRP (Harris County Public Health) |
| **Exposure measures** | | |
| Pre-existing diabetes, obesity, hypertension, and cardiovascular conditions (comma delimited) | Individual, dichotomous | CRP (Harris County Public Health) |
| Age | Individual, categorical | CRP (Harris County Public Health) |
| Race/Ethnicity<br>Non-Hispanic White<br>Non-Hispanic Black<br>Hispanic/Latino<br>Non-Hispanic Asian<br>Other | Individual, categorical | CRP (Harris County Public Health) |
| Gender | Individual, dichotomous | CRP (Harris County Public Health) |
| SVI (All themes) | Census tract, continuous | US Census |
| $PM_{2.5}$ | Census tract, continuous | NASA |
| Congregate Setting | Individual, dichotomous | CRP (Harris County Public Health) |

***Independent variable (exposure)***

**<u>Aim 1, PM2.5 Exposure:</u>**

Particulate Matter, also known as particle pollution, is a mixture of solid particles and liquid droplets found in the air. Fine inhalable particles with diameters of 2.5 micrometers or smaller are named $PM_{2.5}$. NASA utilizes the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument to collect $PM_{2.5}$ data. MODIS is a key instrument aboard the Terra (originally known as EOS AM-1) and Aqua (originally known as EOS PM-1) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths (see MODIS Technical Specifications). To reveal the spatiotemporal variations of $PM_{2.5}$, long-term and high-spatial resolution aerosol optical depths, generated by the MODIS Multi-Angle implementation of Atmospheric Correction (MAIAC) algorithm, were employed to estimate $PM_{2.5}$

concentrations at a 10 km resolution using the Space-Time Extra-Trees (STET) model that scientists from Beijing Normal University, University of Maryland, NASA Goddard Space Slight Center, Shandong University of Science and Technology, and Tsinghua University developed. There are benefits to using satellite data because air monitoring stations are sparse and satellite data has more spatial coverage and can show air pollution variation within smaller geographical areas.

The dataset for Aim 1 comes from the 10km resolution grid mentioned above. Upon receipt of the 365 10 km grid raster files (data from 2019), ArcGIS Pro was utilized to process the raster data to vector data. In ArcGIS Pro the model builder function was used to iterate the process of going from raster to vector file in order to reduce the manual processing of 365 files. The model building process included the following functions: raster calculator (multiply PM2.5 grid code by 10,000 in order to keep the values in integer form) → Int (converts each cell value of a raster to an integer by truncation) → Raster to polygon (converts a raster dataset to polygon features) → Spatial join (joins attributes from the polygon feature to the centroid of the census tract) → Table to excel (Export daily data to excel file). Harris County census tracts took on the $PM_{2.5}$ value of the grid that the centroid of the tract fell in.

The final dataset includes daily averages and therefore there are 365 readings from 2019 for each census tract. The $PM_{2.5}$ dataset will be merged with the COVID-19 mortality data on census tract and the census tract will be removed for de-identification purposes. Most study findings reveal that both long-term and short-term exposure to $PM_{2.5}$ results in adverse health effects (Ferrante & Conti, 2017; Fiore et al., 2019). In this research short-term exposure will be assessed.

<u>Short-Term or Acute Exposure</u>: This research will look at varying lag times based on average hospital admission stay for deceased COVID-19 cases in the dataset and literature review. An analysis done on the source population of this study found that the average time between onset of symptoms and hospital admission date was 7 days and the average time between onset of symptoms and date of death was 25 days. The decided upon lag times are 7, 14, and 28 days(Horne et al., 2018) from the specimen collection date of the COVID-19 case. The specimen collection date is the date that the specimen was collected for the case's first positive SARS-CoV-2 result by PCR. The census tract level $PM_{2.5}$ 7 days average, 14 days average, and 28 days average prior to the specimen collection date of the case was merged on the census tract of the case.

It is important to note that even though the COVID-19 pandemic resulted in a stay-at-home order, air pollution from industries continued and air pollution still affected Houston/Harris County residents. A study from Texas A&M University found that pre and post order air pollution levels were not significantly different in areas where pollution has historically been influenced by industry such as Deer Park, Aldine, and Clinton Park. In fact, $PM_{2.5}$ levels slightly increased after March 20, 2020 at the Aldine site by 14%, at the Clinton Dr. site 12%, and at the Deer Park site 52% (Schade, 2020b).

**Aim2, Pre-existing Chronic Disease Exposure:**

History of chronic disease is assessed during epidemiologist interviews with COVID-19 cases and/or extracting information from the case's medical records. This information is in the COVD-19 dataset provided by Harris County Public Health for this analysis. To note, one limitation of this study is selection bias and misclassification of exposure. Those that were hospitalized were more likely to have accurate chronic disease reporting because medical records were provided to the local health department for these cases. Cases that were not hospitalized would self-report their pre-existing chronic disease conditions. Pre-existing chronic disease conditions that epidemiologist used during interviews are listed in table 2.

**Table 2**: Underlying Health Conditions Defined

| Variable | Included conditions |
|---|---|
| Cardiovascular conditions | Includes coronary artery disease (CAD), cerebrovascular accident/stroke (CVA), peripheral arterial/vascular disease (PAD), congenital heart disease (CHD), congestive heart failure (CHF), rheumatic heart disease (RHD), deep vein thrombosis (DVT) and pulmonary embolism (PE), acute myocardial infarction (AMI), angina, cardiomyopathy, pulmonary (arterial) hypertension (PAH), aneurysm, arrhythmias, heart valve diseases |
| Chronic lung disease | Includes Chronic obstructive pulmonary disease (COPD) chronic bronchitis or emphysema, idiopathic pulmonary fibrosis (IPF), cystic fibrosis (CF), obstructive sleep apnea (OSA), or other chronic lung conditions associated with impaired lung function or that require home oxygen |
| Immune weakening medications/treatment | Include high doses of corticosteroids, biologics (eg, TNF inhibitors, interleukin inhibitors, anti-B cell agents, monoclonal antibodies, etc), immunosuppressants (eg, prednisone (Deltasone, Orasone), budesonide/Entocort EC, prednisolone/Millipred, etc). Common conditions which often require these medications include Multiple Sclerosis (MS), Polymyalgia rheumatica (PMR), Ulcerative Colitis (UC), Crohn's, Systemic Lupus Erythematosus (SLE). |
| Obesity | Obesity (BMI $\geq$ 30) - if available in the medical record or disclosed by the case without prompting. Do not ask the case about BMI (Body Mass Index) or weight. |
| Hypertension | HTN |
| Asthma | Asthma (moderate to severe) - if the grade is not listed, still select this as a comorbidity |
| Diabetes | DM |

**Aim3, Social Vulnerability Index:**

The CDC/ATSDR Social Vulnerability Index (SVI) refers to potential negative effects on communities caused by external stresses on human health and describes vulnerabilities of people to natural stress. Such stresses include natural or human-caused disasters, or disease outbreaks (CDC, 2019). The dataset utilized in this research is the CDC/ATSDR's Social Vulnerability Index (SVI) and is based on the 2018 census data. The score utilizes 4 themes; theme 1:

socioeconomic status; theme 2: household composition & disability; theme 3: minority status & language; theme 4: housing type & transportation. Each theme is defined in table 3. There are several variables in this dataset; however, RPL_Themes (the overall percentile ranking) will be utilized for each theme. Analysis will look at each theme separately as well as composite of all themes. SVI will be merged with COVID-19 datasets based on census tract.

**Table 3:** Description of SVI Themes from ACS 5-year Estimates

| SVI themes | Variable |
|---|---|
| Theme 1: Socioeconomic | % living below poverty line |
| | Unemployment Rate |
| | Per capita income |
| | Percentage with no High School Diploma |
| Theme 2: Household Composition and disability | Aged 65 or older |
| | Aged 17 or younger |
| | Older than age 5 with a disability |
| | Single parent household |
| Theme 3: Minority status and language | Minority |
| | Speaks English "less than well" |
| Theme 4: Housing and transportation | Multi-unit structures |
| | Mobile homes |
| | Crowding |
| | No vehicle |
| | Group quarters |

## Data Analysis

All data analysis was performed in R studio and ArcGIS Pro behind the HCPH firewall. Multivariable and univariable logistic regression was utilized to produce odds ratios and 95% confidence intervals. COVID-19 data including demographics, pre-existing conditions, hospitalization status, and congregate setting status were merged with census tract level $PM_{2.5}$ data and census tract level SVI data.

**Human Subjects Considerations**

This proposal has been reviewed by the University of Texas, School of Public Health Internal Review Board and Committee for the Protection of Human Subjects and was determined to qualify for exempt status according to 45 CFR46.104(d). All data provided by Harris County Public Health (HCPH) was determined to be deidentified by a qualified statistician in the organization. The proposal includes a geographic and time varying aspect; however, HCPH removed census tracts and dates from the dataset before the researcher received the data. This is a secondary data analysis and therefore informed consent was also waived. All of the analysis is done behind the HCPH firewall.

## JOURNAL ARTICLE 1

**Association Between $PM_{2.5}$ and COVID-19 Mortality in Harris County**

**Name of Journal Proposed for Article Submission: Journal of Occupational and Environmental Medicine, American Journal of Public Health, Environmental Health Perspective, Environmental Research, Journal of Health and Pollution, International Journal of Environmental Research and Public Health, Journal of Epidemiology and Community Health**

### 1. Introduction

*1.1 COVID-19 Impacts in Harris County*

In 2019, the severe acute respiratory syndrome- coronavirus 2 (SARS-CoV-2), a positive strand RNA virus was shown to be actively transmitting from human to human (Obukhov et al., 2020). SARS-CoV-2 causes the disease known as Coronavirus Disease 2019 (COVID-19) which is responsible for the current global pandemic. SARS-CoV-2 is a novel virus; therefore, an important public health objective is to identify key modifiable environmental factors that may contribute to the severity of the health outcomes among individuals with COVID-19 (Wu et al., 2020a). Researchers have noted challenges in determining or exploring these risk factors because individual-level data on COVID-19 health outcomes for large, representative populations are not publicly available or accessible to the scientific community (Wu et al., 2020b).

The impacts of COVID-19 are not homogenous and differs by racial/ethnic group. At the national level, for individuals with COVID-19, Black non-Hispanic individuals are 1.9 times more likely to die than non-Hispanic Whites and Hispanic individuals are 2.3 times more likely to die from COVID-19 than non-Hispanic Whites (CDC, n.d.-b). There are several neighborhood-level factors that could be contributing to the occurrence of these Hispanic and Black population's vulnerability (Oluyomi et al., 2021). Over 70% of Harris County's population identifies as a minority (i.e. Hispanic, Black, or Asian) and therefore, it is critical that local researchers explore other contextual relationships that may be contributing to minorities' health disparities during the COVID-19 pandemic, such as air quality (George, 2020). Air quality is an important exposure to assess in Harris County, since it houses one of the largest industrial complexes in the world.

*1.2 $PM_{2.5}$ Explained and its Impacts in Harris County*

Particulate matter is a mixture of solid particles such as dust, dirt, soot, or smoke and liquid droplets found in the air. These particles have two widely accepted sizes for regulatory purposes set by the Environmental Protection Agency (EPA). These two sizes are 10 micrometers and smaller ($PM_{10}$) and 2.5 micrometers and smaller ($PM_{2.5}$). The current EPA regulatory standard for PM2.5 pollution is 12 micrograms per meter cubed [µg/m3]; however, most scientists agree that the new EPA standard should be between 8-10µg/m3 due to the negative health impacts seen at levels lower than 12µg/m3 (Di et al., 2017; Pinault et al., 2017). According to the EPA, most of these particles form in the atmosphere as a result of complex reactions of chemicals emitted from power plants, industries and automobiles (Epa & of Air, 2014). We looked at $PM_{2.5}$ specifically because these fine particles pose the greatest risk to human health due the small size and ability to reach multiple organs including the heart through air exchange in the lungs (Du et al., 2016).

The air quality in Harris County is influenced by multiple sources of $PM_{2.5}$ air pollutants which includes extensive road traffic, proximity to one of the largest petrochemical industry complexes in the United States, and port activities in the Houston Ship Channel. It is important to note that even though the COVID-19 pandemic resulted in a stay-at-home order, air pollution from industries continued and air pollution still affected Houston/Harris County residents. A study from Texas A&M University found that pre and post order air pollution levels were not significantly different in areas where pollution has historically been influenced by industry such as Deer Park, Aldine, and Clinton Park (Schade, 2020a).

It is important to note that environmental risks are not uniformly distributed in urban areas like Harris County. Individuals classified with low socioeconomic status (SES) can become overburdened by environmental exposures (Rammah et al., 2019). Additionally, it is well documented that racial/ethnic minorities bear a disproportionate burden from poor air quality (Benmarhnia, 2020)

*1.3 Air Quality and COVID-19*

Prior to the COVD-19 pandemic, an ecologic analysis of the 2003 severe acute respiratory syndrome coronavirus 1 (SARS-CoV-1) reported infected patients who lived in moderate air pollution levels were more likely to die than those in regions with lower air pollution (Cui et al., 2003). Several studies have shown a relationship between PM2.5 air pollution and an increased risk of COVID-19 severity on an ecologic scale (Berg et al., 2021; Cole et al., 2020; Hendryx & Luo, 2020; Konstantinoudis et al., 2021; Petroni et al., 2020; Sasidharan et al., 2020b; Wu et al., 2020c). Additionally, long-term exposure to $PM_{2.5}$ is linked to many of the comorbidities that have been associated with poor prognosis and death in COVID-19 patients, including cardiovascular disease, lung disease, emergency room visits, hospitalization, and mortality; therefore, those with COVID-19 exposed to unsafe levels of $PM_{2.5}$ pollution could be more at risk for poor outcomes (Sasidharan et al., 2020b). Several studies have linked long term $PM_{2.5}$ exposure with cardiovascular disease (Atkinson et al., 2013;

Cesaroni, 2013; Madrigano et al., 2013) thus, this research will explore both relationships of fine particle pollution and history of CVD in deceased COVID-19 patients.

In this study, we performed a retrospective observational analysis of COVID-19 data from Harris County Public Health to understand why there are spatial differences in COVID-19 mortality and why racial and ethnic minorities may be more predisposed to poor outcomes following COVID-19 infection due to their environment.

## 2. Methods

### *2.1. Data source for COVID-19 deaths and cases*

This study utilized individual level data from a database including Harris County Public Health (HCPH) Jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022. Eligibility includes residents that reside within HCPH jurisdiction, tested positive for COVID-19 through confirmatory PCR test between March 1, 2020 – March 31, 2022, have address information, were age 19 and older, and underwent an epidemiological investigation either through medical record review or interviewing the case for self-reported information. HCPH serves the third largest county in the United States and is responsible for disease reporting and surveillance of COVID-19; therefore, all COVID-19 testing facilities with HCPH jurisdiction are required to report all positive and negative results to HCPH. Hospitals also report cases and provide medical records, admission, and discharge notes for cases of COVID-19. Epidemiologists and case investigators utilize these medical records to extract relevant case information such as hospital admission date, discharge date, ICU stay, pre-existing conditions, symptoms, long term care facility admission, etc. Cases have a congregate setting flag if they were residing in a healthcare facility for long periods of time such as nursing home, assisted living facility, rehabilitation facilities, and other long term acute care facilities. They also reach out to hospitals to obtain records for patients who have been reported to us by Electronic Lab Report (ELR). Medical examiner's office (ME), the Institute of Forensic Science (IFS), hospitals, and relatives of deceased residents report deaths due to COVID-19 to HCPH. There are several measures in place to ensure that cases were truly deceased due to COVID-19 and not some other reason such as trauma or another illness and that records were provided to confirm this.

Investigators are instructed not to record a deceased COVID-19 case and only lead epidemiologists are allowed to do so after consulting the local health authority. This process increased the validity of deaths related to COVID-19. Only confirmed cases with address information are included in the analysis. A case meets confirmatory laboratory evidence if there is detection of SARS-CoV-2 RNA in a clinical or autopsy specimen using a molecular amplification test.

*2.2 Data sources for $PM_{2.5}$ air pollution*

Satellite air pollution data was used in this study as opposed to the EPA's monitoring network data because air pollution monitors are not placed uniformly throughout Harris County and there are large geographical areas without a monitor nearby. We know that air pollution concentrations vary dramatically over short distances, so this leaves many geographic gaps in accurate air pollution data when relying on monitoring data. Studies found that the EPA's land-based monitoring network failed to identify 54 counties and 25 million people in the United States that live in areas in violation of the Clean Air Act, Harris County is one of them(Satellites Can Supplement the Clean Air Act's Land-Based Air Monitoring Network, n.d.). Many epidemiological studies are beginning to use satellite data for studying air pollution and the associated health impacts (Holloway et al., 2021).

Satellite data for this study comes from The National Aeronautics and Space Administration (NASA). NASA utilizes the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument to collect $PM_{2.5}$ data. MODIS is a key instrument aboard the Terra (originally known as EOS AM-1) and Aqua (originally known as EOS PM-1) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths (see MODIS Technical Specifications). To reveal the spatiotemporal variations of $PM_{2.5}$, long-term and high-spatial resolution aerosol optical depths, generated by the MODIS Multi-Angle implementation of Atmospheric Correction (MAIAC) algorithm, were employed to estimate $PM_{2.5}$ concentrations at a 10 km resolution using the Space-Time Extra-Trees (STET) model that scientists from Beijing Normal University, University of Maryland, NASA Goddard Space Slight Center, Shandong University of Science and Technology, and Tsinghua University developed. Satellite data is beneficial for understanding air pollution in smaller geographical areas. Ground monitors collecting $PM_{2.5}$ data are sparse and do not accurately assess an individual's exposure to $PM_{2.5}$ pollution due to the distance between each monitor. Many residents of Harris County do not live near an EPA regulatory air monitor and thus the data modelled by the EPA is only an estimate of the exposure. Satellite data provides a wider range of variability in $PM_{2.5}$ data within small geographic areas.

The data utilized in this study is the 10km resolution grid mentioned above. Upon receipt of 365 10 km grid raster files (data from 2019), ArcGIS Pro was utilized to process the raster data to vector data. In ArcGIS Pro the model builder function was used to iterate the process of going from raster to vector file in order to reduce the manual processing of 365 files. The model building process included the following functions: raster calculator (multiply $PM_{2.5}$ grid code by 10,000 in order to keep the values in integer form) → Int (converts each cell value of a raster to an integer by truncation) → Raster to polygon (converts a raster dataset to polygon features) → Spatial join (joins attributes from the polygon feature to the centroid of the census tract) → Table to excel (Export daily data to excel file). Harris County census tracts took on the $PM_{2.5}$ value of the grid that the centroid of the tract fell in. The final dataset includes daily averages and therefore there are 365 readings from 2019 for each census tract. The $PM_{2.5}$ dataset will be merged with the COVID-19 mortality data on census tract. There are 786 census tracts in Harris County and the final dataset consisted of 708 unique census tracts.

Most study findings reveal that both long-term and short-term exposure to $PM_{2.5}$ results in adverse health effects (Ferrante & Conti, 2017; Fiore et al., 2019); however, only short-term impacts were assessed. Considering the time it takes from infection to hospitalization to death in those with COVID-19, we decided to observe exposure at lag times of 7, 14, and 28 days(Horne et al., 2018) from the specimen collection date of the case. The specimen collection date is the date that the specimen was collected for the case's first positive SARS-CoV-2 result by PCR. To consider the varying amount of time it might take from exposure to death in those with COVID-19, the lag times were averaged to produce 7 days average, 14 days average, and 28 days average prior to the specimen collection date.

It is important to note that even though the COVID-19 pandemic resulted in a stay-at-home order, air pollution from industries continued and air pollution still affected Houston/Harris County residents. A study from Texas A&M University found that pre and post order air pollution levels were not significantly different in areas where pollution has historically been influenced by industry such as Deer Park, Aldine, and Clinton Park. In fact, $PM_{2.5}$ levels slightly increased after March 20, 2020, at the Aldine site by 14%, at the Clinton Dr. site 12%, and at the Deer Park site 52% (Schade, 2020b). Additionally, the number of concrete crushing and concrete manufacturing facilities have increased in Harris County. Through the process of storing and manufacturing concrete products, concrete batch plants generate and release particulate matter. These plants operated continuously throughout the COVID-19 pandemic and are a major contributor to PM2.5 pollution in the county.

*2.3 Statistical Analysis*

Data were analyzed from March 1, 2020 – March 31, 2022. We used a retrospective observational study design. All data analysis was performed in R studio and ArcGIS Pro behind the HCPH firewall. We fitted logistic regression models to estimate the association between air pollution and the risk of death following SARS-CoV-2 infection. Multivariable and univariable logistic regression was utilized to produce odds ratios and 95% confidence intervals. Multivariable analysis adjusted for individual level demographics, pre-existing conditions, hospitalization status, congregate setting status, and social vulnerability.

## 3. Results

We measured the association between exposure level to census tract $PM_{2.5}$ pollution and COVID-19 mortality. The source population included a total of 1,048,575 confirmed COVID-19 cases reported to Harris County Public Health between March 1, 2020 and March 31, 2022. After eligibility criteria were implemented, the study population included a total of 350,233 confirmed COVID-19 cases, of which 3,207 of these cases did not survive. To note, 698,342 cases were removed that fell between 0 – 19 years due to the policies regarding research on minors at Harris County Public Health. The descriptive characteristics of these cases are presented in Table 4. Females (45.6%) make up a higher percentage of the cases compared to men (36.7%); however, men (57.9%) have a higher percentage of deaths compared to women (41.9%). The most frequently reported race/ethnicity in COVID-19 cases in Harris County Public Health jurisdiction is Hispanic (31.2%). The majority of cases were below age 49 years; however, as cases increase in age, there is a higher mortality rate. The most frequently reported pre-existing condition in both the cases that survived (4.6%) and the cases that did not survive (69.7%) is hypertension.  There is a higher frequency of individuals living in census tracts with higher social vulnerability (0.5 – 1) in those that passed away (49.2%) compared to those that survived (36%). It is important to note that all cases in this study are living within Harris County Public Health jurisdiction and the urban areas that fall within the Houston Health Department jurisdiction represent more minorities and those who are more socially vulnerable as seen in Figure 2.

**Table 4**: Characteristics of Participants with Positive Results of Polymerase Chain Reaction Testing for SARS – COV- 2

| Characteristic | **No. (%)** | | |
|---|---|---|---|
| | **Total Cases** N = 350233 | **COVID-19 Deceased** N=3207 | **COVID-19 Survivors** N= 347026 |
| **Age** | | | |
| 20 – 29 | 78921 (22.5%) | 27 (0.8%) | 78894 (22.7%) |
| 30 – 39 | 79078 (22.6%) | 110 (3.4%) | 78968 (22.8%) |
| 40 – 49 | 72948 (20.8%) | 233 (7.3%) | 72715 (21.0%) |
| 50 – 59 | 56484 (16.1%) | 422 (13.2%) | 56062 (16.2%) |
| 60 – 69 | 36474 (10.4%) | 687 (21.4%) | 35787 (10.3%) |
| 70 – 79 | 17767 (5.1%) | 804 (25.1%) | 16963 (4.9%) |
| 80+ | 8561 (2.4%) | 924 (28.8%) | 7637 (2.2%) |
| **Race/Ethnicity** | | | |
| Non-Hispanic White | 75940 (21.7) | 1226 (38.2%) | 74714 (21.5%) |
| Non-Hispanic Black | 41440 (11.8%) | 451 (14.1%) | 40989 (11.8%) |
| Hispanic/Latino | 109270 (31.2%) | 1106 (34.5%) | 108164 (31.2%) |
| Other | 38197 (10.9%) | 236 (7.4%) | 37961 (10.9%) |
| Unknown | 85386 (24.4%) | 188 (5.9%) | 85198 (24.6%) |
| **Sex** | | | |
| Male | 128688 (36.7%) | 1856 (57.9%) | 126832 (36.5%) |
| Female (Ref) | 159546 (45.6%) | 1345 (41.9%) | 158201 (45.6%) |
| Unknown/Other | 61999 (17.7%) | 6 (0.2%) | 61993 (17.9%) |
| **Co-morbidities (YES)** | | | |
| Cardiovascular | 5894 (1.7%) | 1477 (46.1%) | 4417 (1.3%) |
| Hypertension | 16074 (4.6%) | 2235 (69.7%) | 13839 (4.0%) |
| Diabetes | 10692 (3.1%) | 1507 (47.0%) | 9185 (2.6%) |
| Obesity (BMI>=30) | 4471 (1.3%) | 1070 (33.4%) | 3401 (1.0%) |
| **Hospitalized** | | | |
| Yes | 13589 (3.9%) | 2636 (82.2%) | 10953 (3.2%) |
| No | 336644 (96.1%) | 571 (17.8%) | 336073 (96.8%) |
| **Congregate Setting** | | | |
| Yes | 12871 (3.7%) | 779 (24.3%) | 12092 (3.5%) |
| No | 337362 (96.3%) | 2428 (75.7%) | 334934 (96.5%) |
| **SVI Composite*** | | | |
| 0.0 – .25 | 94726 (28.0%) | 627 (19.9%) | 94099 (28.1%) |
| .25 – .50 | 121715 (36.0%) | 978 (31.0%) | 120737 (36.0%) |
| .50 – .75 | 84306 (24.9%) | 1033 (32.8%) | 83273 (24.9%) |
| .75 – 1.00 | 37393 (11.1%) | 516 (16.4%) | 36877 (11.0%) |
| **$PM_{2.5}$ (7 days)** | Avg: 9.39<br>Max: 20.86<br>Min: 3.62 | Avg: 9.60<br>Max: 20.72<br>Min: 3.62 | Avg: 9.39<br>Max: 20.86<br>Min: 3.62 |
| **$PM_{2.5}$ (14 days)** | Avg: 9.45<br>Max: 15.83<br>Min: 4.17 | Avg: 9.60<br>Max: 15.78<br>Min: 4.17 | Avg: 9.49<br>Max: 15.83<br>Min: 4.17 |
| **$PM_{2.5}$ (28 days)** | Avg: 9.63<br>Max: 13.76<br>Min: 4.69 | Avg: 9.54<br>Max: 13.69<br>Min: 4.69 | Avg: 9.53<br>Max: 13.76<br>Min: 4.69 |

An analysis done on the source population of this study found that the average time between onset of symptoms and hospital admission date was 7 days and the average time between onset of symptoms and date of death was 25 days. Therefore, we chose to focus on a range of 7 to 28-day lag times. The dataset included a range of $PM_{2.5}$ measurements from 3.62 – 20.86μg/m$^3$. Temporal and spatial variation is seen in $PM_{2.5}$ data from 2019 (Figure 1). Cases that passed away lived in census tracts with a slightly higher average of $PM_{2.5}$ (9.49μg/m$^3$) compared to census tracts where cases that survived lived (9.45μg/m$^3$). Additionally, individuals reporting Black as their race were exposed to higher levels of 7-, 14-, and 28-day average $PM_{2.5}$ levels (9.5, 9.6, and 9.8 μg/m$^3$) compared to Hispanic (9.2, 9.3, 9.5 μg/m$^3$) and non-Hispanic White (9.2, 9.2, and 9.4 μg/m$^3$).

There is a seasonal pattern to $PM_{2.5}$ exposure; however, this seasonality is largely explained by human behavior. For example, celebrations during holidays where people are burning charcoal or lighting fireworks produce large amounts of $PM_{2.5}$. The seasonality is also explained by changes in temperature and humidity when seasons change. Air temperature affects the movement of the air and thus the air pollution. During colder months, chimney smokestacks, burning wood, and thermal inversion trapping cold air closer to the ground are more likely to occur. Additionally, extreme heat creates stagnant air which can increase the levels of particle pollution at the ground level. Particle pollution is mixture of solid particles such as dust, dirt, soot, or smoke and liquid droplets found in the air, therefore, humidity is likely to increase $PM_{2.5}$ pollution in the air(Zhao et al., 2018). Thanksgiving, Christmas, and New Year’s Day were identified as holidays with predictable spikes in $PM_{2.5}$ concentration. Additionally, summer months (June and July specifically) tend to have higher concentrations of $PM_{2.5}$. Zhao et al.

found that the period with highest $PM_{2.5}$ concentration in Harris County was in July. The $PM_{2.5}$ data used in this analysis shows similar patterns with respect to holidays and the highest concentrations are seen in May, June, July, November, and December (Figure 1).

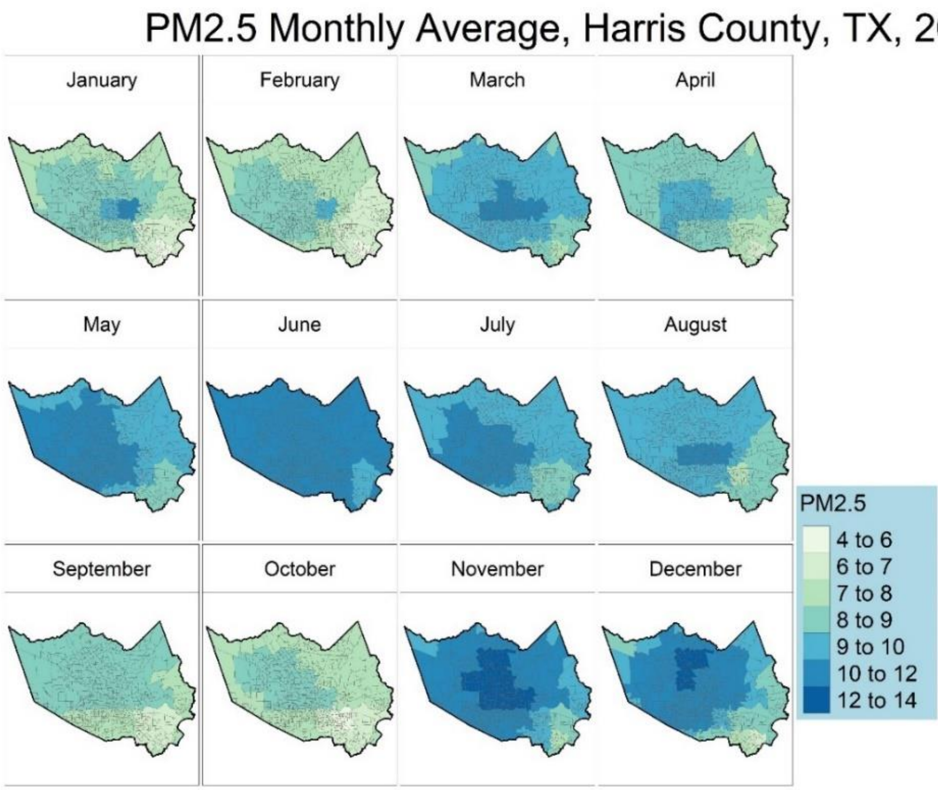


**Figure 1:** Monthly Average PM2.5 Measurements in Harris County Census Tracts

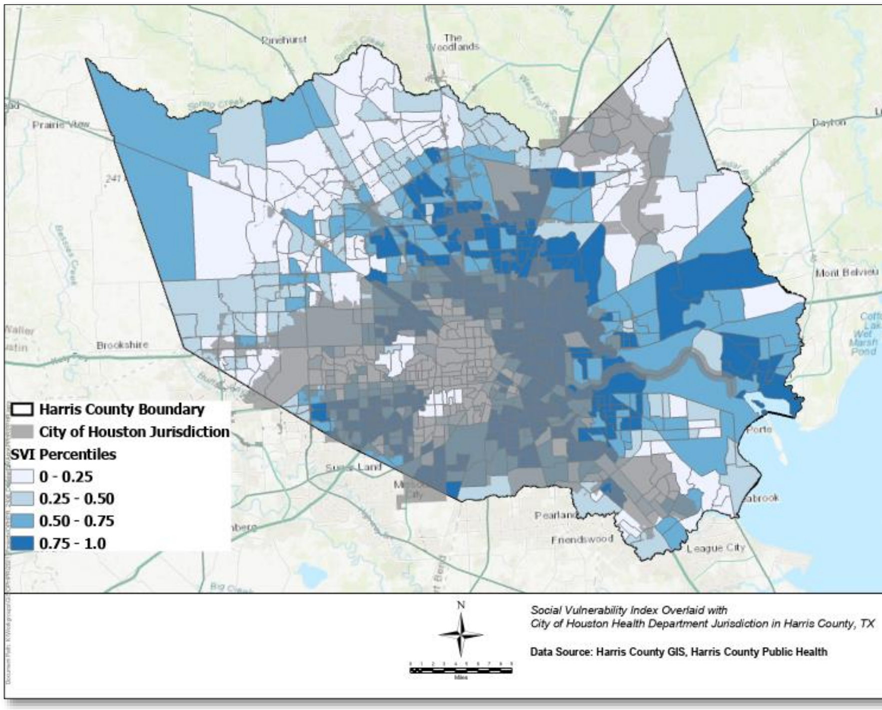


**Figure 2**: Social Vulnerability Index Overlaid with City of Houston Jurisdiction

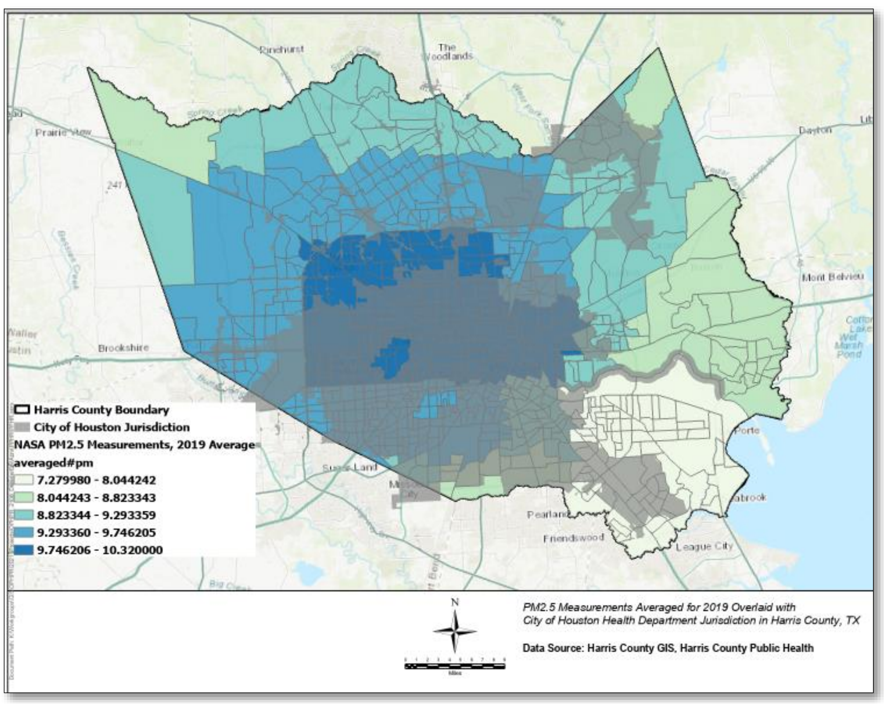


**Figure 3**: Average 2019 $PM_{2.5}$ Measurements Overlaid with City of Houston Jurisdiction

Regression results are presented in Table 5. In model 1 adjusting for age, race, and gender, the odds of COVID-19 mortality were higher in males compared to females (aOR = 1.78, 95% CI, 1.65 – 1.92). The odds of COVID-19 mortality were 37% higher in Hispanic individuals compared to non-Hispanic White individuals (aOR = 1.37, 95% CI, 1.24 – 1.49). The odds of mortality increased proportionately with age and a substantial increase is seen in ages above 60.

When adjusting for preexisting chronic health conditions in Model 2, the odds of COVID-19 mortality were highest among those with preexisting obesity (aOR = 11.00, 95% CI, 9.83 – 12.31) followed by hypertension (aOR = 4.82, 95%CI, 4.33 – 5.36), cardiovascular disease (aOR = 3.79, 95% CI, 3.42 – 4.19), and diabetes (aOR = 2.11, 95% CI, 1.91 – 2.34). After adjusting for pre-existing conditions, the odds of COVID-19 mortality in Black individuals became protective compared to non-Hispanic White individuals (aOR= .84, 95% CI, .73 - .96). Additionally, the odds lowered in Hispanic individuals from 1.37 – 1.29. This finding suggests that if factors contributing to chronic health conditions in minorities were reduced or eliminated, rates of mortality from COVID-19 may decrease.

In the univariable model with $PM_{2.5}$ exposure regressed on the outcome of COVID-19 mortality, none of the lag times produced a significant result. For models 1, 2, and 3, the odds of COVID-19 mortality increased by 3% for every 1μg/$m^3$ increase in the 7-day average of $PM_{2.5}$ pollution exposure (aOR = 1.03, 95% CI, 1.01 – 1.05). An alternate interpretation is that if facilities releasing $PM_{2.5}$ bring the 7-day average $PM_{2.5}$ levels from 8μg/$m^3$ to 12μg/$m^3$, this would increase the odds of death by 24%.

The odds of COVID-19 mortality increased by 3%, 5%, and 6% for models 1, 2, and 3, respectively in the 14-day average of $PM_{2.5}$ exposure. With the 28-day average of $PM_{2.5}$ exposure, results in model 1 were protective and not significant; however, after adding in pre-existing chronic conditions and SVI, the odds of COVID-19 mortality increased by 3%.
This suggests that when adjusting for other chronic conditions and social factors, $PM_{2.5}$ exposure becomes associated with an increased odds of mortality. Table 6 illustrates that the odds ratios for all three lag times remained largely the same.

**Table 5**: Logistic Regression Model Outputs in COVID-19 Cases Reported Between March 1, 2020 – March 31, 2022 to Harris County Public Health Jurisdiction for 7-day $PM_{2.5}$ Lag Exposure.

| Variable | [a]Model 1 adjusted OR | [b]Model 2 adjusted OR | [c]Model 3 adjusted OR | Univariable OR |
|---|---|---|---|---|
| **$PM_{2.5}$ (7-day avg.)** | 1.03 [1.01 – 1.04] | 1.03 [1.01 – 1.05] | 1.03 [1.01 – 1.05] | 1.00 [0.99 – 1.02] |
| **$PM_{2.5}$ (14-day avg.)** | 1.03 [1.01 – 1.05] | 1.05 [1.03 – 1.08] | 1.06 [1.03 – 1.08] | 1.01 [0.99 – 1.03] |
| **$PM_{2.5}$ (28-day avg.)** | .98 [0.95 – 1.00] | 1.03 [1.00 – 1.06] | 1.03 [1.00 – 1.07] | 0.95 [0.92 - .97] |
| **Age** | | | | |
| 20 – 29 (Ref) | Ref | Ref | Ref | Ref |
| 30 – 39 | 4.17 [2.76 – 6.54] | 3.32 [2.19 – 5.21] | 3.36 [2.22 – 5.28] | 4.07 [2.72 – 6.32] |
| 40 – 49 | 9.37 [6.37 – 14.41] | 5.15 [3.48 – 7.95] | 5.26 [3.56 – 8.12] | 9.36 [6.41 – 14.27] |
| 50 – 59 | 21.75 [14.94 – 33.15] | 8.12 [5.54 – 12.45] | 8.31 [5.67 – 12.73] | 21.99 [15.22 – 33.24] |
| 60 – 69 | 55.83 [38.54 – 84.80] | 15.38 [10.53 – 23.52] | 15.61 [10.69 – 23.87] | 56.09 [39.00 – 84.45] |
| 70 – 79 | 139.46 [96.33 – 211.72] | 31.66 [21.65 – 48.44] | 31.95 [21.85 – 48.88] | 138.49 [96.39 – 208.34] |
| 80+ | 365.96 [252.71 – 555.71] | 97.81 [66.87 – 149.69] | 98.06 [67.05 – 150.06] | 353.54 [246.19 – 531.61] |
| **Race/Ethnicity** | | | | |
| Non-Hispanic White | Ref | Ref | Ref | Ref |
| Non-Hispanic Black | 1.20 [1.07 – 1.35] | .84 [0.73 – 0.96] | 0.78 [0.67 – 0.89] | 0.67 [0.60 - 0.75] |
| Hispanic/Latino | 1.37 [1.24 – 1.49] | 1.29 [1.17 – 1.44] | 1.16 [1.04 – 1.29] | 0.62 [0.57 - 0.68] |
| Other | 0.65 [0.56 - 0.75] | 1.00 [0.84 – 1.18] | 0.96 [0.81 – 1.14] | 0.38 [0.33 - 0.44] |
| Unknown | 0.27 [0.24 - 0.33] | 0.66 [0.55 – 0.79] | 0.62 [0.52 – 0.75] | 0.13 [0.12 - 0.16] |
| **Gender** | | | | |
| Male | 1.78 [1.65 – 1.92] | 1.79 [1.64 – 1.95] | 1.81 [1.66 – 1.98] | 1.72 [1.60 – 1.85] |
| Female (Ref) | Ref | Ref | Ref | Ref |
| Unknown/Other | 0.01 [.003 - .024] | 0.03 [0.01 – 0.07] | 0.03 [.009 - .069] | 0.01 [0.01 - 0.02] |
| **Co-morbidities** | | | | |
| **(YES)** | | 3.79 [3.42 – 4.19] | 3.73 [3.37 – 4.13] | 66.22 [61.40 – 71.42] |
| Cardiovascular | | 4.82 [4.33 – 5.36] | 4.79 [4.30 – 5.33] | 55.36 [51.26 – 59.82] |
| Hypertension | | 2.11 [1.91 – 2.34] | 2.07 [1.87 – 2.29] | 32.61 [30.33 – 35.05] |
| Diabetes | | 11.00 [9.83 – 12.31] | 11.19 [10.00 – 12.53] | 50.59 [46.65 – 54.84] |
| Obesity (BMI>=30) | | | | |
| **SVI Composite** | | | | |
| 0.00 – 0.25 (Ref) | | | Ref | Ref |
| 0.25 - 0.50 | | | 1.20 [1.06 – 1.36] | 1.22 [1.10 – 1.34] |
| 0.50 – 0.75 | | | 1.59 [1.41 – 1.80] | 1.86 [1.69 – 2.06] |
| 0.75 – 1.00 | | | 1.77 [1.53 – 2.05] | 2.10 [1.87 – 2.36] |

a: Model 1: DeceasedCOVID19 ~ pm25_7f + Race + Gender + Age_Group
b: Model 2: DeceasedCOVID19 ~ pm25_7f + Race + Gender + Age_Group + CVD + Obesity + Hypertension + Diabetes
c: Model 3: DeceasedCOVID19 ~ pm25_7f + Race + Gender + Age_Group + CVD + Obesity + Hypertension + Diabetes + Overall_SVI

**Table 6**: Logistic Regression Model Outputs for the Outcome COVID-19 Death in COVID-19 Cases Reported Between March 1, 2020 – March 31, 2022, to Harris County Public Health Jurisdiction for 7-day, 14-day, and 28-day PM2.5 exposure lag times.

| Variable | PM2.5 7-day lag | PM2.5 14-day lag | PM2.5 28-day lag |
|---|---|---|---|
| **Age** | | | |
| 20 – 29 (Ref) | Ref | Ref | Ref |
| 30 – 39 | 3.36 [2.22 – 5.28] | 3.28 [2.16 – 5.15] | 3.15 [2.07 – 4.96] |
| 40 – 49 | 5.26 [3.56 – 8.12] | 5.21 [3.52 – 8.05] | 5.17 [3.49 – 7.99] |
| 50 – 59 | 8.31 [5.67 – 12.73] | 8.08 [5.51 – 12.40] | 7.76 [5.28 – 11.91] |
| 60 – 69 | 15.61 [10.69 – 23.87] | 15.26 [10.44 – 23.35] | 14.75 [10.08 – 22.58] |
| 70 – 79 | 31.95 [21.85 – 48.88] | 31.92 [21.82 – 78.86] | 30.32 [20.70 – 46.46] |
| 80+ | 98.06 [67.05 – 150.06] | 95.13 [64.99 – 145.67] | 92.65 [63.22 – 142.02] |
| **Race/Ethnicity** | | | |
| Non-Hispanic White | Ref | Ref | Ref |
| Non-Hispanic Black | 0.78 [0.67 – 0.89] | 0.78 [.68 - .90] | 0.81 [0.70 – 0.94] |
| Hispanic/Latino | 1.16 [1.04 – 1.29] | 1.16 [1.03 – 1.30] | 1.17 [1.05 – 1.31] |
| Other | 0.96 [0.81 – 1.14] | 0.99 [0.83 – 1.18] | 1.02 [0.85 – 1.21] |
| Unknown | 0.62 [0.52 – 0.75] | 0.62 [0.52 - 0.74] | 0.62 [.0070 - 0.071] |
| **Gender** | | | |
| Male | 1.81 [1.66 – 1.98] | 1.84 [1.69 – 2.01] | 1.82 [1.66 – 1.99] |
| Female (Ref) | Ref | Ref | Ref |
| Unknown/Other | 0.03 [.009 - .069] | 0.02 [0.01 - 0.06] | 0.03 [0.01 - 0.07] |
| **Co-morbidities (YES)** | | | |
| Cardiovascular | 3.73 [3.37 – 4.13] | 3.69 [3.33 – 4.09] | 3.75 [3.37 – 4.17] |
| Hypertension | 4.79 [4.30 – 5.33] | 4.55 [4.08 – 5.08] | 4.43 [3.96 – 4.96] |
| Diabetes | 2.07 [1.87 – 2.29] | 2.08 [1.87 – 2.30] | 2.04 [1.83 – 2.27] |
| Obesity (BMI>=30) | 11.19 [10.00 – 12.53] | 11.13 [9.92 – 12.48] | 10.99 [9.77 – 12.36] |
| **SVI Composite** | | | |
| 0.00 – 0.25 (Ref) | Ref | Ref | Ref |
| 0.25 - 0.50 | 1.20 [1.01 – 1.05] | 1.20 [1.03 – 1.08] | 1.21 [1.06 – 1.37] |
| 0.50 – 0.75 | 1.59 [1.41 – 1.80] | 1.62 [1.06 – 1.36] | 1.64 [1.44 – 1.87] |
| 0.75 – 1.00 | 1.77 [1.53 – 2.05] | 1.77 [1.53 – 2.05] | 1.76 [1.51 – 2.05] |

Model: DeceasedCOVID19 ~ PM2.5 (7, 14, and 28 day lag) + Race + Gender + Age_Group + CVD + Obesity + Hypertension + Diabetes + Overall_SVI

## 4. Discussion

The multivariable analysis outcome of this study is consistent with our hypothesis that a $1 \mu g/m^3$ increase in census tract level $PM_{2.5}$ exposure is associated with an increase in the odds of COVID-19 mortality in Harris County Public Health jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022. We found that after adjusting for age, race, and gender, a 1µg/$m^3$ increase in the 7-day and 28-day average exposure to $PM_{2.5}$ could increase the odds of COVID-19 mortality by 3%. After adjusting for age, race, gender, pre-existing chronic disease, and social vulnerability, a 1µg/$m^3$ increase in the 14-day average $PM_{2.5}$ exposure increases the odds of mortality by 6%.

These are significant findings considering that there are cumulative impacts of pollution. The EPA refers to cumulative impacts as the "total burden of pollution (positive, negative, or neutral) from chemical or non-chemical stressors that affect the health, well-being, and quality of life of an individual or population" (Julius et al., 2022). Cumulative impacts include exposures that are occurring where people live in recent time as well as past exposures that have lingering effects in present time. Although a 3% increase in the odds of COVID-19 mortality may seem like a small percentage, this increase within a range of 7 – 28 days can be significant when considering communities that are experiencing multiple acute chemical releases within permitted limits on a regular basis. Facilities releasing $PM_{2.5}$ could bring the 7-day average $PM_{2.5}$ levels from 8µg/$m^3$ to 12µg/$m^3$, increasing the odds of death by up to 24%.

*Implications*

These results add to the body of literature that indicate air pollution is likely a significant contributor to morbidity and mortality related to COVID-19 (Berg et al., 2021a; Hendryx & Luo, 2020; Konstantinoudis et al., 2021; Zhou et al., 2021; Zoran et al., 2020).There are few studies in the current literature for individual-level analysis of ambient air pollution and poor health outcomes following COVID-19 diagnosis. The studies that have been done consist mostly of ecologic studies at the county level that introduce ecologic fallacy and results that are unable to be generalized to populations with greater air pollution variation in smaller geographic units.

Harris County, being home to one of the largest industrial complexes in the world, houses many polluting facilities in addition to the extensive road traffic. The facilities are concentrated in different areas of the county, primarily near the ship channel on the eastern side of the county. The highway system also landlocks certain communities in the middle of intersecting road traffic. These differences in where residents live, creates large variations in ambient pollution exposure for Harris County residents. In Harris County, Black and Hispanic communities are disproportionately exposed to PM2.5 air pollution due to their proximity to extensive road traffic as well as industrial polluters and the Houston Ship Channel (Linder et al., 2008; Loustaunau & Chakraborty, 2019). It is important to note that even after adjusting for all pre-existing chronic conditions and social vulnerabilities, Hispanics are the only group that maintain an association of increased risk for COVID-19 mortality compared to non-Hispanic Whites. This may indicate that factors outside of lifestyle choices and chronic disease burden such as air pollution may be contributing to their increased risk of death. During the COVID-19 pandemic response, Harris County Public Health targeted populations with high social vulnerability as well as communities with larger percentages of Black and Hispanic residents for testing, vaccination, and outreach. However, in preparation for future infectious disease outbreaks, not only should health departments ramp up efforts to mitigate chronic disease prevalence, but also as evidenced in this research, efforts to mitigate air pollution.

The current national ambient air quality standard (NAAQS) that the EPA has set for $PM_{2.5}$ is 12μg/m$^3$ yearly and 35μg/m$^3$ for a 24-hr average. These standards are currently under review by the EPA and could be lowered. The literature indicates that there are health impacts seen at yearly $PM_{2.5}$ levels as low as 8μg/m$^3$ (Di et al., 2020). Nearly all of Harris County

Residents experience yearly $PM_{2.5}$ levels at 10 μg/$m^3$ (Roy, n.d.-b). Local public health departments are in a position to contest EPA national ambient air quality standards as well as decisions made by the Texas Commission on Environmental Quality (TCEQ) that negatively impact public health. It is imperative that local health departments use the data that they collect during infectious disease outbreaks such as the COVID-19 pandemic to understand how environmental exposures are impacting poor health outcomes following viral infection to inform mitigation strategies.

*Limitations*

The methods used in this analysis should inform future studies on this topic to understand more about the relationship between $PM_{2.5}$ pollution exposure and poor health outcomes such as mortality following viral respiratory illness. Due to the HIPPA regulations and security of data at the local health department level, we could not adjust for population density, average day sunlight, precipitation, and heat; however, future studies should adjust for these variables. There are several limitations to this study. The major limitation is that the source population for the data used in this analysis consists only of residents living in Harris County Public Health jurisdiction. This jurisdiction excludes the City of Houston (Figure 2). The City of Houston has a larger concentration of high $PM_{2.5}$ levels due to more cement batch plants, highway traffic, and other facilities producing $PM_{2.5}$ pollution in the inner city. Another limitation is the resolution of the data used in this analysis. The NASA data was in a 10km grid versus a 1km grid. Additionally, $PM_{2.5}$ data is from 2019 and this study assumed that 2019 data is similar to 2020 data. Future studies should look at the available data from 2020 at the 1km grid level to have a more accurate representation of $PM_{2.5}$ levels at a more granular geographic unit. Finally, this study did not adjust for access to healthcare or cultural perceptions of seeking healthcare. Although SVI is good proxy for both access and perception, this was not directly controlled for.

## 5. Conclusion

In conclusion, this research is an excellent starting point to understand the impacts of air pollution on populations experiencing outbreaks of respiratory illness caused by an infectious agent. There are important, practical implications that result from this study. The identification of key modifiable environmental factors may contribute to mitigating the risk of COVID-19 and minimize the impact of future pandemics. Knowledge regarding the link between air pollution and COVID-19 mortality will help public health preparedness and response identify vulnerable populations for future epidemics and pandemics. This knowledge should be a consideration for offices of public health preparedness when writing plans and strategizing for public health interventions in communities more at risk for poor health outcomes.

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## JOURNAL ARTICLE 2

**Association Between Pre-existing Chronic Disease and COVID-19 Mortality in Harris County**

**Name of Journal Proposed for Article Submission: American Journal of Public Health, Journal of Primary Care and Community Health, American Journal of Respiratory and Critical Care Medicine, BMC Public Health**

### 1. Introduction

*1.1 Chronic Disease Impacts in Harris County*

It is still unclear why certain racial and ethnic groups are disproportionality affected by COVID-19; however, this could be related to the prevalence of certain chronic diseases in these racial groups. According to Harris Cares, 2020 there is a deficiency in access to secondary or specialty care for heart disease, cancer, and mental health in Harris County. 21% of individuals in Harris County are uninsured and of those 65% are minorities. Low-income, Black, and Hispanic populations are at higher risk for many chronic conditions, including high blood pressure, diabetes, and obesity (Price et al., 2013). From 2013-2017, 78.7% of Black and 75.7% of Hispanic Harris County residents were overweight or obese compared to 64.4% of White residents and 68.0% of all Texans. The rate of heart disease in Black residents (7.9%) is more than double that of Hispanic residents (3.2%), and Blacks are more likely to have asthma (19.5%) compared to Whites (11.7%) and Hispanics (5.3%) in Harris County (*Texas Department of State Health Services*, *BRFSS*, n.d.).

Nationally, the CDC reports Non-Hispanic Black adults (49.6%) have the highest age-adjusted prevalence of obesity, followed by Hispanic adults (44.8%), non-Hispanic White adults (42.2%) and non-Hispanic Asian adults (17.4%) (*Adult Obesity Facts | Overweight & Obesity | CDC*, n.d.). The CDC's National Diabetes Statistics report reported non-Hispanic Blacks have the highest prevalence of diabetes (13.3% [11.9 – 14.9]), followed by non-Hispanic Asians (11.2% [9.5 – 13.3]), Hispanics (10.3% [8.1 – 13.1]), and non-Hispanic Whites (9.4% [8.4 – 10.5])(CDC, 2020).

*1.2 Cardiovascular disease*

The current literature suggests that mortality from coronavirus disease 2019 (COVID-19) is strongly associated with cardiovascular disease (CVD), diabetes, and hypertension (Hanff et al., 2020; Pranata, Huang, et al., 2020). Further evidence for investigating heart disease specifically is the mechanism of angiotensin-converting enzyme 2 (ACE2) proteins. ACE2 has been identified as a functional receptor for SARS-CoV-1 and SARS-CoV-2 and infection is triggered by binding of the spike protein of the virus to ACE2, which is highly expressed in the heart's cells (Turner et al., 2004). Although SARS-CoV-2 mainly invades alveolar epithelial cells, resulting in respiratory symptoms, these symptoms are more severe in patients with CVD. The increased severity in patients with CVD might be associated with increased expression of ACE2 in these patients compared with healthy individuals. Given that ACE2 is a functional receptor for SARS-CoV-2, antihypertension therapies with ACE inhibitors in patients with COVID-19 should be carefully considered (Zheng et al., 2020).

*1.3 Hypertension*

Hypertension is the most commonly reported pre-existing condition reported in those who have died due to COVID-19. There are reports in animal models and humans suggesting that the expression of ACE2 may be increased after treatment with an ACEI or ARB, which might augment patients' susceptibility to viral host cell entry and propagation (Gao et al., 2020).

Meta-analysis also shows that hypertension is associated with increased morbidity and mortality in individuals with COVID-19 (Pranata, Lim, et al., 2020).

*1.4 Obesity*

Obesity has been identified as one of the key factors associated with severe COVID-19 outcomes (Phe, 2020; Williamson et al., 2020). A cohort study out of the UK found that a higher BMI, waist circumference, waist-to-hip ratio and waist-to-height ratio were each associated with a greater risk of death from COVID-19, influenza/pneumonia and CHD in both sexes (Peters et al., 2021). Another study found a strong negative correlation was found between age and BMI in 265 patients admitted to an intensive care unit (ICU), and it was concluded that obesity can shift severe forms of COVID-19 to a younger age (Kass et al., 2020). This could be related to a number of different factors including the fat deposition around upper airways, higher prevalence of obstructive sleep apnea in obese individuals, and a heavier thorax all resulting in poor outcomes following intubation. To note, the relationship between obesity and COVID-19 mortality may be explained by the propensity of those with obesity to have diabetes. This research will adjust for diabetes when looking at obesity as an exposure.

*1.5 Diabetes*

Diabetes Mellitus (DM) is one of the most prevalent chronic condition that Americans face (Saeedi et al., 2019). A meta-analysis showed that DM is associated with morbidity and mortality in individuals with COVID-19. The meta-regression indicates that the association with morbidity and mortality is influenced by age ($p = 0.003$) and hypertension ($p < 0.001$)(Huang et al., 2020). Both age and hypertension are included in the model of this research.

## 2. Methods

*2.1 Data source for COVID-19 deaths and cases*

This study utilized individual level data from a database including Harris County Public Health (HCPH) Jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022. Eligibility includes residents that reside within HCPH jurisdiction, tested positive for COVID-19 through confirmatory PCR test between March 1, 2020 – March 31, 2022, have address information, were age 19 and older, and underwent an epidemiological investigation either through medical record review or interviewing the case for self-reported information. HCPH serves the third largest county in the United States and is responsible for disease reporting and surveillance of COVID-19; therefore, all COVID-19 testing facilities with HCPH jurisdiction are required to report all positive and negative results to HCPH. Hospitals also report cases and provide medical records, admission, and discharge notes for cases of COVID-19. Epidemiologists and case investigators utilize these medical records to extract relevant case information such as hospital admission date, discharge date, ICU stay, pre-existing conditions, symptoms, etc. They also reach out to hospitals to obtain records for patients who have been reported to us by Electronic Lab Report (ELR). If records are not available, epidemiologists conduct phone interviews to determine pre-existing conditions of cases using the definitions in Table 2.

Medical examiner's office (ME), the Institute of Forensic Science (IFS), hospitals, and relatives of deceased residents report deaths due to COVID-19 to HCPH. There are several measures in place to ensure that cases were truly deceased due to COVID-19 and not some other reason such as trauma or another illness and that records were provided to confirm this.

Investigators are instructed not to record a deceased COVID-19 case and only lead epidemiologists are allowed to do so after consulting the local health authority. This process increased the validity of deaths related to COVID-19. Only confirmed cases with address information are included in the analysis. A case meets confirmatory laboratory evidence if there is detection of SARS-CoV-2 RNA in a clinical or autopsy specimen using a molecular amplification test.

### *2.2 Statistical analysis*

Data were analyzed from March 1, 2020 – March 31, 2022. We used a retrospective observational study design. All data analysis was performed in R studio and ArcGIS Pro behind the HCPH firewall. We fitted logistic regression models to estimate the association between pre-existing chronic disease and the risk of death following SARS-CoV-2 infection. Multivariable and univariable logistic regression was utilized to produce odds ratios and 95% confidence intervals. Multivariable models adjusted for individual level demographics, PM2.5 exposure, and social vulnerability.

## 3. Results

We analyzed the association between individual level pre-existing chronic disease and COVID-19 mortality. The source population included a total of 1,048,575 confirmed COVID-19 cases reported to Harris County Public Health between March 1, 2020, and March 31, 2022. After eligibility criteria were implemented, the study population included a total of 350,233 confirmed COVID-19 cases, 3,207 of these cases passed away.

The descriptive characteristics of these cases are presented in Table 7. Compared to survivors, deceased cases were older, were more often male, and had higher prevalence of pre-existing chronic disease. There is a higher frequency of individuals living in census tracts with higher social vulnerability (0.5 – 1) in those that passed away (49.2%) compared to those that survived (36.0%). The majority of deceased cases were hospitalized (82.2%) and the majority of survivors were not hospitalized (96.8%).

16,074 (5%) of individuals had at least 1 chronic condition, hypertension being the most frequently reported (Table 8). 40% of those with pre-existing chronic conditions had at least 2 concurrent conditions. The 2 most frequent concurrent conditions in this dataset are hypertension and diabetes, while the 3 most frequent concurrent conditions are CVD, hypertension, and diabetes. Hispanic individuals make up the highest percentage of individuals with diabetes (48.6%), obesity (35.9%), and hypertension (39.2%). Non-Hispanic White individuals make up the highest percentage of individuals with cardiovascular disease (40.9%). In all pre-existing chronic conditions, the majority of individuals were male (Table 8).

In individuals that are obese, Hispanic individuals make up the highest percentage (35.9%) followed by non-Hispanic White (34.4%), and non-Hispanic Black (20.8%). Additionally, the most frequently reported age in those with obesity was age 50 – 59 (21.9%) (Table 8).

**Table 7**: Characteristics of Individuals with Positive Results of Polymerase Chain Reaction Testing for SARS – COV- 2 reported to Harris County Public Health During March 2020 – March 2022

| **Variable** | **No. (%)** | | |
|---|---|---|---|
| | **COVID-19 Deceased** N=3207 | **COVID-19 Survivors** N= 347026 | **COVID-19 Hospitalization** N= 13589 |
| **Age** | | | |
| 20 – 29 (Ref) | 27 (0.8%) | 78894 (22.7%) | 769 (5.7%) |
| 30 – 39 | 110 (3.4%) | 78968 (22.8%) | 1378 (10.1%) |
| 40 – 49 | 233 (7.3%) | 72715 (21.0%) | 1950 (14.3%) |
| 50 – 59 | 422 (13.2%) | 56062 (16.2%) | 2446 (18.0%) |
| 60 – 69 | 687 (21.4%) | 35787 (10.3%) | 2749 (20.2%) |
| 70 – 79 | 804 (25.1%) | 16963 (4.9%) | 2426 (17.9%) |
| 80+ | 924 (28.8%) | 7637 (2.2%) | 1871 (13.8%) |
| **Race/Ethnicity** | | | |
| Non-Hispanic White (Ref) | 1226 (38.2%) | 74714 (21.5%) | 4994 (36.8%) |
| Non-Hispanic Black | 451 (14.1%) | 40989 (11.8%) | 2430 (17.9%) |
| Hispanic/Latino | 1106 (34.5%) | 108164 (31.2%) | 4431 (32.6%) |
| Other | 236 (7.4%) | 37961 (10.9%) | 1065 (7.8%) |
| Unknown | 188 (5.9%) | 85198 (24.6%) | 719 (5.3%) |
| **Gender** | | | |
| Male | 1856 (57.9%) | 126832 (36.5%) | 6941 (51.1%) |
| Female (Ref) | 1345 (41.9%) | 158201 (45.6%) | 6555 (48.2%) |
| Unknown/Other | 6 (0.2%) | 61993 (17.9%) | 93 (0.7%) |
| **Pre-existing cond. (YES)** | | | |
| Cardiovascular | 1477 (46.1%) | 4417 (1.3%) | 2879 (21.2%) |
| Hypertension | 2235 (69.7%) | 13839 (4.0%) | 5339 (39.3%) |
| Diabetes | 1507 (47.0%) | 9185 (2.6%) | 3832 (28.2%) |
| Obesity (BMI>=30) | 1070 (33.4%) | 3401 (1.0%) | 2489 (18.3%) |
| **Hospitalized** | | | |
| Yes | 2636 (82.2%) | 10953 (3.2%) | N/A |
| No | 571 (17.8%) | 336073 (96.8%) | N/A |
| **Congregate Setting** | | | |
| Yes | 779 (24.3%) | 12092 (3.5%) | 1287 (9.5%) |
| No | 2428 (75.7%) | 334934 (96.5%) | 12302 (90.5%) |
| **SVI Composite** | | | |
| 0.00 – 0.25 (Ref) | 627 (19.9%) | 94099 (28.1%) | 3063 (22.5%) |
| 0.25 - 0.50 | 978 (31.0%) | 120737 (36.0%) | 4471 (32.9%) |
| 0.50 – 0.75 | 1033 (32.8%) | 83273 (24.9%) | 3532 (26.0%) |
| 0.75 – 1.00 | 516 (16.4%) | 36877 (11.0%) | 1729 (12.7%) |

**Table 8**: Demographic Characteristics of Individual COVID-19 Cases in the Study Population by Pre-existing Chronic Disease

| Characteristic | Diabetes N=10692 | CVD N=5894 | Obesity N= 4471 | Hypertension N = 16074 |
|---|---|---|---|---|
| **Age** | | | | |
| 20 – 29 (Ref) | 195 (1.8%) | 93 (1.6%) | 310 (6.9%) | 232 (1.4%) |
| 30 – 39 | 702 (6.6%) | 218 (3.7%) | 673 (15.1%) | 1012 (6.3%) |
| 40 – 49 | 1722 (16.1%) | 547 (9.3%) | 912 (20.4%) | 2429 (15.1%) |
| 50 – 59 | 2628 (24.6%) | 994 (16.9%) | 980 (21.9%) | 3876 (24.1%) |
| 60 – 69 | 2693 (25.2%) | 1381 (23.4%) | 876 (19.6%) | 3870 (24.1%) |
| 70 – 79 | 1811 (16.9%) | 1424 (24.2%) | 524 (11.7%) | 2758 (17.2%) |
| 80+ | 941 (8.8%) | 1237 (21.0%) | 196 (4.4%) | 1897 (11.8%) |
| **Race/Ethnicity** | | | | |
| Non-Hispanic White | 2569 (24.0%) | 2411 (40.9%) | 1536 (34.4%) | 4837 (30.1%) |
| Non-Hispanic Black | 1937 (18.1%) | 1130 (19.2%) | 930 (20.8%) | 3542 (22.0%) |
| Hispanic/Latino | 5195 (48.6%) | 1786 (30.3%) | 1604 (35.9%) | 6299 (39.2%) |
| Other | 657 (6.1%) | 389 (6.6%) | 215 (4.8%) | 937 (5.8%) |
| Unknown | 334 (3.1%) | 178 (3.0%) | 186 (4.2%) | 459 (2.9%) |
| **Gender** | | | | |
| Male | 5508 (51.5%) | 3039 (51.6%) | 2362 (52.8%) | 8428 (52.4%) |
| Female (Ref) | 5143 (48.1%) | 2820 (47.8%) | 2089 (46.7%) | 7559 (47.0%) |
| Unknown/Other | 41 (0.4%) | 35 (0.6%) | 20 (0.4%) | 87 (0.5%) |

Of the 16,074 individuals who had at least one pre-existing chronic condition, up to 40% of those individuals had more than one pre-existing condition. The most frequently reported combination of pre-existing conditions was CVD, hypertension, and diabetes. Due to the frequent occurrence of multiple pre-existing chronic conditions, we first included all conditions in the model. Table 9 summarizes results of a multivariable logistic regression model for COVID-19 mortality when looking at all pre-existing chronic disease in the model together (i.e., Model 1: COVID-19 Mortality ~ Age + Race + Gender + Obesity + Hypertension + CVD + Diabetes). In model 1, the odds of COVID-19 mortality in those with obesity was 11.09 times the odds of mortality in those who did not have obesity and obesity had the highest risk of all reported chronic conditions (aOR = 11.09, 95% CI 9.94 – 12.38). In model 2, after adding SVI into the model, all aORs lowered. After adding SVI, the odds of COVID-19 mortality in those with obesity was 11.05 [9.89 – 12.35] times the odds of mortality in those who did not have obesity. Additionally, the next highest odds was found in those with hypertension in Model 3 such that the odds of COVID-19 mortality in those reporting hypertension was 4.79 times the odds of mortality in those who did not report hypertension after adjusting for age, race, gender, SVI, and $PM_{2.5}$ pollution exposure. When all pre-existing conditions are included in the model, Hispanic individuals are more likely to die following COVID-19 infection compared to non-Hispanic White individuals (aOR = 1.32, 95% CI 1.20 – 1.47).

Table 10 summarizes results of logistic regression analysis for COVID-19 mortality when looking at each pre-existing chronic disease separately in the model (ex: Model 1: COVID-19 Mortality ~ Age + Race + Gender + Obesity). Model 1 adjusts for age, race, and gender. When adjusting for age, race, and gender, the odds of COVID-19 mortality in those with pre-existing obesity are 37.30 times the odds of COVID-19 mortality in those without pre-existing obesity (aOR = 37.30, 95% CI, 33.85 – 41.10). Obesity is still the pre-existing condition with the highest odds associated with mortality when adjusting for age, race, and gender followed by hypertension (aOR = 17.62, 95% CI, 16.19 – 19.20), CVD (aOR = 15.48, 95% CI, 14.23 – 16.83), and diabetes (aOR = 10.85, 95% CI, 10.02 – 11.76). However, this analysis with each chronic disease separately does not provide an accurate picture due to the correlation these conditions have with one another and the fact that many records in this dataset have more than one chronic condition.

After adding race to the model, the OR for COVID-19 mortality in all pre-existing chronic disease had a percent change greater than 10% which indicates that race may confound the association between pre-existing chronic conditions and COVID-19 mortality (obesity 22% change, hypertension 11% change, diabetes 13% change, and CVD 21% change).

**Table 9**: Logistic Regression Model Outputs for COVID-19 Mortality in Cases Reported Between March 1, 2020 – March 31, 2022 to Harris County Public Health Jurisdiction.

| Variable | [a]Model 1 adjusted OR | [b]Model 2 adjusted OR | [c]Model 3 adjusted OR | Univariable OR |
|---|---|---|---|---|
| **Age** | | | | |
| 20 – 29 (Ref) | Ref | Ref | Ref | Ref |
| 30 – 39 | 3.32 [2.21 – 5.17] | 3.39 [2.24 – 5.32] | 3.36 [2.22 – 5.28] | 4.07 [2.72 – 6.32] |
| 40 – 49 | 5.21 [3.55 – 7.98] | 5.33 [3.60 – 8.22] | 5.26 [3.56 – 8.12] | 9.36 [6.41 – 14.27] |
| 50 – 59 | 8.09 [5.55 – 12.29] | 8.49 [5.79 – 13.00] | 8.31 [5.67 – 12.73] | 21.99 [15.22 – 33.24] |
| 60 – 69 | 15.53 [10.71 – 23.54] | 16.35 [11.20 – 24.97] | 15.61 [10.69 – 23.87] | 56.09 [39.00 – 84.45] |
| 70 – 79 | 31.86 [21.95 – 48.32] | 33.33 [22.82 – 50.96] | 31.95 [21.85 – 48.88] | 138.49 [96.39 – 208.34] |
| 80+ | 96.66 [66.56 – 146.63] | 101.81 [69.68 – 155.68] | 98.06 [67.05 – 150.06] | 353.54 [246.19 – 531.61] |
| **Race/Ethnicity** | | | | |
| Non-Hispanic White | Ref | Ref | Ref | Ref |
| Non-Hispanic Black | 0.84 [.74 - .96] | 0.79 [.69 - .90] | 0.78 [0.67 – 0.89] | 0.671 [.601 - .747] |
| Hispanic/Latino | 1.32 [1.20 – 1.47] | 1.17 [1.06 – 1.31] | 1.16 [1.04 – 1.29] | 0.623 [.574 - .676] |
| Other | 0.99 [.84 – 1.17] | 0.96 [.81 – 1.13] | 0.96 [0.81 – 1.14] | 0.379 [.329 - .435] |
| Unknown | 0.69 [.58 - .82] | 0.62 [.52 - .74] | 0.62 [0.52 – 0.75] | 0.134 [.115 - .156] |
| **Gender** | | | | |
| Male | 1.81 [1.66 – 1.96] | 1.79 [1.65 – 1.95] | 1.81 [1.66 – 1.98] | 1.72 [1.60 – 1.85] |
| Female (Ref) | Ref | Ref | Ref | Ref |
| Unknown/Other | 0.042 [.017 - .086] | 0.043 [.017 - .087] | 0.03 [.009 - .069] | 0.011 [.005 - .023] |
| **Pre-existing cond.** (yes/no) | | | | |
| Cardiovascular | 3.71 [3.36 – 4.10] | 3.68 [3.33 – 4.06] | 3.73 [3.37 – 4.13] | 66.22 [61.40 – 71.42] |
| Hypertension | 5.16 [4.64 – 5.73] | 5.03 [4.53 – 5.60] | 4.79 [4.30 – 5.33] | 55.36 [51.26 – 59.82] |
| Diabetes | 2.08 [1.88 – 2.30] | 2.01 [1.82 – 2.22] | 2.07 [1.87 – 2.29] | 32.61 [30.33 – 35.05] |
| Obesity (BMI>=30) | 11.09 [9.94 – 12.38] | 11.05 [9.89 – 12.35] | 11.19 [10.00 – 12.53] | 50.59 [46.65 – 54.84] |
| **SVI Composite** | | | | |
| 0.00 – 0.25 (Ref) | | Ref | Ref | Ref |
| 0.25 - 0.50 | | 1.15 [1.05 – 1.34] | 1.20 [1.06 – 1.36] | 1.22 [1.10 – 1.34] |
| 0.50 – 0.75 | | 1.58 [1.40 – 1.78] | 1.59 [1.41 – 1.80] | 1.86 [1.69 – 2.06] |
| 0.75 – 1.00 | | 1.76 [1.52 – 2.03] | 1.77 [1.53 – 2.05] | 2.10 [1.87 – 2.36] |
| **PM2.5** | | | 1.03 [1.01 – 1.05] | 1.004 [.99 – 1.02] |

a: Model 1: DeceasedCOVID19 ~ Race + Gender + Age_Group + Diabetes + CVD + Hypertension + Obesity
b: Model 2: DeceasedCOVID19 ~ Race + Gender + Age_Group + CVD + Obesity + Hypertension + Diabetes + Overall_SVI
c: Model 3: DeceasedCOVID19 ~ Race + Gender + Age_Group + CVD + Obesity + Hypertension + Diabetes + Overall_SVI + PM2.5

**Table 10**: Logistic Regression Outputs of Deceased COVID-19 Cases on Pre-existing Chronic Disease Factors

| Pre-existing Chronic Disease | Model 1 Adjusted OR | Model 2 Adjusted OR | Model 3 adjusted OR | Unadjusted OR |
|---|---|---|---|---|
| **Diabetes** | 10.85 [10.02 – 11.76] | 10.12 [9.33 – 10.97] | 9.95 [9.16 – 10.81] | 32.61 [30.33 – 35.05] |
| **CVD** | 15.48 [14.23 – 16.83] | 14.71 [13.51 – 16.02] | 14.39 [13.19 – 15.69] | 66.22 [61.40 – 71.42] |
| **Hypertension** | 17.62 [16.19 – 19.20] | 16.69 [15.31 – 18.20] | 15.97 [14.64 – 17.45] | 55.36 [51.26 – 59.82] |
| **Obesity** | 37.30 [33.85 – 41.10] | 35.94 [32.57 – 39.66] | 35.08 [31.74 – 38.78] | 50.59 [46.65 – 54.84] |

## 4. Discussion

The results of the multivariable analysis done in this study are consistent with the hypothesis that there is an increased odds of mortality in individuals with COVID-19 who have a history of cardiovascular disease, diabetes, hypertension, or obesity compared to those who do not have a history of pre-existing chronic disease, controlling for relevant factors. Based on many years of scientific research, it is evident that chronic diseases such as hypertension, diabetes, cardiovascular disease, and obesity lead to decreased quality of life and decreased ability for the body to fight off infection. There is also an intersection between race/ethnicity and chronic disease which may explain why racial/ethnic minorities are dying from COVID-19 at higher rates (Ahmad et al., 2020). Minorities are more likely to develop chronic illnesses such as diabetes, obesity, hypertension, and cardiovascular disease (Mennis et al., 2022) due to systemic inequities that discourage healthy behaviors and limit access to healthcare. For example, red lining is a major system that put minorities near batch plants, railroad tracks, and major highways (Richardson et al., 2020). In addition, these areas designated for minorities are considered food desserts due to the lack of access to fresh produce and whole foods. These areas have become undesirable to those with resources which leads to failing education and infrastructure systems that would otherwise enhance the willingness to embrace public health interventions. We found that of all the pre-existing chronic diseases, obesity has the highest association with COVID-19 mortality and the Hispanic cases within the dataset make up the highest percentage of these obese cases. In addition, Hispanics make up the highest percentage in the highest social vulnerability quartile (0.75 – 1.00). Obesity has detrimental impacts alone, but it is also a risk factor for hypertension, cardiovascular disease, and diabetes (Field et al., n.d.) which are all associated with an increased risk of COVID-19 mortality evidenced in this analysis. According to the CDC, from 1999 –2000 through 2017 – March 2020, US obesity prevalence increased from 30.5% to 41.9% (*Adult Obesity Facts | Overweight & Obesity | CDC*, n.d.). With the increasing prevalence of obesity, it is imperative that local health departments strengthen their intervention strategies to help decrease prevalence of obesity within the population they serve. There is also a larger issue at the national level where the United States spends large amounts of money on healthcare but has worse health outcomes compared to other "high-income" countries. In 2018, the United States spent 17.7% of the nation's gross domestic product (GDP) on health care, compared to the Organization for Economic Cooperation and Development (OECD[1]) average of 8.8% GDP (Roosa Tikkanen and Melinda K. Abrams, 2020). Despite the greater spending on healthcare, chronic disease burden is higher in the United States compared to the OECD average. This speaks to the need to shift our healthcare systems to focus more on the underlying social and economic issues that public health can address rather than focusing on curative care. These underlying social and economic drivers consist of education,

[1] OECD average comprises 10 high-income member countries Australia, Canada, France, Germany, the Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

early childcare, environmental exposures, transportation infrastructure, among others (Rollston & Galea, 2020).

*Implications*

Most studies measuring the association between pre-existing chronic diseases and COVID-19 mortality are done at the county level. This study adds to the current body of literature on pre-existing chronic diseases associated with COVID-19 mortality by performing an individual level analysis rather than ecological. Additionally, many studies are utilizing hospital data which has benefits regarding the accuracy of the data; however, there is a bias when only including those individuals who were hospitalized as these individuals may have poorer health compared to the general population. This analysis is providing a broader look on what the odds of mortality to COVID-19 are compared to a more general population of healthy individuals.

*Limitations*

There are limitations to this study. One being misclassification of exposure because cases that were not hospitalized self-reported their pre-existing chronic disease history. Self-reporting can result in not reporting chronic disease that is truly present or even over reporting chronic disease that is not present. Cases that were hospitalized provided medical records, and therefore, a more accurate history of chronic disease. Further analysis should look at these associations after obtaining medical records for all cases in the source population. All cases in this analysis resided outside of the City of Houston and thus did not give an accurate analysis of the entire Harris County. Additionally, collecting BMI as a continuous variable would result in more evidence for the change in risk for mortality between BMI classes.

## 5. Conclusion

In conclusion, efforts should be made at local health departments to continue essential public health operations such as chronic disease prevention during public health emergencies like the COVID-19 pandemic. Good health is one key to making individuals and communities more resilient to disasters. Those with chronic diseases are more likely to have disabilities, medication, and power dependencies that make it difficult to manage their health during disasters. Not only would a reduction of chronic diseases within Harris County communities effectively reduce morbidity and mortality during infectious disease outbreaks as evidenced in this research, but also during hurricanes and other public health emergencies.

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## JOURNAL ARTICLE 3

**Association Between SVI and COVID-19 Mortality in Harris County**
**Name of Journal Proposed for Article Submission: JOEM, AJPH, Journal of Health Care for the Poor and Underserved (Meharry U, Hopkins Press), Journal of Urban Health**

### 1. Introduction

*1.1 CDCs Social Vulnerability Index*

To examine social vulnerability and community resilience, the CDC in partnership with the Agency for Toxic Substances and Disease Registry (ATSDR) created the Social Vulnerability Index (SVI). The index includes themes that represent socioeconomic status, household composition, race/ethnicity and language, and housing and transportation. The CDC/ATSDR SVI refers to potential negative effects on communities caused by external stresses on human health and describes vulnerabilities of people to natural stress. Such stresses include natural or human-caused disasters, or disease outbreaks (CDC, 2019). The score utilizes 4 themes mentioned previously; theme 1: socioeconomic status; theme 2: household composition & disability; theme 3: minority status & language; theme 4: housing type & transportation. Social vulnerability is used by local health departments to target various services and in the case of COVID-19, the services include vaccination and testing points of distribution. With this index being a key tool that determines who will be able to receive services from local public health, it is very important that we understand if this index truly reflects those who are most at risk for poor health outcomes following disasters. We will explore this association between SVI and COVID-19 mortality to further understand its use.

*1.2 Social Vulnerability Index and COVID-19*

Due to their lack of adequate medical care, transportation, and nutrition, socially vulnerable populations are more at-risk during disasters (Rufat et al., 2015). During the COVID-19 pandemic, socially vulnerable communities suffered disproportionately (Karaye & Horney, 2020a). For example, an analysis showed increased odds of in-hospital death with COVID-19 for older people; men; people of Black, Asian, or mixed ethnicities; and those who live in areas of high socioeconomic deprivation (Bakhai et al., 2020). This can be explained by the systemic inequities that these communities face such as income, environment, education, nutrition, etc. For example, African Americans are more likely to live in environmentally polluted neighborhoods than non-Hispanic Whites (Bell & Ebisu, 2012; Karaye & Horney, 2020a; Perez et al., 2015) and this pollution can cause health issues that lead to COVID-19 morbidity such as asthma and cardiovascular disease (*Asthma and African Americans - The Office of Minority Health*, n.d.). Poor housing and crowded spaces (SVI theme 4) also made it difficult for socially vulnerable communities to remain socially distanced. In addition to increased exposure due to their living spaces, these individuals are more likely to be exposed in the workplace (Rufat et al., 2015). Essential workers and public transit riders are disproportionally composed of racial minorities, which may increase their risk of exposure to and subsequent infection with COVID-19 (Biggs et al., 2021). The socially vulnerable also have less of an opportunity to improve their physical health and diet, leading them to have chronic diseases such as heart disease and diabetes. These comorbidities are associated with poor prognosis in those with COVID-19 (Kruglikov et al., 2020). A recent study found that of the theme-specific SVI measurements, minority status and language (Theme 1) was found to have the strongest relationships with COVID-19 incidence (aRR: 1.36, 95% CI: 1.12-1.49) after adjusting for the other SVI subthemes and population density. For each percentile increase in overall SVI, the COVID-19 incidence increased by a multiplicative factor of 1.52 (95% CI: 1.41-1.65) after adjusting for population density (Biggs et al., 2021). For COVID-19 mortality, a recent study by Johnson et al. found that there is a 1.73-fold greater risk for COVID-19 related death in counties with highest composite vulnerability(Johnson et al., 2021).

## 2. Methods

### *2.1. Data source for COVID-19 deaths and cases*

This study utilized individual level data from a database including Harris County Public Health (HCPH) Jurisdiction residents who tested positive for COVID-19 between March 1, 2020 – March 31, 2022. Eligibility includes residents that reside within HCPH jurisdiction, tested positive for COVID-19 through confirmatory PCR test between March 1, 2020 – March 31, 2022, have address information, were age 19 and older, and underwent an epidemiological investigation either through medical record review or interviewing the case for self-reported information. HCPH serves the third largest county in the United States and is responsible for disease reporting and surveillance of COVID-19; therefore, all COVID-19 testing facilities with HCPH jurisdiction are required to report all positive and negative results to HCPH. Hospitals also report cases and provide medical records, admission, and discharge notes for cases of COVID-19. Epidemiologists and case investigators utilize these medical records to extract relevant case information such as hospital admission date, discharge date, ICU stay, pre-existing conditions, symptoms, etc. They also reach out to hospitals to obtain records for patients who have been reported to us by Electronic Lab Report (ELR). Medical examiner's office (ME), the Institute of Forensic Science (IFS), hospitals, and relatives of deceased residents report deaths due to COVID-19 to HCPH. There are several measures in place to ensure that cases were truly deceased due to COVID-19 and not some other reason such as trauma or another illness and that records were provided to confirm this. Investigators are instructed not to record a deceased COVID-19 case and only lead epidemiologists are allowed to do so after consulting the local health authority. This process increased the validity of deaths related to COVID-19. Only confirmed cases with address information are included in the analysis. A case meets confirmatory laboratory evidence if there is detection of SARS-CoV-2 RNA in a clinical or autopsy specimen using a molecular amplification test.

*2.2 Social Vulnerability Index*

The dataset utilized in this research is the CDC/ATSDR's Social Vulnerability Index (SVI) and is based on the 2018 census data. Each theme has incorporated variables from the U.S Census American Community Survey (ACS) and these variables are presented in table 11. There are several variables in this dataset; however, RPL_Themes (the overall percentile ranking) will be utilized for each theme. For this analysis, the index has been divided into four quartiles 0 - 0.25, 0.25 – 0.50, 0.50 – 0.75, and 0.75 – 1.00. The analysis will look at each theme separately as well as a composite of all themes. SVI will be merged with the COVID-19 datasets by census tract where each individual case will be assigned the index of the census tract the case resides in.

**Table 11**: CDC Social Vulnerability Index (SVI) Themes Defined

| SVI themes | Variable |
|---|---|
| Theme 1: Socioeconomic | % living below poverty line |
| | Unemployment Rate |
| | Per capita income |
| | Percentage with no High School Diploma |
| Theme 2: Household Composition and disability | Aged 65 or older |
| | Aged 17 or younger |
| | Older than age 5 with a disability |
| | Single parent household |
| Theme 3: Minority status and language | Minority |
| | Speaks English "less than well" |
| Theme 4: Housing and transportation | Multi-unit structures |
| | Mobile homes |
| | Crowding |
| | No vehicle |
| | Group quarters |

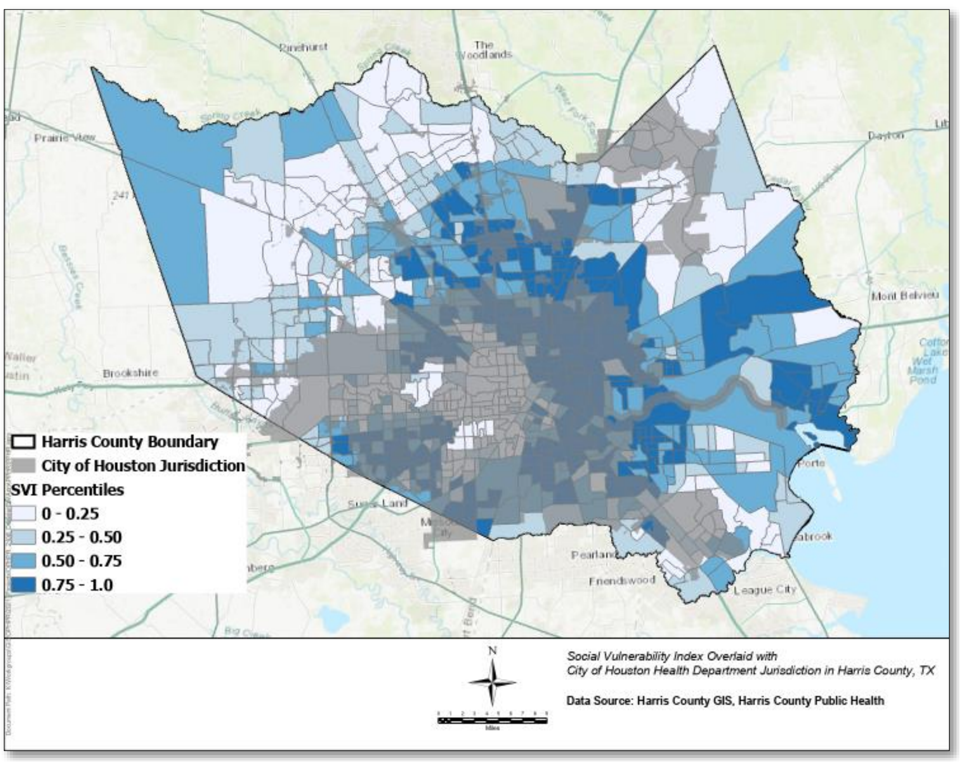


**Figure 4**: Map of Social Vulnerability Index in Harris County Census Tracts with City of Houston Health Department Jurisdiction Overlay

*2.3 Statistical Analysis*

Data were analyzed from March 1, 2020 – March 31, 2022. We used a retrospective observational study design. All data analysis was performed in R studio and ArcGIS Pro behind the HCPH firewall. We fitted logistic regression models to estimate the association between social vulnerability index and the risk of death following SARS-CoV-2 infection. Multivariable and univariable logistic regression was utilized to produce odds ratios and 95% confidence intervals. Multivariable analysis adjusted for individual level demographics, pre-existing conditions, hospitalization status, and exposure to air pollution. The glm2 package in R was used for logistic regression models.

**3. Results**

*3.1 Descriptive characteristics*

We analyzed the association between exposure to census tract level PM2.5 pollution and COVID-19 mortality. The source population included a total of 1,048,575 confirmed COVID-19 cases reported to Harris County Public Health between March 1, 2020, and March 31, 2022. After eligibility criteria were implemented, the study population included a total of 350,233 confirmed COVID-19 cases, of which 3,207 cases did not survive. To note, 698,342 cases were removed due to age being between 0 – 19 years old in compliance with Harris County Public Health privacy rules. There are 786 census tracts in Harris County and the final dataset consisted of 708 unique census tracts.

Table 12 describes characteristics of individuals with positive results from polymerase chain reaction testing for SARS – COV- 2 reported to Harris County Public Health During March 2020 – March 2022. In those that did not survive, there was a greater percentage (16.4%) of individuals in the highest vulnerability category for overall SVI (.75 – 1.00) compared to those that did survive (11.0%). For the second highest vulnerability category (0.50 – 0.75), the same is observed where there was a greater percentage in those that did not survive (32.8%) compared to those that did survive (24.9%). Table 13 describes counts of COVID-19 cases by quartile of SVI and by deceased status. For deceased cases, subtheme 4, housing and transportation, had the highest percentage of cases in the highest vulnerability category (0.75 – 1.00). Additionally, Hispanics make up the highest percentage of cases in the most vulnerable group (Overall SVI = 0.75 – 1.00) (Table 14).

**Table 12**: Characteristics of Individuals with Positive Results of Polymerase Chain Reaction Testing for SARS – COV- 2 Reported to Harris County Public Health During March 2020 – March 2022

| **Characteristic** | **No. (%)** | | |
|---|---|---|---|
| | **Total Cases**<br>N = 350233 | **COVID-19 Deceased**<br>N=3207 | **COVID-19 Survivors**<br>N= 347026 |
| **Age** | | | |
| 20 – 29 | 78921 (22.5%) | 27 (0.8%) | 78894 (22.7%) |
| 30 – 39 | 79078 (22.6%) | 110 (3.4%) | 78968 (22.8%) |
| 40 – 49 | 72948 (20.8%) | 233 (7.3%) | 72715 (21.0%) |
| 50 – 59 | 56484 (16.1%) | 422 (13.2%) | 56062 (16.2%) |
| 60 – 69 | 36474 (10.4%) | 687 (21.4%) | 35787 (10.3%) |
| 70 – 79 | 17767 (5.1%) | 804 (25.1%) | 16963 (4.9%) |
| 80+ | 8561 (2.4%) | 924 (28.8%) | 7637 (2.2%) |
| **Race/Ethnicity** | | | |
| Non-Hispanic White | 75940 (21.7) | 1226 (38.2%) | 74714 (21.5%) |
| Non-Hispanic Black | 41440 (11.8%) | 451 (14.1%) | 40989 (11.8%) |
| Hispanic/Latino | 109270 (31.2%) | 1106 (34.5%) | 108164 (31.2%) |
| Other | 38197 (10.9%) | 236 (7.4%) | 37961 (10.9%) |
| Unknown | 85386 (24.4%) | 188 (5.9%) | 85198 (24.6%) |
| **Sex** | | | |
| Male | 128688 (36.7%) | 1856 (57.9%) | 126832 (36.5%) |
| Female (Ref) | 159546 (45.6%) | 1345 (41.9%) | 158201 (45.6%) |
| Unknown/Other | 61999 (17.7%) | 6 (0.2%) | 61993 (17.9%) |
| **Co-morbidities (YES)** | | | |
| Cardiovascular | 5894 (1.7%) | 1477 (46.1%) | 4417 (1.3%) |
| Hypertension | 16074 (4.6%) | 2235 (69.7%) | 13839 (4.0%) |
| Diabetes | 10692 (3.1%) | 1507 (47.0%) | 9185 (2.6%) |
| Obesity (BMI>=30) | 4471 (1.3%) | 1070 (33.4%) | 3401 (1.0%) |
| **Hospitalized** | | | |
| Yes | 13589 (3.9%) | 2636 (82.2%) | 10953 (3.2%) |
| No | 336644 (96.1%) | 571 (17.8%) | 336073 (96.8%) |
| **Congregate Setting** | | | |
| Yes | 12871 (3.7%) | 779 (24.3%) | 12092 (3.5%) |
| No | 337362 (96.3%) | 2428 (75.7%) | 334934 (96.5%) |
| **Overall SVI Composite** | | | |
| 0.0 – .25 | 94726 (28.0%) | 627 (19.9%) | 94099 (28.1%) |
| .25 – .50 | 121715 (36.0%) | 978 (31.0%) | 120737 (36.0%) |
| .50 – .75 | 84306 (24.9%) | 1033 (32.8%) | 83273 (24.9%) |
| .75 – 1.00 | 37393 (11.1%) | 516 (16.4%) | 36877 (11.0%) |
| **PM2.5 (14 days)** | Avg: 9.45 | Avg: 9.60 | Avg: 9.49 |

**Table 13**: Counts of COVID-19 Cases by Quartile of SVI Subtheme and by Deceased Status

| Variable | Deceased Counts | Survivor Counts |
|---|---|---|
| **SVI Theme 1 (Socioeconomic)** | | |
| Q1 | 578 (18.3%) | 88846 (26.5%) |
| Q2 | 1169 (37.1%) | 129407 (38.6%) |
| Q3 | 1042 (33.0%) | 86831 (25.9%) |
| Q4 | 365 (11.6%) | 29902 (8.9%) |
| **SVI Theme 2 (Household Composition and Disability)** | | |
| Q1 | 466 (14.8%) | 63028 (18.8%) |
| Q2 | 1021 (32.4%) | 116663 (34.8%) |
| Q3 | 856 (27.1%) | 89148 (26.6%) |
| Q4 | 811 (25.7%) | 66147 (19.7%) |
| **SVI Theme 3 (Minority Status and Language)** | | |
| Q1 | 670 (21.2%) | 89759 (26.8%) |
| Q2 | 1093 (34.7%) | 116417 (34.8%) |
| Q3 | 931 (29.5%) | 93053 (27.8%) |
| Q4 | 460 (14.6%) | 35757 (10.7%) |
| **SVI Theme 4 (Housing and Transportation)** | | |
| Q1 | 883 (28.0%) | 121903 (36.4%) |
| Q2 | 853 (27.0%) | 100961 (30.1%) |
| Q3 | 603 (19.1%) | 60377 (18.0%) |
| Q4 | 815 (25.8%) | 51745 (15.4%) |

**Table 14**: Percentage of COVID-19 Cases Falling in SVI Categories by Race/Ethnicity

| Overall SVI | Quartile 1 (0.00 - 0.25) | Quartile 2 (0.25 – 0.50) | Quartile 3 (0.50 – 0.75) | Quartile 4 (0.75 – 1.00) |
|---|---|---|---|---|
| **Black** | 9% | 13% | 13% | 9% |
| **Hispanic/Latino** | 20% | 31% | 39% | 49% |
| **Other** | 13% | 11% | 9% | 9% |
| **Unknown** | 26% | 26% | 24% | 23% |
| **White** | 32% | 19% | 14% | 10% |

### *3.2 Logistic Regression Analysis*

Table 15 shows the results of multivariable logistic regression analysis. When looking at the crude OR for overall social vulnerability index (SVI) and each SVI subtheme, each had a significant association with COVID-19 mortality. Based on the adjusted logistic regression models, subtheme2 house composition and disability and subtheme 3 minority and language were not significantly associated with COVID-19 mortality as the 95% confidence interval crossed over 1 in all models. In model 1, subtheme 4, housing and transportation, and subtheme 1, socioeconomic, had the strongest association with COVID-19 mortality. In model 1 after adjusting for all SVI subthemes, the odds of COVID-19 mortality were 43% higher in the highest vulnerability category of subtheme 1 compared to those in the lowest vulnerability category of subtheme 1. Additionally in model 1, the odds of COVID-19 mortality were 75% higher in the third highest vulnerability category of subtheme 1 compared to those in the lowest vulnerability category of subtheme 1. In model 1, subtheme 4, the odds of COVID-19 mortality were 79% higher in the highest vulnerability category compared to those in the lowest vulnerability category. After adjusting for age, race, and gender in model 2, the odds of COVID-19 mortality were 62% higher in the highest vulnerability category of subtheme 1 compared to those in the lowest vulnerability category of subtheme 1. Additionally in model 2, the odds of COVID-19 mortality were 34% higher in the highest vulnerability category of subtheme 4 compared to those in the lowest vulnerability category of subtheme 4.

In model 3, after adjusting for age, race, gender, PM2.5 exposure, obesity, hypertension, CVD, and diabetes, the odds of COVID-19 mortality were 84% higher in the highest vulnerability category of subtheme 1 compared to those in the lowest vulnerability category of subtheme 1. Additionally, the odds of COVID-19 mortality were 33% higher in the highest vulnerability category of subtheme 4 compared to those in the lowest vulnerability category of subtheme 4.

Overall SVI had a significant association with COVID-19 mortality in all models. The odds of COVID-19 mortality in the highest vulnerability category of overall SVI were 2.10 times the odds of COVID-19 mortality in the lowest vulnerability category. In model 2, after adjusting for age, race, and gender, the odds of COVID-19 mortality in the highest vulnerability category were 2.03 times the odds of COVID-19 mortality in the lowest vulnerability category. In model 3, after adding pre-existing chronic disease and PM2.5 exposure, the odds of COVID-19 mortality in the highest vulnerability category were 1.77 times the odds of COVID-19 mortality in the lowest vulnerability category.

**Table 15:** Logistic Regression Model Outputs for the Outcome COVID-19 Death in COVID-19 Cases Reported Between March 1, 2020 – March 31, 2022 to Harris County Public Health Jurisdiction Where SVI is the Exposure.

| Variable | Crude OR | Model 1[a] adjusted OR | Model 2[b] adjusted OR | Model 3[c] adjusted OR |
|---|---|---|---|---|
| **Overall SVI *** | | | | |
| 0.00 – 0.25 (Ref) | Ref | | Ref | Ref |
| 0.25 - 0.50 | 1.22 [1.10 – 1.34] | | *1.32 [1.19 – 1.47] | *1.20 [1.06 – 1.36] |
| 0.50 – 0.75 | 1.86 [1.69 – 2.06] | | *1.81 [1.63 – 2.01] | *1.62 [1.43 – 1.84] |
| 0.75 – 1.00 | 2.10 [1.87 – 2.36] | | *2.03 [1.79 – 2.30] | *1.77 [1.53 – 2.05] |
| **Theme 1** | | | | |
| 0.00 – 0.25 (Ref) | Ref | Ref | Ref | Ref |
| 0.25 - 0.50 | 1.39 [1.26 – 1.54] | 1.35 [1.19 – 1.53] | 1.36 [1.20 – 1.55] | 1.42 [1.23 – 1.65] |
| 0.50 – 0.75 | 1.84 [1.67 – 2.04] | 1.75 [1.48 – 2.07] | 1.69 [1.42 – 2.00] | 1.81 [1.48 – 2.23] |
| 0.75 – 1.00 | 1.88 [1.64 – 2.14] | 1.43 [1.16 – 1.76] | 1.62 [1.30 – 2.02] | 1.84 [1.42 – 2.39] |
| **Theme 2** | | | | |
| 0.00 – 0.25 (Ref) | Ref | Ref | Ref | Ref |
| 0.25 - 0.50 | 1.18 [1.06 – 1.32] | 1.06 [0.94 – 1.19] | 1.04 [0.92 – 1.17] | 1.02 [0.89 – 1.18] |
| 0.50 – 0.75 | 1.30 [1.16 – 1.46] | 0.99 [0.87 – 1.13] | 0.97 [0.85 – 1.10] | .93 [ 0.79 – 1.09] |
| 0.75 – 1.00 | 1.66 [1.48 – 1.86] | 1.08 [0.94 – 1.24] | 1.03 [0.90 – 1.19] | .93 [0.78 – 1.10] |
| **Theme 3** | | | | |
| 0.00 – 0.25 (Ref) | Ref | Ref | Ref | Ref |
| 0.25 - 0.50 | 1.26 [1.14 – 1.39] | 0.96 [0.86 – 1.08] | 1.11 [.98 – 1.24] | 1.00 [0.87 – 1.15] |
| 0.50 – 0.75 | 1.34 [1.21 – 1.48] | 0.77 [0.67 - 0.89] | 0.99 [.85 – 1.15] | 0.87 [0.73 – 1.04] |
| 0.75 – 1.00 | 1.72 [1.53 – 1.94] | 0.95 [0.79 – 1.14] | 1.10 [.91 – 1.33] | 0.92 [0.73 – 1.15] |
| **Theme- 4** | | | | |
| 0.00 – 0.25 (Ref) | Ref | Ref | Ref | Ref |
| 0.25 - 0.50 | 1.17 [1.06 – 1.28] | 1.03 [.93 – 1.15] | 0.99 [.89 – 1.10] | 1.04 [0.91 – 1.18] |
| 0.50 – 0.75 | 1.38 [1.24 – 1.53] | 1.14 [1.01 – 1.29] | 1.05 [.93 – 1.20] | 1.09 [0.93 – 1.27] |
| 0.75 – 1.00 | 2.17 [1.98 – 2.39] | 1.79 [1.59 – 2.03] | 1.34 [1.18 – 1.52] | 1.33 [1.14 – 1.54] |

a: Model 1: DeceasedCOVID19 ~ Theme 1 + Theme 2 + Theme 3 + Theme4
b: Model 2: DeceasedCOVID19 ~ Age + Race + Gender + Theme 1 + Theme 2 + Theme 3 + Theme 4
* DeceasedCOVID19 ~ Age + Race + Gender + Overall_SVI
c: Model 3: DeceasedCOVID19 ~ PM2.5 + Age + Race + Gender + Obesity + CVD + Diabetes + Hypertension + Theme 1 + Theme 2 + Theme 3 + Theme 4
*DeceasedCOVID19 ~ PM2.5 + Age + Race + Gender + Obesity + CVD + Diabetes + Hypertension + Overall_SVI

## 4. Discussion

This multivariable analysis showed that overall social vulnerability index was positively associated with COVID-19 mortality even after adjusting for relevant factors: age, race, gender, pre-existing chronic health conditions, and $PM_{2.5}$ pollution exposure. However, after adjusting for all 4 subthemes and relevant factors, only subtheme 1, socioeconomic, and subtheme 4, housing and transportation, were significantly associated with COVID-19 mortality in at least one category. This is another reflection of historic redlining practices that have created an ongoing cycle of inequities in low-income communities (Richardson et al., 2020). Persons with less economic resources and lower socioeconomic status are more likely to have lower education attainment. With no high school diploma, individuals are more likely to have an hourly-paying job that was considered "essential" during the pandemic lockdown. These individuals are more likely to be exposed to COVID-19 at work where others who had the ability to work remotely were more protected from contracting the disease (Rollston & Galea, 2020). Additionally, housing and transportation is important. With no vehicle, individuals are likely taking public transportation. Both public transportation and working in person during COVID-19 lockdowns increase the number of exposures to COVID-19. Mortality also becomes more of a possibility with the increasing number of exposures to COVID-19 (Helle et al., 2021).

Previous studies found that in states in the northwestern and northeastern parts of the United States, minority status and language was more predictive of COVID-19 case counts than housing and transportation. However, in the gulf coast states like Texas, vulnerability to COVID-19 was better explained by housing and transportation (Karaye & Horney, 2020c). This is consistent with our analysis. Without adjusting for any other factors, subtheme 4, housing and transportation, was most strongly associated with COVID-19 mortality. After adjusting for age, race, gender, $PM_{2.5}$ exposure, and pre-existing chronic diseases, subtheme 1, socioeconomic, and subtheme 4, housing and transportation, were still positively associated with COVID-19 mortality while the other two subthemes showed non-significant results. With each addition of external factors such as $PM_{2.5}$ exposure and pre-existing chronic conditions to the model, there is a stronger association between subtheme 1, socioeconomic, with COVID-19 mortality. This could mean that socioeconomic status plays a critical role in vulnerability to COVID-19 mortality despite one's pre-existing chronic disease status. Social vulnerability likely plays a critical role in COVID-19 outcomes and SVI was and is still utilized by HCPH to target vaccination, testing, and outreach for COVID-19. With SVI being a key indicator for residents' access to HCPH resources, an analysis showing this indictor as a predictor for poor outcomes following COVID-19 illness is extremely important. This analysis infers that local health departments should continue to use this index among others as an indicator for targeting public health intervention such as PPE, outreach, testing, and vaccination during emergencies such as the COVID-19 pandemic.

*Limitations*

Although previous studies found that population density did not distort the relationship between SVI and COVID-19 incidence (Biggs et al., 2021). This was not assessed at the census tract level. Further studies should look at population density as part of multivariable analysis to adequately assess the association. Population density is likely to impact any respiratory or airborne disease transmission. Due to privacy consideration, SVI was taken as a categorical variable instead of a continuous one. Future research should use SVI as a continuous variable in analysis. This would allow researchers to understand what the risk of COVID-19 mortality is based on a 1 percentile increase in SVI. The largest limitation of this study is that our source population only included cases reported to Harris County Public Health and did not include cases that resided in the City of Houston. The City of Houston has the largest concentration of highly vulnerable populations according to the CDCs SVI and is seen in (Figure 1).

**5. Conclusion**

The findings in this paper support many arguments that the United States faces significant challenges in its handling of the COVID-19 epidemic, particularly when it comes to the social determinants of health (Rollston et al., 2020). Local health department and emergency management initiatives to address the social determinants of health in strategic planning are needed to address not only the health impacts, but also the mental and financial stress related to the COVID-19 pandemic that we are currently seeing in socially vulnerable communities. This research informs public health planners on the community level factors that may be increasing morbidity and mortality to be better prepared for future infectious disease response efforts. SVI is easily accessible from the CDC’s website and is provided in small geographic units like the census tract for more granular targeting at the local jurisdiction level. This research also adds to the growing body of literature on the CDC’s Social Vulnerability Index by demonstrating the importance of the housing and transportation subtheme that has a stronger association with COVID-19 mortality along the gulf coast. The disparities we are seeing in the current COVID-19 pandemic must be addressed through bold policy action and societal investment to prevent the same disparities from occurring in future epidemics or pandemics.

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# CONCLUSION

This analysis used multivariable logistic regression modelling to determine the odds of COVID-19 mortality based on the following exposures: $PM_{2.5}$ air pollution, pre-existing diabetes, cardiovascular disease, hypertension, obesity, and social vulnerability index. It was estimated that the odds of COVID-19 mortality increased by 6% for every 1μg/$m^3$ increase in the average of 14-day $PM_{2.5}$ levels and increased by 3% for every 1μg/$m^3$ increase in the average 28-day $PM_{2.5}$ levels when adjusting for age, race, gender, social vulnerability index, and pre-existing diabetes, obesity, cardiovascular disease, and hypertension.

Further, obesity was the strongest predictor of COVID-19 mortality among all pre-existing conditions assessed in this analysis. The odds of COVID-19 mortality in those reporting obesity as a pre-existing condition were 11.19 times the odds of mortality in those who did not report obesity when adjusting for age, race, gender, pre-existing cardiovascular disease, hypertension, $PM_{2.5}$ pollution exposure, and social vulnerability index. Additionally, the odds of COVID-19 mortality in those with hypertension were 4.79 times the odds of mortality in those who did not report hypertension. For cardiovascular disease the odds were 3.73 and diabetes 2.07.

Finally, the odds of COVID-19 mortality in the highest vulnerability category of overall SVI were 2.10 times the odds of COVID-19 mortality in the lowest vulnerability category. After adjusting for age, race, gender, PM2.5 exposure, obesity, hypertension, CVD, and diabetes, the odds of COVID-19 mortality were 84% higher in the highest vulnerability category of subtheme 1 compared to those in the lowest vulnerability category of subtheme 1. Subtheme 1, socioeconomic and subtheme 4, housing and transportation, had the strongest association with COVID-19 mortality.

Unlike most other studies in the literature on COVID-19, this study was able to look at the association of COVID-19 mortality with air pollution and social vulnerability index at the individual level. No other studies have been published using individual level data from Harris County to assess the association between $PM_{2.5}$ pollution and COVID-19 mortality. This individual level analysis can help inform Harris County Public Health strategies to target populations that may be more at risk for mortality following COVID-19. Because air pollution is associated with an increased risk of mortality from COVID-19, pollution control services should remain one of the essential services that county government provides during public health emergencies such as a pandemic to help reduce morbidity and mortality within the Harris County community. Similarly, chronic disease prevention should be an essential service that remains staffed with resources during public health emergencies such as the COVID-19 Pandemic to reduce morbidity and mortality as evidenced in this research.

There are limitations in this study that myself or other researchers should address in the continuation of the research aims presented in this dissertation. This analysis does not capture the odds of COVID-19 mortality in all of Harris County, rather this is only generalizable to the population that Harris County Public Health serves. Additionally, there were two methods of retrieving information on pre-existing chronic diseases for individuals which could lead to a bias of exposure misclassification. One method was medical record review; however, the other was through self-reporting which can lead to an information bias for these individuals. Lastly, the $PM_{2.5}$ data used in this analysis was a 10km grid rather than a 1km grid. This grid size difference impacted the ability to detect more variation in smaller geographic units. The $PM_{2.5}$ data was also from 2019 and this study assumed that 2019 data was similar to 2020 data.

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