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County-Level Social Determinants of Health and COVID-19 Health Outcomes

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ABSTRACT

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Social determinants of health are associated with a variety of negative health outcomes, including COVID-19 morbidity and mortality. However, most research evaluating this relationship have been case studies, retrospective cohort studies, and case series studies and/or have used use analytic techniques, such as linear regression, that can struggle to adequately model the social determinants' complex nature. This study used United States county-level social determinants of health data and March 2020-December 2020 COVID-19 morbidity and mortality data. Structural equation modeling was used to develop a latent measurement model for the social determinants of health. Substantial cross-loadings among the social determinants of health precluded the estimation of the originally proposed measurement model. However, a more parsimonious model was estimated, with adequate factor loadings and model fit statistics. A multi-level, two-part structural equation model further validated the relationship between social determinants of health and COVID-19 morbidity and mortality. The model's predictive performance was moderate to strong, which validates and extends previous research using structural equation modeling to evaluate the relationship between social determinants of health and COVID-19 morbidity. The study adds to the theoretical and empirical foundation supporting the use of structural equation modeling to study the social determinants of health.

Keywords: social determinants of health, structural equation modeling, COVID-19, morbidity, mortality

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Health equity is a societal moral imperative (Berwick, 2020) achieved when "everyone has a fair and just opportunity to be as healthy as possible" (Robert Wood Johnson Foundation, 2021, para. 1). The opportunity to be healthy is considered a fundamental human right (World Health Organization [WHO], 2021). Fortunately, achieving health equity has become a core commitment for national governments as well as prominent international and health care organizations around the world such as the World Health Organization (WHO) (2021), United Nations (n.d.), United States Centers for Disease Control and Prevention (CDC) (2020), and National Academies of Sciences, Engineering, and Medicine (NASEM) (2021).

Unfortunately, progress toward health equity has been slow and much of the world's population still lacks access to essential health resources, such as clean air and water, nutritious food, safe housing, preventive health care, and basic medical interventions (WHO, 2021). Such health inequities have been particularly prevalent and persistent in the United States, largely due to the influence of social determinants of health (NASEM, 2021; Singh et al., 2017). Social determinants of health, such as a person's economic stability, access to quality healthcare and education, neighborhood, race, ethnicity, gender, and sexual orientation have a tremendous influence on health and mortality (Marmot, 2015).

The COVID-19 pandemic in particular has brought the influence of social determinants of health into stark focus. A substantial body of research suggests COVID-19 morbidity and mortality rates have been significantly higher for people in poverty (Little et al., 2021; McLaughlin et al., 2021), with lower health literacy (Wang et al., 2021), without health insurance (Wray et al., 2021), who live in overcrowded areas

(Kamis et al., 2021), and/or are from racial and ethnic minority groups (Chen & Krieger, 2021; Dalsania et al., 2021; Gershengorn et al., 2021; Mackey et al., 2021; Magesh et al., 2021; Sze et al., 2020).

While evidence about the relationship between social determinants and COVID-19 morbidity and mortality is compelling, much of it is derived from studies using methodological designs that do not support hypothesis testing and generalization of their results (Nissen & Wynn, 2014; Upshaw et al., 2021) (e.g. case studies, retrospective cohort studies, and case series studies), and/or use analytic techniques, such as linear regression, that can struggle to adequately model the social determinants' complex nature. This study's purpose was to build upon prior research by using structural equation modeling to 1) develop a latent measurement model for the social determinants of health, and 2) further test some of the proposed relationships between social determinants of health and COVID-19 morbidity and mortality. Structural equation modeling was used to analyze United States county-level data on social determinants of health, known COVID-19 risk factors, and COVID-19 morbidity and mortality.

The findings indicate a parsimonious measurement model is an adequate measurement model for social determinants of health in this context, and that county-level social determinants of health explain a significant amount of the variability in county-level COVID-19 case rates and death rates. The findings also illustrate some of the theoretical and empirical challenges and opportunities associated with using structural equation modeling to study the social determinants of health. These findings further validate the relationship between social determinants of health and COVID-19 health outcomes, and help lay a foundation for additional analyses of the relationship between health and its social determinants.

Literature Review

Social Determinants of Health

The social determinants of health are a significant source of health inequity that must be addressed. Social determinants of health are the "conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks" (U.S. Department of Health and Human Services [HHS], 2020b, para 1). Social determinants of health include many aspects of a person's life. The HHS model (see Figure 1) groups the social determinants into five categories: (1) economic stability, (2) education access and quality, (3) health care access and quality, (4) neighborhood and built environment, and (5) social and community context. While other models and categories for the social determinants of health have been proposed, a general consensus across academic institutions, public health professionals, not-for-profit organizations, governments, urban planners, and healthcare organizations supports the categories in the HHS social determinants of health model (Elias et al., 2019). Table 1 includes definitions and example indicators for each of these categories.

Social determinants have a significant influence on many aspects of a person's health. This influence has been well-documented (Lucyk & McLaren, 2017). For example, in terms of life expectancy, social determinants of health are associated with a 35-year difference in average life expectancy across countries (Commission on Social Determinants of Health, 2008), and a 20-year difference within the United States (Marmot, 2015). Some other health impacts of social determinants include chronic lung disease (Assari et al., 2020), depression (Assari et al., 2018), less medication adherence (Wilder et al., 2021), mental health issues (Abdi et al., 2021), worse maternal and birth outcomes (Amjad et al., 2019), higher infant mortality (Reno & Hyder, 2018), more child maltreatment (Hunter & Flores, 2021), poorer health outcomes for children with congenital heart disease (Davey et al., 2020), low back pain (Karran et al., 2020), decreased sexual health (MacPhail & McKay, 2018); increased mortality from opioid use (Sugarman et al., 2020), greater mortality after heart failure (Sterling et al., 2020), and more childhood accidents (Ribeiro et al., 2019).

Individually, and in combination, social determinants influence people's opportunities to live healthy lives (Lucyk & McLaren, 2017). The mechanisms by which these social determinants influence health are "numerous, interconnected, and complex" (Figueroa et al., 2020, p. 1553). For example, a person experiencing economic instability may necessitate working in a hazardous environment, living in a neighborhood with more crime, poorer air quality, and less access to healthy foods, quality education, and healthcare. Or, a person living in a social context in which they are marginalized due their racial, ethnic, gender, or sexual identity may experience fewer opportunities for education, employment, safety, proper health care, and access to critical social support systems. As illustrated in these examples, the interconnectedness of the social determinants of health means any one social determinant is often accompanied by others.

The ability to measure the social determinants of health, and incorporate those measures into appropriate statistical models, is necessary to better understand their impact on health and evaluate interventions intended to mitigate that impact. While there is consensus supporting the social determinants of health categories found in the HHS (2020b) model, there is less agreement about how to measure the social determinants of health (Elias et al., 2019). A systematic review of tools used to measure social determinants of health (Elias et al., 2019) illustrates this lack of consensus. Elias et al. (2019) identified 18 different measurement tools actively used or updated since 2008. Collectively, those tools contained 676 unique indicators of social determinants of health, 509 of which were only used in one tool. Differences across measurement tools and indicators makes meta-analyses and comparisons across studies difficult. Although resolving those differences is beyond the scope of this thesis, rationale for selecting the indicators used in the present study is provided so readers can understand the conceptual basis guiding the subsequent analyses. A substantial, sustained effort among those studying the social determinants of health will be needed to achieve consensus regarding which indicators are both conceptually aligned with the HHS (2020b) model and practical for empirical analyses. As described in detail later, a primary purpose of the present study is to develop and evaluate a statistical measurement model that may be useful for future research on social determinants of health.

COVID-19

COVID-19, more formally known as Severe Acute Respiratory Syndrome Coronavirus-2, refers to a coronavirus-related illness, originating in late 2019, which quickly spread to become a global pandemic (CDC, 2020). Coronaviruses are actually quite common in humans and animals, and generally cause respiratory infections with fairly mild symptoms and no long-term complications. However, some coronaviruses, such as severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), can cause severe illness and even death. Often, the most impactful coronavirus strains are those that circulate among animals and then crossover to infect humans. The novelty of these coronavirus strains makes them particularly hard for human immune systems to recognize and fight off. In the meantime, the virus replicates within its human hosts and is spread (CDC, 2020).

COVID-19 has been particularly dangerous for several reasons. First, the initial strains of the virus were novel, so the general population had not developed any natural immunity to it. Second, infections were difficult to detect. The original strain of the virus could incubate and replicate for 2-14 days before causing any symptoms. In many cases, the symptoms were mild or even undetectable, thus allowing people to unknowingly spread COVID-19 to others. Third, COVID-19 spreads easily, most likely through respiratory droplets. Simply talking can propel infectious droplets into the air, which can enter the mouths and noses of others nearby. Fourth, COVID-19 infections can have severe consequences. While some people briefly experience mild symptoms or none at all, others' symptoms can last months and may be severe enough to cause death. Finally, during the first year of the pandemic, there was little knowledge of which available antiviral treatments were effective against COVID-19, making supportive care the primary treatment strategy (CDC, 2020).

As of this writing, COVID-19 infections are continuing to spread, causing illness and death around the world. On June 27, 2022, there were over 546.3 million reported cases and over 6.3 million deaths globally, with the United States reporting nearly 87 million of those cases and over 1 million deaths. Fortunately, several effective vaccines have been developed and are being distributed and administered in many countries. Globally, over 11.6 billion doses have been administered, with over 591 million doses administered in the United States (Center for Systems Science and Engineering at Johns Hopkins University, 2022).

COVID-19 and Social Determinants of Health

There is a growing body of evidence supporting the relationship between the social determinants of health and COVID-19 morbidity and mortality. As with prior pandemics, the impact of COVID-19 has disproportionately been borne by the vulnerable in society (Bambra et al., 2020; Bonanad et al., 2020; Izurieta et al., 2021; Singhal et al., 2021; Sze et al., 2020; Tan et al., 2022). Risk factors for COVID-19 include poverty, living in a rural area, household crowding, economic segregation, being uninsured, smoking, obesity, fewer available healthcare providers and services, less social capital, and being of a race other than white (Chen & Krieger, 2021; Peters, 2020).

Each category in the HHS (2020b) social determinants of health model has implications for both health generally and COVID-19 health outcomes specifically. As such, the HHS (2020b) model provides a reasonable conceptual framework for modeling risk factors for COVID-19 morbidity and mortality. Rationale for this supposition is provided in the following subsections.

Economic Stability

Economic stability has been linked to both general health and COVID-19 specific health outcomes. Not having reliable access to the financial means necessary to meet basic needs is associated with higher rates of illness, psychological stress, anxiety, depression (Viseu et al., 2018), and job insecurity and injury (Petitta et al., 2020). Indicators of economic instability, such as unemployment, have long been associated with poorer general health (Hollederer, 2019). Evidence suggests a similar relationship between COVID-19 related health risk and socioeconomic status (Thomason et al., 2021), unemployment and individual-level poverty (Goutte et al., 2020; Sun et al., 2021; Yoshikawa & Kawachi, 2021), and county-level economic factors (Little et al., 2021; McLaughlin et al., 2021). Given the similar relationships between economic stability and both general heath and COVID-19 morbidity and mortality, it follows that economic stability category should be considered when modeling COVID-19 related risk.

Education Access and Quality

Education access and quality are also relevant to health generally and COVID-19 outcomes specifically. Education is thought to influence health through several difference mechanisms, but most directly through the ability to perceive the need for healthcare and seek appropriate healthcare options (Levesque et al., 2013). Less directly, education may also influence the ability to access locations where healthcare is provided, the ability to pay for healthcare, and the ability to engage effectively with the healthcare system itself (Levesque et al., 2013; Zimmerman & Woolf, 2014). While the empirical relationship between individual education levels and general health is under debate (Xue et al., 2021), the positive health benefits of parental education on children is well-established (Balaj et al., 2021), as is the relationship between literacy and life expectancy (Wirayuda & Chan, 2021). General literacy is a precursor to health literacy, which has a positive relationship with better COVID-19 outcomes (Bin Naeem, & Kamel Boulos, 2021; Patil et al., 2021; Wang et al., 2021). Greater health literacy is associated with the ability to recognize and avoid spreading misinformation, as well as adherence to protective health behaviors supported by science and public health officials (Patil et al., 2021; Wang et al., 2021). Based on this reasoning, education access and quality are important for modeling risk for COVID-19 morbidity and mortality.

Health Care Access and Quality

Health care access and quality have implications for both general and COVID-19-specific health outcomes. Access to quality healthcare is shaped by a dynamic interaction between both individual and system-level factors (Levesque et al., 2013). For example, while a person with limited education may struggle to recognize their health needs or engage effectively with the healthcare system, health systems can support them through outreach campaigns offering health information, screening opportunities, and access to healthcare navigators. Similarly, people experiencing economic instability may not have the financial means to pay for healthcare directly, charity care provided by health systems and government-subsidized health insurance can help overcome their financial barriers (Levesque et al., 2013). Health insurance, a primary indicator of access to healthcare, has been linked to improved health status (Barker & Li, 2020; Gopalan et al., 2022; Yeung et al., 2021; Courtin et al., 2020). Similarly, health insurance has been linked to improved COVID-19 morbidity and mortality (Hawkins, 2020; Hawkins et al., 2020). A portion of this relationship may be attributable to higher COVID-19 testing rates in areas where more people are insured (Mody et al., 2021), and/or insured people having access to and utilizing more effective health care services than those who are not (Lowe et al., 2021). Including access to quality healthcare when modeling risk for COVID-19 morbidity and mortality has both conceptual and empirical support.

Neighborhood and Built Environment

Neighborhood and built environment influence people's living conditions, and ultimately their health. People's living conditions can influence their risk for psychological stress, physical injury, violence, infectious disease, exposure to environmental toxins, as well as access to opportunities for physical activity, information, and leisure. Neighborhood (Barnett et al., 2018; Lee, Donley et al., 2021) and housing (Alidoust & Huang, 2021) have both been empirically linked to health outcomes. Overcrowding is a specific aspect of the housing environment that is associated with COVID-19 morbidity and mortality (Bryan et al., 2021; Khanijahani et al., 2021; Kamis et al., 2021; Rios et al., 2022; Varshney et al., 2021). Because COVID-19 is an infectious disease, crowded conditions make it harder to mitigate its spread through quarantining and appropriate social distancing. Increased disease transmission in crowded areas ultimately leads to more COVID-19 infections and deaths (Bryan et al., 2021; Leibowitz et al., 2021). Including access to quality healthcare when modeling risk for COVID-19 morbidity and mortality has both conceptual and empirical support.

Social and Community Context

Social and community context, including social participation and social connections are associated with health (Calderón-Larrañaga et al., 2021). Although additional research is needed to better understand how relationships influence health (Lem et al., 2021), social support, social participation, and social networks are associated with healthy eating (Emmons et al., 2007; Nishio et al., 2021) and physical activity (Emmons et al., 2007; Kim, Jung, et al., 2020), tempered responses to social stressors (Eisenberger at al., 2007), and reduced inflammatory markers (Loucks et al., 2006). It follows that health is worse in social and community contexts characterized by less robust social support, social participation, and social networks.

Racial and/or ethnic discrimination are features of a toxic social and community context, and are linked to poorer health (Benner et al., 2018; Carter et al., 2019). Recent meta-analyses (e.g. Magesh et al., 2021; Mude et al., 2021; Tan et al., 2022) also indicate being of a race other than white is associated with greater risk for COVID-19 infection and mortality. The relationship between ethnicity and COVID-19 morbidity and mortality is generally supported, but somewhat mixed. For example, Mackey et al's, (2021) systematic review identified an association between Hispanic ethnicity and increased COVID-19 morbidity and mortality than the non-Hispanic white population. Gross et al's (2020) cross-sectional study of 28 states' data similarly identified Hispanic ethnicity was related to higher mortality rates. Sze et al's (2020) additionally found individuals of Black or Asian ethnicity had increased COVID-19 infections rates, compared to White individuals. However, Raharja et al's (2021) meta-analyses identified Hispanic ethnicity was not associated with higher COVID-19 mortality. The discrepancy in findings may be attributable to inadequate representation of people in ethnic minorities in the data sets used (Labgold et al., 2020; Mackey et al., 2021). This possibility is supported by Labgold et al. (2020), who did find an association between ethnicity and COVID-19 morbidity and mortality, but noted that their estimates improved significantly after using quantitative bias analysis to account for non-random missing ethnicity information in the data set. The information presented here provides strong conceptual and empirical support for considering social and community context when modeling risk for COVID-19 morbidity and mortality.

Structural Equation Modeling

Structural equation modeling is a family of statistical methods that has the potential to contribute significantly to the study of social determinants of health. Many epidemiological studies addressing social factors related to COVID-19 morbidity and mortality use linear or logistic regression (e.g. Fielding-Miller et al., 2020). While regression is a powerful analytic technique, structural equation modeling may have some unique conceptual and empirical advantages over regression (Hox, 2013; Lei & Wu, 2007) for studying social determinants of health. These potential advantages include structural equation modeling's use of latent variables, ability to model complex relationships, and capacity for hypothesis testing. Each potential advantage is discussed in more detail below.

Latent Variables

Structural equation modeling includes measurement models with latent variables. Latent variables are variables are of interest in a model, but cannot be measured directly. Because direct measurement is not possible, the latent variable is represented in the measurement model by using a combination of other variables (called indicators) that can be measured and are thought to be representative of the latent variable (Heck & Thomas, 2020).

The conceptual advantage of using latent variables is that they can be developed to incorporate multiple aspects of complex phenomena (Heck & Thomas, 2020). This is important because concepts like social determinants of health cannot be measured directly and are multi-faceted. For example, a county may have a low unemployment rate, but still have substantial poverty and overcrowding due to low wages and employment inequities associated with race and ethnicity. A latent variable is well-suited for modeling the complex nature of social determinants of health because it can simultaneously incorporate indicators for each of these factors. Modeling these indicators as a single, latent variable reflects their conceptual relatedness and incorporates more of the conceptual complexity of social determinants of health into the model. Using latent variables allows for a statistical model that is better aligned with the conceptual model it is meant to represent (Tarka, 2018).

The primary empirical advantages of using latent variables arise from explicitly modeling the sources of measurement error associated with latent variables (Heck & Thomas, 2020). First, modeling sources of measurement error makes it possible to evaluate and improve the latent variable's ability to measure what it was intended to measure. Consider an analysis in which one social determinant of health indicator contributes significant measurement error to the latent variable. A researcher could then make an informed decision about how to manage that indicator, with consideration for both the conceptual reasons for including that indicator as part of the variable and the empirical information about its contribution to measurement error.

Second, modeling sources of measurement error makes it possible to partition out the influence of measurement error when evaluating relationships among variables in the model (Heck & Thomas, 2020). As a result, estimated coefficients representing those relationships are more reliable. Building on the prior example, consider a situation in which a researcher wants to understand how social determinants of health relate to a county-level health indicator. By modeling social determinants of health as a latent variable, the researcher ensures the variation in social determinants of health attributable to measurement error is not modeled as part of the relationship between social determinants and the health indicator.

Complex Models & Hypothesis Testing

Structural equation modeling is also well-suited to complex modeling and hypothesis testing (Lei & Wu, 2007; Tarka, 2018). Structural equation modeling can be used for complex models that simultaneously include measurement models, latent and observed variables, interaction effects among variables, multiple dependent variables, longitudinal data, and multiple levels of measurement (e.g. students nested within classrooms that are nested within schools) (Heck & Thomas, 2020). The capacity for complex modeling makes it possible to develop statistical models that reflect the conceptual relationships among the variables being studied (Tarka, 2018), which results in better hypothesis testing. While a series of regression models could be used to replicate many functions of a complex structural equation model, doing so would be resource-intensive and increases the risk of obtaining false-positive results. While using structural equation modeling for hypothesis testing does have potential pitfalls to avoid (Tarka, 2018), a well-fitted structural model with a sound theoretical foundation can provide substantial information about the hypotheses being tested.

Limitations of Extant Research and Research Purpose

While evidence about the relationship between social determinants and COVID-19 morbidity and mortality is compelling, our understanding of that relationship could be strengthened using methods better suited to modeling their complexity. Although structural equation modeling has potential to contribute to our understanding of social determinants of health, extensive searches of the literature have only yielded one study in which the social determinants of health were conceptualized as a latent variable in a structural equation model (Lee, Paul, et al., 2021). Lee, Paul, et al. (2021) used individual-level data to study the relationship between social determinants of health and COVID-19 diagnosis. Their model was able to account for 27% of the variance in COVID-19 diagnoses, and demonstrated the potential benefits of using this approach to study social determinants of health.

Therefore, the primary purpose of this study, was to build upon prior research by 1) using structural equation modeling to develop a measurement model for social determinants of health (Figure 2), and 2) further test some of the proposed relationships between social determinants of health and COVID-19 morbidity and mortality (Figure 3). If this approach proves practical and effective, structural equation modeling should be strongly considered as a statistical method for additional research on the social determinants of health and their relationship with other indicators of public health.

Methods

Sample and Procedures

Data for this study was curated from several different sources, as no current, existing data sets with adequate measures of social determinants of health were available. Of the 18 tools Elias et al. (2019) identified for measuring the social determinants of health, only four address all the social determinant categories in the

(2020b) model (Elias et al., 2019). Only three of those four tools had been used to collect a national data set, and none had been updated more recently than 2014. Thus, this study used United States' county-level data from the American Community Survey (ACS) (United States Census Bureau, 2020a), the National Center for Education Statistics (NCES) (n.d.), Google Community Mobility Reports (n.d.), and COVID-19-related data compiled and reported by the New York Times (2021). Data was included for all 3,224 counties (and county-equivalent areas) in the United States and its territories. Data spanning March 2020-December 2020 were the focus for this study. March 2020 was selected as the beginning time point for this study because the CDC declared COVID-19 a pandemic on March 15, 2020. Data collection and availability become markedly better after that declaration. December 2020 was chosen as an end point for the study because the data necessary to control for the effects of the COVID-19 vaccine (which became available to significant portions of the public after December 2020) was not available. These data were accessed through the Social Explorer (2021) data repository (mask use data was accessed through Github.com [Katz et al., 2020]), downloaded into Microsoft Excel spreadsheets, and merged into a single file using Stata 17.0 (StataCorp, 2021). The merged data file was imported into MPlus 8.5 (Muthén & Muthén, 1998 –2017) using the "stata2mplus" command in Stata (Statistical Consulting Group, n.d.).

Measures

Dependent Variables

COVID-19 Morbidity Rates. Morbidity rates are a monthly, cumulative rate of how many people in each county tested positive for COVID-19 per 100,000 population. Standardizing the data in this way provides a morbidity rate that is comparable across counties of different sizes. The rate includes cases in which COVID-19 was confirmed through laboratory testing and those in which COVID-19 infection was determined “probable”, based on state and federal criteria that consider testing results, symptoms, and exposure to COVID-19 (CDC, Division of Health Informatics and Surveillance, 2020).

This data were obtained from reporting by the New York Times (2021). Through its own staff, as well as collaborating reporters and news agencies, the New York Times (2021) gathers and publishes a variety of COVID-19 related data. The primary data sources for COVID-19 morbidity and mortality rates are state, county, and local departments of health.

COVID-19 Mortality Rates. Mortality rates is a monthly, cumulative rate of how many people in each county have died from COVID-19 per 100,000 population. The rate includes deaths in which COVID-19 was a confirmed or probable cause of death (based on state and federal criteria). Standardizing the data by dividing by 100,000 provides a death rate that is comparable across counties of different sizes. This data was also obtained from reporting by the New York Times (2021).

Independent Variables

The following factors were included in the study as indicators of a single latent variable representing the social determinants of health. They were selected to be representative of the HHS (2020b) social determinants of health categories. When this study was initially conceptualized, it was anticipated the measurement model would include five latent variables – one for each social determinants of health categories – with multiple indicators for each latent variable (Figure 2). The indicators initially selected for each latent variable were those conceptually aligned with the HHS (2020b) model, measured at the county level, and accessible through federal sources, not-for-profit organizations, or database subscriptions paid by Brigham Young University. As described later, in the *Analytic Procedures* section of this thesis, it was not possible to achieve convergence with such a complex model.

As a result, both conceptual and empirical rationale were applied to create a more parsimonious measurement model for the social determinants of health. The factors below were selected for inclusion in the more parsimonious model because they had conceptual alignment with the HHS (2020b) model, and prior research had empirically supported their association with COVID-19 morbidity and mortality. The following subsections provide context and rationale for the selections made.

Economic Stability. In the initial model, economic stability was intended to be modeled as a latent variable, with county-level indicators representing sources of income (unemployment), significant living expenses (gross rent exceeding 50% of income, gross home expenses greater than 50% of income), and actual income in relation to federal poverty standards (children in poverty, adult poverty, and people 65 and older in poverty). Ultimately, unemployment and adult poverty were retained in the parsimonious model.

Having reliable access to the financial resources to meet basic needs is the essence of economic stability. Of all the initial indicators, unemployment was the only indicator of not having direct access to financial resources. Employment can be a key source of economic stability for individuals and families. Employment generally provides regular income to help meet immediate financial needs, and sometimes provides other benefits (e.g. training opportunities, insurance, and retirement plans) that can help mitigate potential financial crises and address long-term financial needs (HHS, 2020a; Thompson & Dahling, 2019). Employment generally provides regular income to help meet immediate financial needs, and sometimes provides other benefits (e.g. training opportunities, insurance, and retirement plans) that can help mitigate potential financial crises and address long-term financial needs (HHS, 2020a; Thompson & Dahling, 2019). Higher county-level unemployment rates were anticipated to be associated with higher COVID-19 morbidity and mortality rates.

Poverty rate was retained because it indicates how adequately a household's income can meet estimated living expenses. Employment alone is not always sufficient to ensure an adequate income (Polizzi et al., 2022), and economic stability is simply not possible without adequate income (Thompson & Dahling, 2019). In terms of income, poverty rate calculations incorporate sources of financial support beyond earned income (e.g. workers compensation, Supplemental Security Income, public assistance, alimony, child support). In terms of expenses, poverty rate calculations include estimated expenses for rent, utilities, food, and other household goods and services. As a result, poverty rates likely provide a more robust measure of financial stability than do gross rent and home expenses as a percentage of income. Poverty rate among people ages 18-64 (rather than poverty among children or adults 65 and older) was retained as the most generalizable indicator of poverty – their age range being the largest and their poverty calculations the most likely to include dependent children and older adults. Higher county-level adult poverty rates were anticipated to be associated with higher COVID-19 morbidity and mortality rates.

Unemployment. Unemployment rate is the percentage of people in the county who are 16 or older, not employed, and actively seeking employment. Unemployment rates were obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a). ACS data is collected annually by United States Census Bureau (2020a) field workers. Data is collected from a sample of individuals representative of the larger population. Sample data is then used to generate estimates of population-level measures, such as county-level employment rates. The Census Bureau generates one set of estimates based on data from the most recent year, and another set of estimates based on data collected over the previous 5 years.

The 5-year estimates were selected for this study for two reasons. First, counties with populations less than 65,000 people are not reported in the 1-year estimates (United States Census Bureau, 2020b). Using the 5-year estimates made it possible to be more inclusive of counties that were smaller, and likely more rural. Second, while the 1-year estimates are more current, the 5-year estimates provide more reliable estimates, particularly in less populated counties. The 5-year estimates are based on larger sample sizes than the 1-year estimates, giving the 5-year estimates smaller margins of error and narrower confidence intervals (United States Census Bureau, 2020b). This analysis used the Census Bureau's most recent 5-year estimates, which were based on data from 2014-2019.

Adult Poverty. Adult poverty rate is the percentage of people 18-64 years old in a county whose income is below the federal poverty threshold for their particular family size and composition. The adult poverty rate was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Education Access and Quality. In the initial model, education access and quality was intended to be modeled as a latent variable, with county-level indicators including the proportion of people with less than a high school education, with limited literacy, limited numeracy, and limited English proficiency. Of these, only limited literacy was retained for the parsimonious model.

Education access and quality means having access to educational support and opportunities necessary to develop essential life skills (e.g., language, reading, and math), as well as preparation for gainful employment (HHS, 2020b; Artiga & Hinton, 2018). Due to a paucity of direct measures for educational support and opportunity, most research on this topic uses educational outcomes (e.g., test scores, degrees earned, academic achievements) as proxies for education access and quality. While these proxy measures are more easily accessible, it is difficult to select any individual or group of indicators that fully represent a county's level of education access and quality.

Literacy was retained for this model because it is a more foundational, easily acquired life skill than English proficiency or high school-level education. Literacy refers to the ability to read, understand, and use printed and written language. These are foundational skills necessary to support subsequent learning, active engagement in society, and meaningful employment (United Nations Educational, Scientific, and Cultural Organization, n.d.). Developing literacy only requires access to a very rudimentary level of education, not necessarily any formal education. While numeracy is a similarly fundamental life skill, literacy was chosen for its stronger conceptual and empirical relationship with COVID-19. Compared to numeracy, the ability to read and understand information about prevalence, risk factors, and protective behaviors against COVID-19 was expected to be a better indicator of COVID-19 risk. Also, previous research has linked health literacy to COVID-19 outcomes, while the relationship between numeracy and COVID-19 remains essentially unexplored. As such, higher county-level rates of limited literacy were expected to be associated with higher COVID-19 morbidity and mortality rates.

Literacy. The focus of this analysis was on county-level vulnerability, so the percentage of people in a county with literacy proficiency below level 1 was used. Individuals at this proficiency level may lack basic vocabulary knowledge, and may, when prompted to find a single, specific piece of information in a simple, printed text, be unable to do so.

Literacy data was obtained from the National Center for Education Statistics (n.d.). As part of their Program for International Assessment of Adult Competencies (PIAAC), the NCES (n.d.) (part of the United States Department of Education and the Institute of Education Sciences) collects data regarding adult literacy, numeracy, and other academic skills. The PIAAC collected data in three stages, spanning 2012-2017. Literacy proficiency data was collected for 12,330 adults, across every county and county-equivalent area in the United States. Using that sample data, the NCES estimated the proportion of 16-65 year old people in each county at each of 5 different literacy proficiency levels (as well as those below the lowest proficiency level).

Healthcare Access and Quality. In the initial model, healthcare access and quality was anticipated to be modeled as a latent variable, with indicators including the counties' proportion of uninsured adults and children, people with limited access to healthy food, and the number of primary care providers, dentists, and psychiatrists per 100,000 population. In the more parsimonious model, only the proportion of uninsured adults was retained.

Healthcare access and quality are dynamic and conceptually complex (Levesque et al., 2013). Health outcomes are generally used as proxy measures of health care access (e.g., Fullman et al., 2018) and quality (e.g., Kruk et al., 2018) because they are more simply defined and more broadly available than measures more directly associated with healthcare access and quality (e.g., health literacy, language barriers, transportation, distrust in the healthcare system, and proximity to healthcare facilities and personnel, and the availability of equipment [Douthit et al., 2015; Lu & Myerson, 2020]).

For this study, health insurance was retained for the model because it is a primary determinant of access to adequate healthcare (Lazar & Davenport, 2018; Lu & Myerson, 2020). For most people living in the United States, having health insurance is crucial for accessing primary care providers, dentists, and psychiatrists, and experiencing the benefits of health care (Wray et al., 2021). While access to healthy food is associated with better general health (WHO, 2021), there was little conceptual or empirical basis for expecting healthy food would have a stronger relationship with COVID-19 morbidity and mortality rates than would health insurance.

Lack of Health Insurance. The proportion of adults without health insurance in each county is calculated by dividing the number of 0-64 year old people who do not have private or public health insurance coverage by the total number of people in the county aged 0-64. This health insurance data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Neighborhood and Built Environment. In the initial model, neighborhood and built environment was intended to be modeled as a latent variable with indicators including proximity to others (living in overcrowded housing or group quarters), basic amenities (plumbing and internet access), and environmental hazards (air and water pollution). The proportion of people in the county living in overcrowded housing was retained for the analysis.

Conceptually, neighborhood and built environment is complex and multi-faceted, and would likely best be modeled using a diverse array of indicators. However, for this analysis, overcrowded living conditions was selected because of its presumed relevance to acquiring (and potentially dying from) an infectious disease. From March 2020-December 2020, the primary means of avoiding COVID-19 infection was social distancing and quarantining. Overcrowded living conditions made such protective behaviors unreasonable, if not impossible (Bryan et al., 2021; Kamis et al., 2021). Although the risk and mechanism of acquiring COVID-19 would likely be similar for individuals living in group quarters (such as group homes, prisons, or skilled nursing facilities), people living in overcrowded housing were expected to have higher mobility within the community and thus a broader potential impact on community-level COVID-19 morbidity and mortality. While there are general health implications associated with lack of access to basic amenities and with exposure to environmental hazards, living in overcrowded housing has a stronger conceptual and empirical link to the risk of spreading a droplet-borne infectious disease.

Overcrowding. The proportion of people in a county whose housing is overcrowded is calculated by dividing the number of crowded households (defined as having more than 1 person per room) by the total number of households in the county. For this calculation, the ACS defines rooms as, "whole rooms used for living purposes…[including] living rooms, dining rooms, kitchens, bedrooms, finished recreation rooms, enclosed porches suitable for year-round use, and lodger's rooms" (United States Census Bureau, 2020c, p. 32). This data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Social and Community Context. In the initial model, social and community context was anticipated to be modeled as a latent variable, with indicators including the proportion of people in the county who were born outside of the United States, identifying as a race other than white, and identifying as Hispanic or Latino. Ultimately, race and ethnicity were both retained as indicators of social and community context.

Supportive relationships are at the heart of social and community context. However, identifying meaningful ways to quantify the presence and strength of such relationships is difficult, resulting in a paucity of population-level data relevant to this category of social determinants of health. However, there is substantial evidence suggesting interpersonal and structural racism remain prevalent and pernicious forces in the United States, and that they create a challenging and harmful social context people of racial and ethnic minorities (Misra et al., 2021; Skinner-Dorkenoo et al., 2021). While knowing a community's racial and ethnic composition does not necessarily provide direct insight into family and social relationships, it is clear that race and ethnicity remain a powerful influence on social and community context. Although there was strong conceptual support for all three indicators of social and community context, the relationships between race, ethnicity, and COVID-19 health outcomes have a stronger empirical basis at this time.

Race & Ethnicity. For this study, race was the proportion of people in each county who identified as a race other than white. Race data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a). Ethnicity was the proportion of people in the county who identified as being Hispanic or Latino. Ethnicity data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Control Variables

The between-level control variables selected were: county-level population density, proportion of the population aged greater than 65, mask use, work mobility, and month. Notably, COVID-19 immunization rates were not included in this study. During the time period for this study (March 2020-December 2020), immunization availability was limited to those participating in initial safety and efficacy trials and largely unavailable to the general public.

Age Greater Than 65. Age greater than 65 is the proportion of people in the county whose age is greater than 65 years old. Pijls et al's (2021) meta-analysis indicates COVID-19 infections rates are higher in older adults. In terms of mortality, physiological factors related to aging (i.e. lower immune function and a higher prevalence of co-morbid conditions) likely increased mortality rates in the older adults who did become infected with COVID-19 (Bonanad, 2020; Singhal et al., 2021). Age data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Population Density. Population density is the county's total population, divided by the county's land area in square miles. A systematic review of 21 studies in which population density was considered (Zhang et al., 2022) indicated population density had a significant, negative relationship with COVID-19 death rates. A more nuanced picture of the relationship between population density might be found in other county-level analyses that indicate per capita COVID-19 case rates and death rates were lower in rural counties during the early months of the pandemic (Karim & Chen, 2021), but became higher in rural areas after December 2020 (Sun et al., 2022). Population density data was also obtained from the ACS 2019 5-year estimates (United States Census Bureau, 2020a).

Mask Use. Mask use is the estimated proportion of people in each county who rarely or never wear a masks, based on a sample who were asked. "How often do you wear a mask in public when you expect to be within six feet of another person?" (New York Times, 2020). A number of studies and reviews indicate mask use was associated with lower COVID-19 morbidity and mortality (e.g. Itzhak et al., 2022; Kim et al., 2022; Motallebi et al., 2022). Mask use was expected to serve as both a useful indicator of personal protective behavior and a control variable because it is associated with other protective behaviors (e.g. increased hand hygiene, regular use of disinfectants, social distancing), but not associated with sociodemographic variables (e.g. gender, education, employment status, living in an urban or rural setting) (Šuriņa et al., 2021). Mask use data was also obtained from reporting by the New York Times (2020). From July 2-14, 2020 the New York Times (2020) also gathered survey data regarding mask use frequency from 250,000 respondents across the United States.

Work Mobility. Work mobility is a monthly measure (from March-December 2020) of how much people's travel to workplaces differed from a baseline level of travel established in 2020 prior to COVID-19 being declared a global pandemic. Evidence suggests COVID-19 infection rates (and the resulting deaths) were associated with increased mobility during the pandemic (Ilin et al., 2021; Nouvellet et al., 2021). Compared to the general population, the frontline workers required to travel to their workplace during the pandemic had less education and lower pay, and were more likely to be immigrants, of racial minorities, and /or of ethnic minorities (Blau et al., 2021).

Work Mobility data was obtained from Google's Community Mobility Reports (Google, n.d.). Google (n.d.) collects location data from users of its products who have turned on the "Location History" feature. One way Google has used this data is to estimate relative changes in a population's geographic mobility (e.g. travel to parks, workplaces, retail centers) over time, compared to baseline mobility levels established from January 3rd through February 6th, 2020. Google makes these Community Mobility Reports publicly available online.

Month. Month is simply the months of the year associated with each of the monthly data points. Including month as a control variable helps account for variance in COVID-19 morbidity and mortality attributable to the non-uniform county-level spread of COVID-19. For example, the rapid spread of COVID-19 occurred earlier in urban counties with travel hubs, but persisted in rural counties long after morbidity and mortality began to wane in urban areas (McMahon et al., 2022).

Analytic Procedures

First, descriptive statistics were estimated using Stata 17.0 (StataCorp, 2021). Descriptive statistics (Table 2) were carefully reviewed to check for data management errors, missing data, and study variables with non-normal distributions. Based on that review, logarithmic transformations were applied to the COVID-19 morbidity and mortality rates, as well as the measure of population density. Then, structural equation modeling procedures were conducted in MPlus version 8.5 (Muthén & Muthén, 1998 –2017). Fit indices used were the Tucker-Lewis Fit Index (TLI), comparative fit index (CFI), and the root mean squared error of approximation (RMSEA). Acceptable fit criteria were TLI ≥ 0.95, CFI ≥ 0.95, and RMSEA ≤ 0.06 (Hu & Bentler, 1999). Factor loadings 0.4 or greater are generally considered adequate, with factor loadings > 0.7 considered strong (Clark & Bowles, 2018; Heene et al., 2011).

Confirmatory Factor Analysis

Confirmatory factor analysis was used to estimate how well the sample data fit the specified theoretical model. The initial model specified included five latent variables, each representing one category in the HHS (2020b) social determinants of health model. The latent variables in this study were modeled as reflective. A defining feature of reflective latent variables is that the regression relationships are specified to suggest the indicators reflect (rather than cause) variation in the underlying latent variable (Chang et al., 2016). When indicators potentially cause a latent variable, some scholars advocate for using formative latent variables, in which the regression relationships' direction imply a causal relationship between indicators and the latent variable (Bollen & Diamantopoulos, 2017). Modeling with reflective latent variables in this study may seem conceptually counterintuitive, given that some indicators included in the study, such as race and ethnicity, likely influence (but are not reflective of) the conditions in which people live.

The reasons for using reflective latent variables are as follows: First, neither reflective nor formative latent variables offer a clear conceptual advantage over the other. While race and ethnicity are clearly not reflective of social determinants of health, the relationship between social determinants of health and many other indicators (e.g. unemployment, poverty, and low literacy) could reasonably be considered reflective, causal, or both. Second, the published literature does not offer clear guidance for using formative latent variables. Scholars are actively debating formative latent variables in the literature and there remains no clear consensus about their theoretical basis, under what circumstances they should be used, how to model them, or their practical advantages (Bollen & Diamantopoulos, 2017; Guyon, 2018; Markus, 2018). Third, evidence suggests there are no empirical disadvantages to using reflective latent variables to model constructs that could be conceptualized as formative (Chang et al., 2016). In fact, reflective latent variables may be as good or better than formative latent variables at providing less biased estimates of population parameters and identifying differences within a population.

Before attempting to combine all five latent variables into a single measurement model, a stepwise approach was used to estimate factor loadings and model fit indices for each latent variable separately. While acceptable factor loadings and model fit indices were achieved for each latent variable individually, factor loadings and model fit became inadequate when any more than two latent variables were included in the model. Further examination revealed the poor model fit was likely the result of substantial cross-loadings (indicators with high factor loadings on more than one latent variable) and high residual correlations. The substantial cross-loadings were not entirely unexpected, given that the social determinants of health are highly interrelated with each other.

When indicators in a model cross-load strongly on an unintended latent variable, the resulting model fit can be poor. While removing cross-loading indicators is a common technique for addressing such model fit issues in confirmatory factor analysis (Farrell & Rudd, 2009), doing so can have important implications for research in which the resulting model is used. Removing an indicator that uniquely represents a piece of the theoretical model detracts from how well the measurement model reflects the original theoretical model. As the theoretical and measurement models become more dissimilar from each other, the measurement model becomes less useful for coming to any meaningful conclusions about the theoretical model.

In hopes of retaining all the indicators in the model, the confirmatory factor analysis was then conducted using Bayesian structural equation modeling (Asparouhov et al., 2015; Muthén & Asparouhov, 2012), which could better account for the interrelatedness among the indicators of social determinants of health. Compared to maximum likelihood methods, Bayesian methods are better suited for estimating complex models with cross-loadings (Muthén & Asparouhov, 2012). As such, it was anticipated a Bayesian approach might make it possible to retain a measurement model reflective of the complex, multi-faceted nature of the social determinants of health.

Bayesian analyses estimate model parameters use a data set supplied by the researcher and previously known information about the model parameters (Asparouhov

& Muthén, 2021). This previously known information (expressed as a mean and probability distribution for a given parameter) is called a prior distribution (often shortened to "prior"). Priors provide a starting point statistical software can use to estimate that parameter (Depaoli et al., 2021). Priors are "informative" when they are derived from a theory or evidence from previous studies and have a relatively narrow distribution that is intended to influence the final parameter estimates (called posterior distributions, or "posteriors"). Priors that accurately reflect the underlying population can influence have a positive influence on the posteriors' accuracy (Depaoli et al., 2021). Because inaccurate priors can cause biased posteriors (Depaoli 2014; Kim, Huh, et al., 2020), caution should be used when only sparse (or conflicting) theoretical and empirical guidance is available. In such cases, using an uninformative prior is recommended. Uninformative priors use a purposefully diffuse distribution to mitigate their influence on posterior estimates (Hox et al., 2012; van Erp et al., 2018). While some researchers note that uninformative priors can substantially influence posterior estimates in studies with small sample sizes (Smid & Winter, 2020), simulations demonstrate the effect of uninformative priors is negligible with samples greater than 500 (Asparouhov & Muthén, 2021).

The Bayesian structural equation model used for the present study was conducted using the MPlus (Muthén & Muthén, 1998 –2017) default priors, which are designed to be uninformative. The present study's large sample size was anticipated to substantially mitigate the potential risks of using uninformed priors, whereas the literature offered little guidance for selecting accurate priors. However, even using a Bayesian approach, convergence of the measurement model could not be achieved.

Next, a more parsimonious measurement model for the social determinants of health was specified and estimated using confirmatory factor analysis (Figure 4). The parsimonious model was developed using a deliberate process, guided by the conceptual and empirical rationale provided in the *Independent Variables* section of this thesis. In each social determinants category, indicators potentially duplicative of other indicators were removed. The resulting measurement model still had five latent variables (one for each category), and each latent variable had three indicators. A confirmatory factor analysis was conducted with the individual latent variables to ensure adequate factor loadings. For several latent variables, the factor loadings were no longer adequate. In these cases, another indicator was removed, with those thought to have the strongest conceptual or empirical relationship with COVID-19 morbidity and mortality retained. Because two-indicator latent variables are just identified, their factor loadings could not be estimated. However, the resulting latent variables were conceptually justifiable, so they were again added to a larger measurement model in a stepwise fashion, with model fit statistics estimated after each latent variable was added. As with the original measurement model, due to substantial cross-loadings and high residual correlations, fit statistics became inadequate when any three of the latent variables were included in the model. At that point, additional indicators were removed, with the indicators most uniquely reflective of their intended social determinant category retained, resulting in only 1-2 indicators per category. Specifying a distinct latent variable for each category was no longer possible, so the remaining indicators were collapsed into a single latent variable representing the social determinants of health.

While specifying a simpler measurement model was empirically justified, removing indicators risked discrepancies between the measurement and theoretical model. To maintain close alignment between the measurement and theoretical model, the HHS (2020b) model was carefully considered while selecting which indicators to retain in the measurement model. As discussed previously, the indicators were retained based on their conceptual alignment with the HHS (2020b) model, and prior research supporting their association with COVID-19 morbidity and mortality. The resulting parsimonious measurement model was a single latent variable with 1-2 observed indicators for each category in the HHS (2020b) social determinants of health model. Confirmatory factor analysis was used to estimate factor loadings and model fit indices for the new latent variable. Factor loadings and model fit indices for the measurement model were adequate (Table 3).

Notably, the original measurement model (Figure 2) specified the social determinants of health as a second-order latent variable, whereas the parsimonious measurement model (Figure 4) specified them as a single latent variable. While the 1-2 indicators for each social determinant category were thoughtfully selected to preserve the best theoretical alignment possible, it should be noted that a single latent variable measurement model is unlikely to fully reflect the complexity of the social determinants of health. This should be considered when interpreting results associated with the parsimonious measurement model. However, the parsimonious model's simplicity provides practical advantages. Specifically, it requires less data, fewer computational resources, and is less likely to overfit the data. Its relative simplicity also allowed model convergence, which also helps justify its use for research purposes.

Structural Equation Modeling

Model 1. With the measurement component of the model established, a two-part, multi-level structural equation model (Wang et al., 2020) was used to estimate the relationship between the latent variable representing county-level social determinants of health and county-level COVID-19 case rates and death rates from March-December 2020 (Figure 5). Multi-level analysis was used to account for the monthly repeated measures of work mobility COVID-19 case rate and death rate within each county (Geiser, 2021). As illustrated in Figure 5, the monthly measures (month, work mobility, COVID-19 morbidity rate, and COVID-19 mortality rate) were included in the model as within county variables, while the annual measures were included as between county variables. In the within county portion of the model, the black dots indicate the intercepts for COVID-19 morbidity and mortality rate were modeled as random intercepts. The heterogeneity of those intercepts is included in the between portion of the model as latent variables of COVID-19 morbidity and mortality. In this model, the effect of month on COVID-19 morbidity and mortality was modeled as a fixed slope rather than a random slope, which reduced the model's sensitivity to county-level, time-related differences in COVID-19 morbidity and mortality, but also kept the model simpler and improved the chance of convergence. A two-part model was selected because the COVID-19 case rates and death rates had a zero-inflated probability distribution (many counties had no COVID-19 cases or deaths within the early months of the pandemic).

The first part of the two-part model used logistic regression to estimate how well the model predicted COVID-19 case and death rates of zero versus more than zero. The second part of the two-part model used maximum likelihood with robust standard errors to estimate how well the model explained variability in COVID-19 case and death rates when those rates were greater than 0. To account for some COVID-19 risk not related to the social determinants of health, three control variables were included in the structural model - population density, age, and face mask use during the pandemic. Model 1 converged normally.

Model 2. After convergence was achieved with Model 1, a second structural equation model (Model 2) was estimated - with the effects of time on COVID-19 morbidity and mortality modeled as random slopes (Figure 6). Modeling random slopes allows each county to have its own slopes representing the relationships between time and COVID-19 mortality/morbidity rates, rather than choosing a single, fixed slope to represent those relationships for all counties. Thus, using random slopes was anticipated to better account for county-level, time-related differences in COVID-19 morbidity and mortality, and thus estimate the effects of the other independent variables more precisely. Because maximum likelihood estimation is not currently capable of modeling random effects in longitudinal data (Geiser, 2021), Bayesian structural equation modeling (Muthén & Asparouhov, 2012) was used to estimate this model. The MPlus (Muthén & Muthén, 1998 –2017) default uninformative priors were used for this analysis. Model 2 converged normally. However, the variance coefficients for the random slopes were all less than 0.01, suggesting the relationship between time and COVID-19 morbidity and mortality differed very little difference across counties. In practical terms, this finding indicates Model 2 does not contribute any substantial advantages compared to the more parsimonious Model 1. As such, results from Model 2 will not be presented here.

Results

Descriptive statistics were estimated for each of the control variables (Table 2). In general, the results from the descriptive statistics were as expected. Interestingly, however, work mobility in some counties increased substantially from June-November 2020, beginning just as the United States' first wave of COVID-19 plateaued and extending well into the second wave.

Measurement Model

Factor loadings for the social determinants of health latent variable were adequate, ranging from 0.536-0.817, with model fit indices CFI=0.988, TLI=0.95, RMSEA=0.016 (Table 3). These findings help validate the theorized relationship among the social determinants of health, and justify moving forward with the next step in the analysis – specifically, using a structural model to examine the relationship between the latent social determinants of health variable and health outcomes.

Structural Model

Between County Model

The between county portion of the model (Table 4) is of primary interest for this analysis because they offer insights into how differences in county-level social determinants of health might explain differences in county-level COVID-19 health outcomes.

For the part of structural equation model in which case and death rates were set to either 0 or > 0, the proportion of a county's population age 65 or greater had a negative, significant relationship with COVID-19 case rate ($\beta = -0.190$, $p < 0.001$), and a non-significant relationship with COVID-19 death rate ($\beta = 0.027$, $p < 0.168$). Population density had a positive, significant relationship with both COVID-19 case rate ($\beta = 0.720$, $p = 0.197$) and death rate ($\beta = 0.760$, $p < 0.001$). The proportion of a county's population that wore masks "rarely" or "never" had a non-significant association with COVID-19 case rates ($\beta = 0.040$, $p < 0.381$) and a positive, significant association with death rates ($\beta = 0.089$, $p < 0.001$). The latent social determinant of health variable had a statistically significant relationship with both COVID-19 case rates ($\beta = 0.804$, $p < 0.001$) and death rates ($\beta = 0.750$, $p < 0.001$). The model was able to account for 80.4% and 75% of between-county variance in COVID-19 case rates and death rates, respectively. Based on guidelines proposed by Hair et al. (2011), the model's predictive performance is characterized as "substantial".

For the part of the structural equation model in which case and death rates were > 0, the proportion of a county's population age 65 or greater had a negative, significant relationship with COVID-19 case rate ($\beta = -0.200$, $p < 0.001$), and a significant, positive relationship with

COVID-19 death rate (β = 0.246, $p < 0.001$). Population density had a non-significant relationship with COVID-19 case rates (β = 0.039, $p = 0.197$), but did have a significant, negative relationship with COVID-19 death rate (β = -0.269, $p < 0.001$). The proportion of a county's population that wore masks "rarely" or "never" was significantly, positively associated with both COVID-19 case rates (β = 0.526, $p < 0.001$) and death rates (β = 0.317, $p < 0.001$). The latent social determinant of health variable had a statistically significant relationship with both COVID-19 case rates (β = 0.648, $p < 0.001$) and death rates (β = 0.388, $p < 0.001$). The model was able to account for 73% and 51% of between-county variance in COVID-19 case rates and death rates, respectively. Based on guidelines proposed by Hair et al. (2011), the model's predictive performance is characterized as "moderate".

Within County Model

The within county portion of the model (Table 5) is also of interest for this analysis because it offers insight into how time and work mobility within counties contributed to differences in county-level COVID-19 health outcomes.

For the part of the structural equation model in which case and death rates were set to either 0 or > 0, month had a negative, significant relationship with COVID-19 case rate (β = -0.219, $p < 0.001$) and death rate (β = -0.220, $p < 0.001$). Work mobility had a positive, significant relationship with COVID-19 case rate (β = 0.166, $p < 0.001$), and a negative, significant relationship with death rate (β = -0.108, $p < 0.001$). The model accounted for 7.8% and 5.8% of the within county variance in COVID-19 case rates and death rates, respectively. This model's predictive performance does not meet the criteria for "weak" (Hair et al., 2011).

For the part of the structural equation model in which case and death rates were > 0, month had a negative, significant relationship with COVID-19 case rate (β = -0.309, $p < 0.001$)

and death rate ($\beta = -0.223$, $p < 0.001$). Work mobility had a non-significant relationship with COVID-19 case rate ($\beta = 0.007$, $p < 0.306$), and a negative, significant relationship with death rate ($\beta = -0.178$, $p < 0.001$). The model accounted for 9.5% and 7.9% of the within county variance in COVID-19 case rates and death rates, respectively. This model's predictive performance also does not meet the criteria for "weak" (Hair et al., 2011).

Discussion

The results show the parsimonious measurement model (Figure 5) is an adequate measurement model for social determinants of health. The results also show that county-level social determinants of health explain a significant amount of the variability in COVID-19 case rates and death rates. These findings align with and build upon a substantial body of evidence indicating a strong relationship between a broad array of social determinates of health.

Between County Control Variables

Results from the present analysis indicate a relationship between a larger proportion of individuals greater than 65 years of age and COVID-19 morbidity and mortality. The negative association between age and COVID-19 infection rate conflicts with Pijls et al. (2021), although the reason for this conflict is unclear. One possibility is that personal and lifestyle factors associated with aging may have reduced COVID-19 exposure and infection during the pandemic (Duru, 2020). For example, people aged 65 and greater may have been more likely to isolate themselves, social distance in public, and quarantine when infected than were younger people (Clavel et al., 2021), thus mitigating the spread of infection within the county. However, there is also conflicting evidence suggesting older adults may actually engage in fewer protective behaviors (Daoust 2020; Litwin & Levinsky, 2021; Pasion et al., 2020). A remote possibility is that older adults truly did experience higher infection rates (as Pijls et al's [2021] findings would suggest), but high infection rates among the older adults did not translate into higher infection rates for the county overall. This study's reliance on county-level data precludes more detailed analyses of the relationship between age and COVID-19 infection rates. The results relating age and COVID-19 mortality are aligned with previous studies showing age is a significant risk factor for COVID-19 (Bonanad, 2020; Singhal et al., 2021).

In the first part of the structural equation model (in which case and death rates were set to either 0 or > 0), population density had a significant relationship with both COVID-19 morbidity and mortality. In the second part of the structural equation model (in which case and death rates were > 0), population density did not have a significant relationship with COVID-19 case rates, but did have a significant, negative relationship with COVID-19 death rates. These findings are generally consistent with prior research, which indicated COVID-19 case rates and death rates were lower in rural areas between March-December 2020 (Karim & Chen, 2021; Sun et al., 2022). Based on data spanning December 2019-May 2020, Hamidi et al. (2020) similarly found no statistically significant relationship between population density and COVID-19 cases, and a significant, negative relationship between population density and COVID-19 deaths. However, it was beyond the scope of the present study to conduct detailed analyses on the control variables.

The finding that lower mask use was generally associated with higher COVID-19 case and death rates was expected, given the substantial amount of data supporting the protective effects of masks against COVID-19 spread (Itzhak et al., 2022; Kim et al., 2022; Motallebi et al., 2022). It is important to consider that mask use may have been associated with other protective behaviors (e.g. proper social distancing, quarantining when sick, and hand hygiene) (Šuriņa et al., 2021) that amplified the relationship detected here between mask use and COVID-19 morbidity and mortality. Data related to these other protective behaviors were not available, thus were not included in the analysis.

Social Determinants of Health

This study provides several important contributions to the literature on social determinants of health. The first contribution relates to the theoretical structure of the HHS (2020b) social determinants of health model. The original, more complex measurement model of social determinants of health could not be estimated. When each category of social determinants of health was modeled as a unique latent variable, their respective indicators cross-loaded substantially on the other latent variables. This finding suggests there is misalignment between the HHS's current theoretical social determinants of health model and the data set for this study. Of course, findings from this study do not constitute conclusive evidence that the HHS's model requires revision, but they do suggest the social determinants of health are interrelated enough that separating them into distinct categories may not be feasible. However, the indicators included in the parsimonious measurement model loaded adequately on the latent social determinants of health variable, and the fit indices were adequate. These findings provide some empirical validation of a simpler theoretical social determinants of health model.

Second, this study generally validates a substantial and growing body of work linking the social determinants of health to COVID-19 health outcomes. The latent variable for social determinants of health had a statistically significant association with COVID-19 case rates and death rates. Continuing to examine and document this relationship helps justify and inform actions addressing the social determinants of health. For example, evidence showing how strongly health is related to social determinants could justify the allocation of time, money, and other resources to address them. Because the present study focused on developing a measure for the social determinants of health and validating their relationship with health outcomes, the findings do not provide guidance about specific social determinants of health for policy-makers to address, or specific interventions to implement. However, the findings do highlight the complex relationships among the social determinants, which could guide federal, state, and municipal governments, private insurance companies, health care systems, and employers toward using a collaborative, multifaceted approach to address them.

Third, this study adds to the theoretical and empirical foundation supporting the use of structural equation modeling to study the social determinants of health. The findings, as well as the strengths and limitations of this study's conceptual motivation, design, and analysis, can inform studies that will improve upon this one. Structural equation modeling should be strongly considered as a statistical method for additional research on the social determinants of health, their relationship with COVID-19 morbidity and mortality and other indicators of public health.

Model Predictive Performance

Based on guidelines proposed by Hair et al. (2011), the between county model's predictive performance was moderate to strong. The first part of the model explained 80.4% and 75% of between county variance in whether counties experienced any COVID-19 cases or deaths, respectively. The second part of the model explained 73% and 51% of between-county variance in COVID-19 case rates and death rates, respectively. Only one other study modeling social determinants of health as a latent variable could be found for comparison (Lee, Paul, et al., 2021). Their model explained 27% of the variance in COVID-19 infections at the individual level. The predictive performance of the present model suggests structural equation modeling is feasible and effective for modeling social determinants of health.

In summary, the parsimonious theoretical model specified for the social determinants of health and their relationship to COVID-19 morbidity and mortality aligned well with the empirical data. This can be seen in the factor loadings, the model fit indices, the statistically significant relationship between the social determinants of health and COVID-19 health outcomes, and the model's relatively high predictive performance. Specifically, the adequate factor loadings and model fit indices help confirm previous theoretical and empirical work suggesting the social determinants of health are interrelated. The statistically significant relationship between the social determinants of health help confirm prior theoretical claims and empirical data suggesting the same. Finally, the model's predictive performance illustrates the degree to which the model can account for variance in COVID-19 morbidity and mortality rates. This finding validates the work of Lee, Paul, et al. (2021), but also extends it by accounting for more variance in COVID-19 infections and including a model for COVID-19 mortality.

Conclusion

A two-part, multi-level structural equation model was used to study the relationship between county-level social determinants of health and COVID-19 morbidity and mortality in the United States. Factor loadings for the latent social determinants of health variable were adequate, as were the fit indices for the measurement model. The first part of the model explained 80.4% and 75% of between county variance in whether counties experienced any COVID-19 cases or deaths, respectively, while the second part of the structural model accounted for 51% and 73% of the variance in county-level COVID-19 morbidity and mortality rates, respectively. These findings further validate the relationship between the social determinants of health and COVID-19 health outcomes. The study also adds to the theoretical and empirical foundation supporting the use of structural equation modeling to study the social determinants of health.

This study has several limitations, each of which can be addressed through future research. First, the timeline for this study extended through December 2020. As a result, this excluded the influence of vaccines, targeted therapeutic treatments, and several COVID-19 variants that have since emerged. Future research could attempt to account for some of those developments, while also evaluating the validity of the model presented here for subsequent phases of the pandemic. Second, while county-level data can be used to evaluate social factors that contribute to population-level health risks, more granular data (zip code, neighborhood, and individual-level data) would provide more information about how the intersectionality of various social factors shape personal health risks. Ideally, future research studies would employ a multi-level design to account for the influence of both population-level and individual-level factors on health. Third, this study used cross-sectional data for all of the predictor variables, except for work mobility, resulting in some lost sensitivity in the analysis and precluding analysis of causal factors. In this study, annual measures were likely acceptable for variables that are relatively consistent over the course of a year (e.g. literacy levels). However, other factors (e.g. unemployment, poverty, and mask use) may have fluctuated significantly from month-to-month during the COVID-19 pandemic. When practical, future research studies should use longitudinal data, collected frequently enough to detect significant fluctuations. Fourth, the social determinants of health were modeled as a reflective latent variable for this analysis, meaning its indicators were considered to be manifestations of an underlying degree of "social determinants of health" within the county. Of course, it is conceptually clearer to consider those indicators as social factors that contribute to a county's level of risk for health problems. Some scholars (e.g. Bollen & Diamantopoulos, 2017) suggest it is more appropriate to use a formative latent variable when the indicators contribute to (rather than reflect) the latent variable's presence. Other scholars (Guyon, 2018) suggest formative latent variable are not truly latent variables at all, and should not be modelled as such. Future research should continue to explore meaningful ways to model the social determinants of health, their effects, and interventions to mitigate those effects. Fifth, this research did not take into account the various cultural, political, and health infrastructure differences that may have influenced COVID-19 morbidity and mortality. Future research should attempt to include these factors in their analyses to more comprehensively model the factors influencing health.

In spite of these limitations, this study has some important implications for both public health policy and research. For public health policy, this study further validates the relationship between social determinants and health outcomes, providing additional justification for addressing public health through the social determinants of health. This study also empirically validates the theorized interrelatedness of the social determinants of health, which can help public health professionals and policy-makers to make better-informed decisions about resource allocation, program development, and legislation to improve public health. For example, recognizing the relationship between education, employment, poverty, insurance, household crowding, and race may guide the development of a public health program or policy that employs a multi-faceted approach addressing the social determinants.

For researchers, this study helps justify and inform additional exploration of the significant role social factors play in a community's health. Specifically, the use of multi-level structural equation modeling and the latent variable used to model social determinants of health may warrant further exploration. Within the context of the COVID-19 pandemic, structural equation modeling may be useful to replicate the present study with 2021 and/or 2022 data. Although accounting for COVID-19 vaccination rates would be necessary, such a study would still provide helpful information about the robustness of the social determinants of health latent variable. Beyond the context of the COVID-19 pandemic, researchers may find it worthwhile to explore whether the social determinants of health latent variable also explains significant variation in other indicators of public health, including other infectious diseases, premature death rates, and infant mortality rates.

The social determinants of health have complex relationships with each other, and have a powerful influence on health. Structural equation modeling shows promise as a statistical method for appropriately modeling those relationships and studying their relationship with indicators of public health. Additional study in this area can justify and inform public health professionals and policy-makers' efforts to improve health by addressing its social determinants. Although difficulty, the work of addressing the social determinants of health is necessary to realize the dream of achieving health equity.

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Figure 1: Social Determinants of Health Model

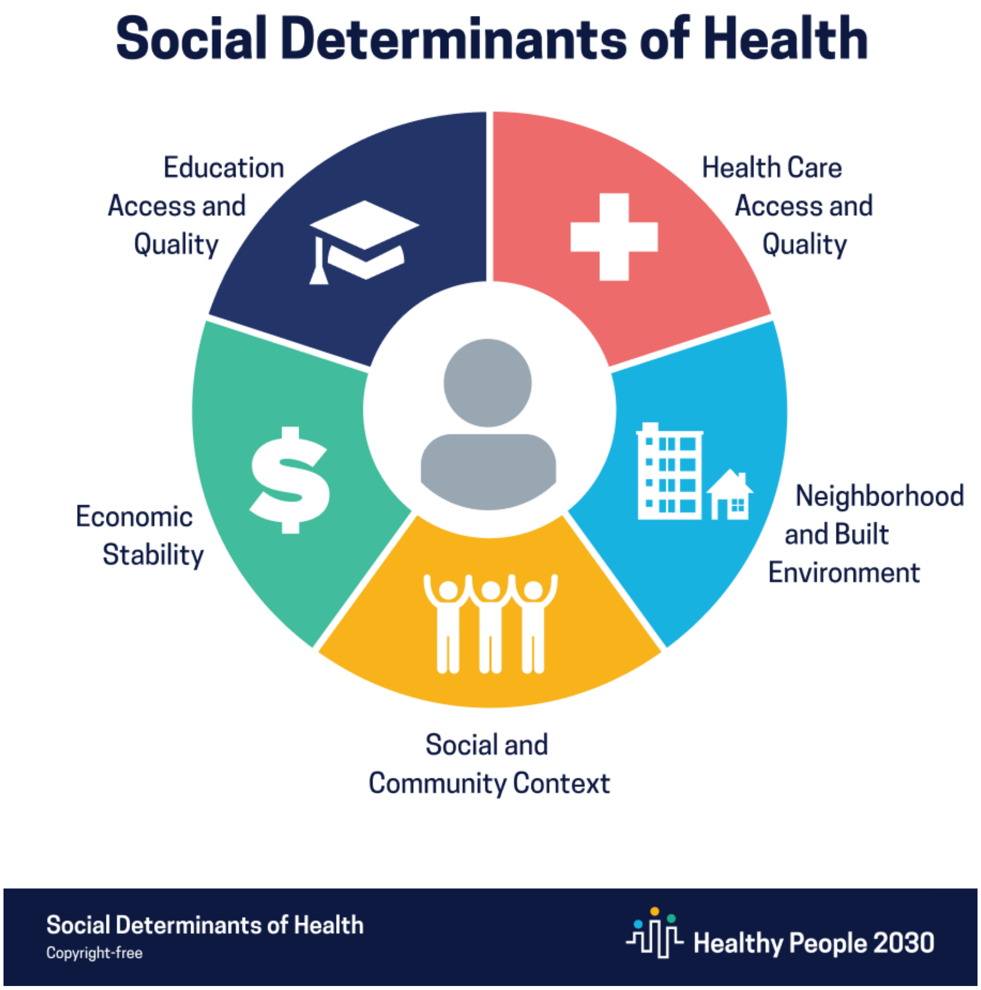


Figure 2: Social Determinants of Health Complex Measurement Model

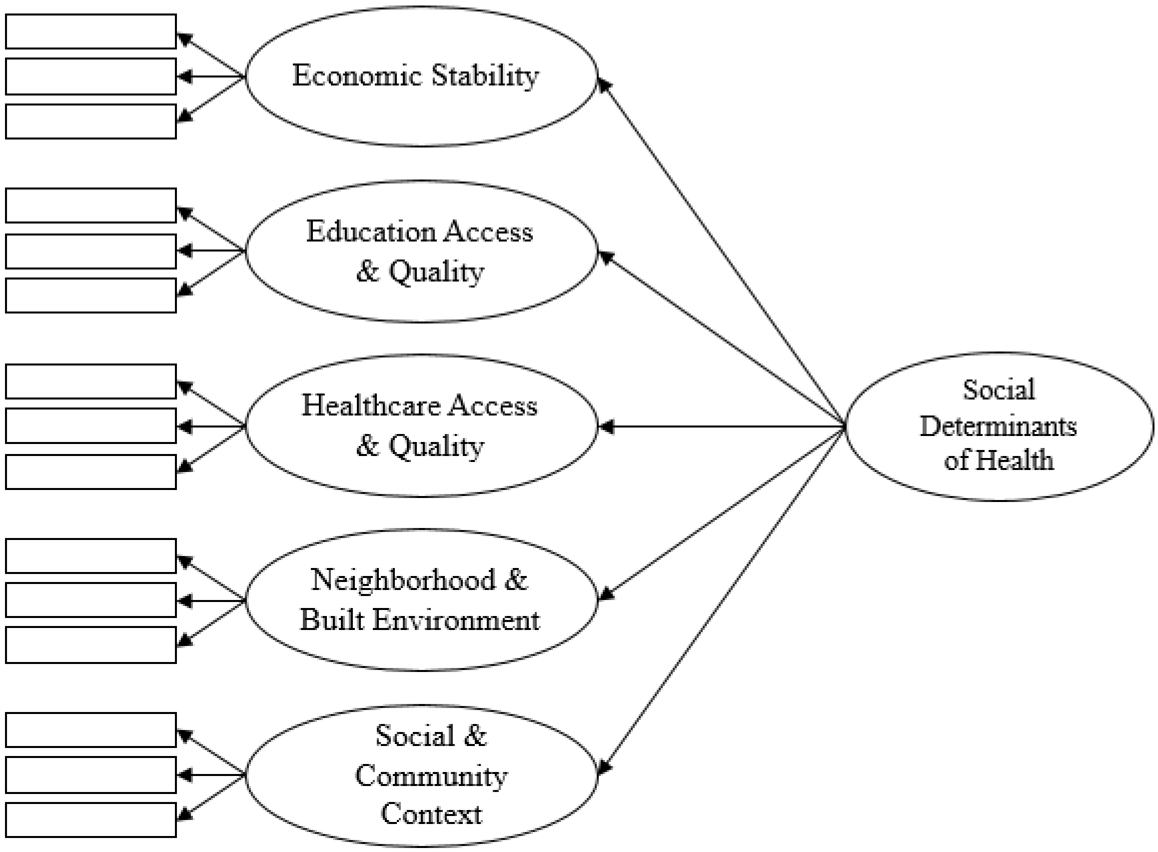


Figure 3: Social Determinants of Health Complex Structural Model

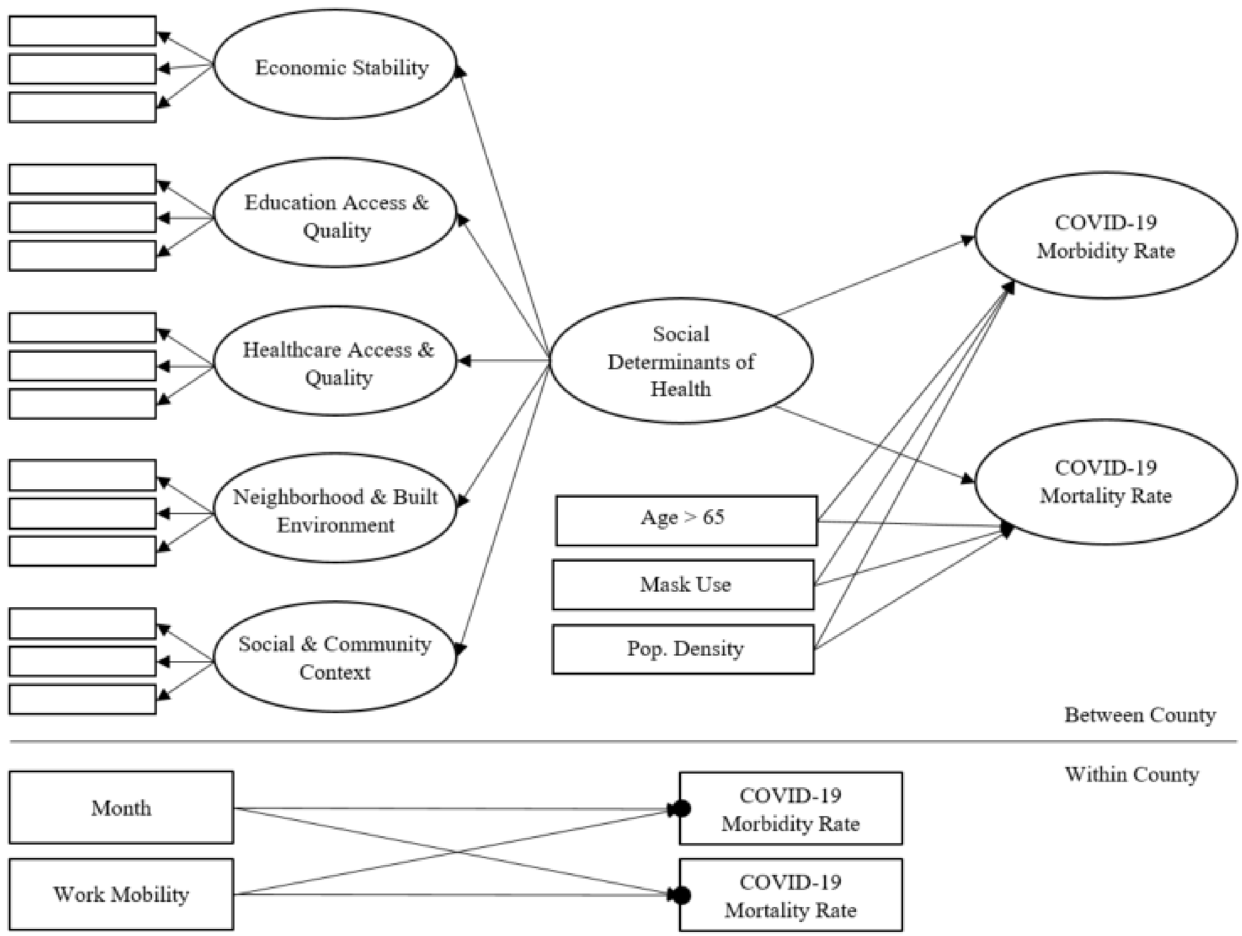


Figure 4: Social Determinants of Health Parsimonious Measurement Model

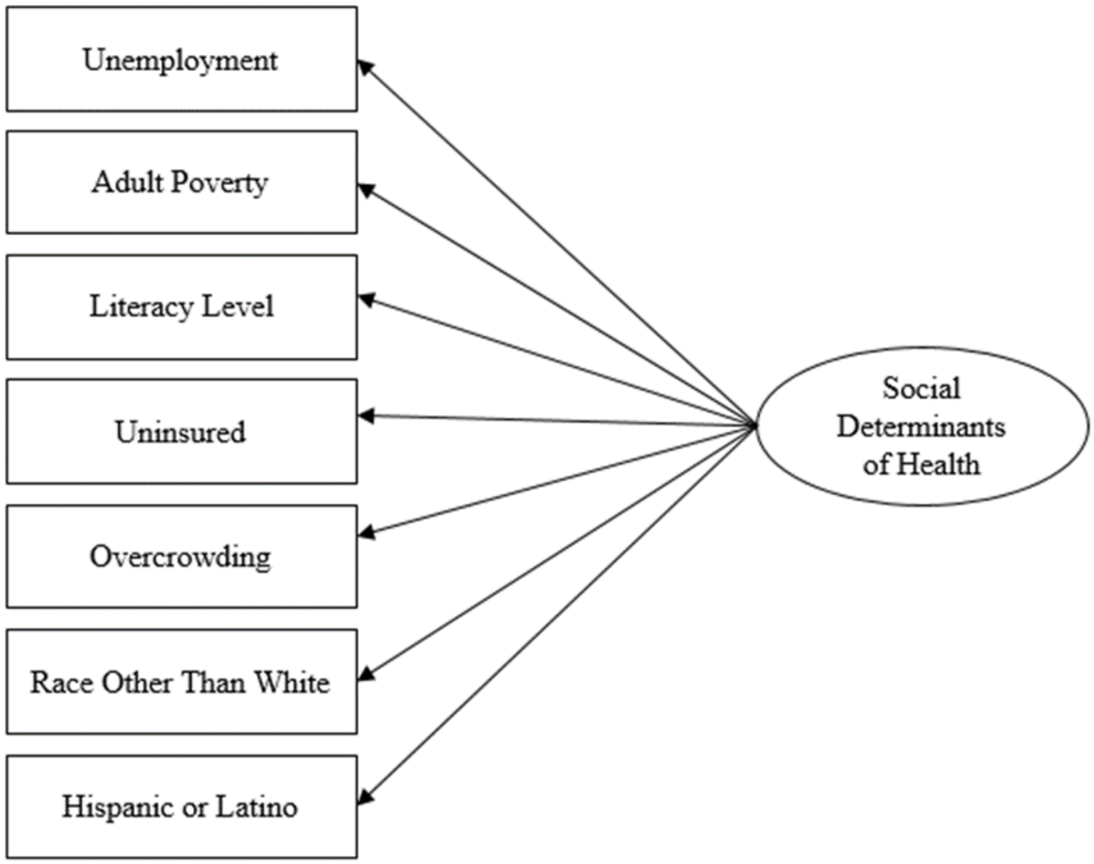
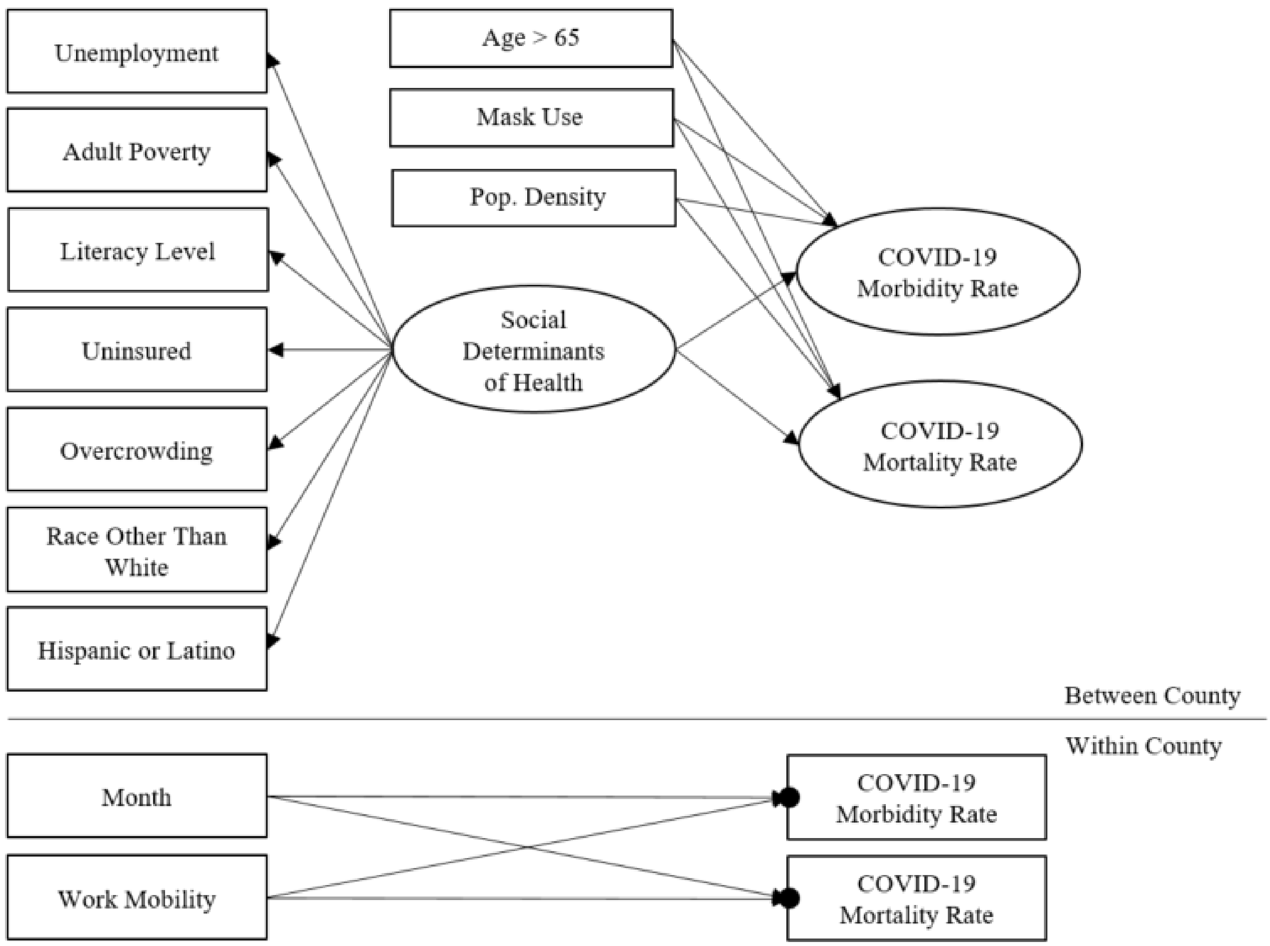
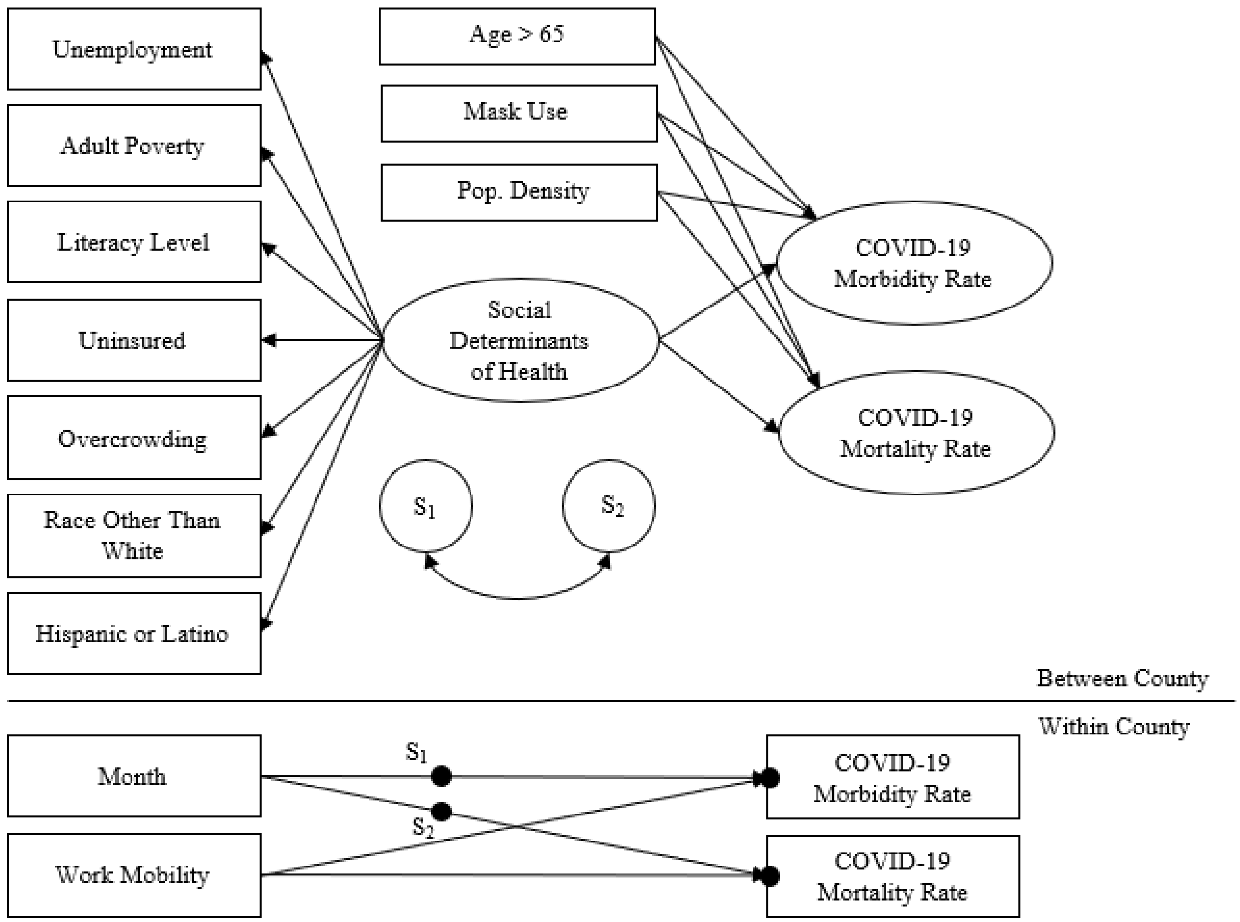


Figure 5: Model 1: Social Determinants of Health Parsimonious Structural Model – With Effects of Month on COVID-19 Morbidity and Mortality Modeled as Fixed Slopes*



*Estimated as a two-part model, one part in which COVID-19 morbidity and mortality rates were treated as dichotomous variables (0 vs. > 0), and another part in which COVID-19 morbidity and mortality rates greater than 0 were treated as continuous variables. To improve readability, residual variances are not depicted in the diagram.

Figure 6: Model 2: Social Determinants of Health Parsimonious Structural Model – With Effects of Month on COVID-19 Morbidity and Mortality Modeled as Random Slopes*



*Estimated as a two-part model, one part in which COVID-19 morbidity and mortality rates were treated as dichotomous variables (0 vs. > 0), and another part in which COVID-19 morbidity and mortality rates greater than 0 were treated as continuous variables. To improve readability, residual variances are not depicted in the diagram.

Table 1: Social Determinants of Health

Social Determinants of Health Category	Definition	Example Indicators
Economic stability	Reliable access to the financial resources necessary to meet basic needs (e.g. food, housing, and healthcare).	Employment, income, expenses, cost of living, access to banking and financing, sources of financial support
Education access and quality	Access to educational support and opportunities necessary to develop essential life skills (e.g. language, reading, and math), as well as preparation for gainful employment.	Literacy, language, access to education (early childhood, vocational, post-secondary)
Health care access and quality	Timely, affordable access to high-quality preventative and acute healthcare services, medication, and health information.	Access to primary care provider, hospital services, insurance, availability of affordable, healthy food
Neighborhood and built environment	Neighborhood living conditions that allow a healthy lifestyle and do not pose health risks (e.g. violence, pollution, unsafe traffic) to residents.	Housing, safety, transportation, parks, walkability, internet access, pollution
Social and community context	Family and social relationships that support physical and mental health, learning, and personal development.	Race, ethnicity, discrimination (based on any number of factors, including gender and sexual orientation), stress, social support systems, engagement in the community

(HHS, 2020b; Artiga & Hinton, 2018)

Table 2: Descriptive Statistics of Main Study Variables

Variable	N	Mean	SD	Min	Max
Age 65 and Over	2815	18.8%	4.6%	3.2%	56.7%
Population Density	2815	253.55	999.14	0.0	70,019.2
Mask Use	2815	16.3%	0.9%	0.1%	55.8%
Unemployment	2815	5.6%	3.4%	0%	34.1%
Adult Poverty	2815	15.3%	7.8%	0%	67.2%
Literacy Level	2815	21.7%	8.3%	5.6%	70.1%
Uninsured Adults	2815	13.3	6.1	2.7	42.4
Overcrowding	2815	2.395	2	0	36
Race	2815	17.3%	1.6%	4%	94.9%
Ethnicity	2815	9.2%	1.4%	0%	99.1%
Work Mobility March 2020	2,142	-15.1%	5.6%	-43%	0%
Work Mobility April 2020	2,312	-37.8%	8.5%	-71%	0%
Work Mobility May 2020	2,727	-28.7%	8.0%	-67%	0%
Work Mobility June 2020	2,738	-22.4%	6.9%	-55.1%	0%
Work Mobility July 2020	2,741	-25.6%	6.9%	-60%	13.6%
Work Mobility August 2020	2,762	-23.3%	6.7%	-66%	31.3%
Work Mobility September 2020	2,745	-20%	7.9%	-63.2%	39.2%
Work Mobility October 2020	2,752	-18.5%	7.1%	-61.3%	31.9%
Work Mobility November 2020	2,786	-23.5%	6.8%	-67.3%	-4.2%
Work Mobility December 2020	2,797	-26.5%	6.8%	-65.8%	-9.1%

Table 3: Social Determinants of Health Indicators and Standardized Factor Loadings

Social Determinant of Health	Indicator(s)	Standardized Factor Loadings
Economic Stability	Unemployment	0.643*
	Adult Poverty	0.536*
Education Access and Quality	Literacy Level	0.727*
Health Care Access and Quality	Uninsured	0.746*
Neighborhood and Built Environment	Overcrowding	0.704*
Social and Community Context	Race Other Than White	0.613*
	Hispanic or Latino	0.817*

Model fit indices: CFI=0.988, TLI=0.95, RMSEA=0.016

*$p < 0.05$

Table 4: Structural Equation Model Predicting COVID-19 Health Outcomes: Between Counties, Standardized Results

	Model Part 1 Cases and Deaths = 0 vs. > 0		Model Part 2 Cases and Deaths > 0	
	COVID-19 Case Rate	COVID-19 Death Rate	COVID-19 Case Rate	COVID-19 Death Rate
Social Determinants of Health	0.364*	0.479*	0.648*	0.388*
Age Greater Than 65	-0.190*	0.027	-0.200*	0.246*
Mask Use (Rarely or Never)	-0.040	0.089*	0.526*	0.317*
Population Density	0.720*	0.760*	-0.039	-0.269*
R-Square	0.804*	0.750*	0.730*	0.510*

*$p < 0.05$

Table 5: Structural Equation Model Predicting COVID-19 Health Outcomes: Within Counties, Standardized Results

	Model Part 1 Cases and Deaths = 0 vs. > 0		Model Part 2 Cases and Deaths > 0	
	COVID-19 Case Rate	COVID-19 Death Rate	COVID-19 Case Rate	COVID-19 Death Rate
Month	-0.219*	-0.220*	-0.309*	-0.223*
Work Mobility	0.166*	-0.108*	-0.007	-0.178*
R-Square	0.078*	0.058*	0.095*	0.079*

*$p < 0.05$