Socioeconomic Vulnerability, COVID-19, and the Opioid Epidemic

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Abstract

Increasing attention has been paid to how social factors, such as the circumstances in which people are born, grow up, live, work and age, affect individual well-being rather than solely clinical factors. However, previous research tends to focus on one disease at a time, whereas my research compares to determinants of two different mortalities. Comparing factors affecting deaths due to opioid misuse and deaths due to COVID-19 allows for a heightened understanding of which socioeconomic factors and vulnerability are more dominant and universally applicable. The study uses US county level data on mortality due to COVID-19 in 2020 and opioid overdose in 2019 (latest year available) and 2000, in conjunction with the Centers for Disease Control's (CDC) Social Vulnerability Index and socioeconomic data from the US Census. This research finds that areas with higher minority population are associated with higher COVID-19 death rates and that areas with a higher white population are associated with higher opioid related death rates in 2019. In contrast, other factors such overall socioeconomic vulnerability are only associated with COVID-19 mortality and not opioid mortality. This research has implications for how policymakers' direct resources in times of crisis and plan for future epidemics.

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Introduction

Currently the United States is facing two simultaneous epidemics that both pose a threat to society and are in urgent need of investigation. The opioid epidemic and COVID-19 virus have been working their way across the United States and integrating into nearly all facets of life. A major part of this investigation is understanding individual factors that make individuals more susceptible to dying because of COVID-19 or opioid misuse. Comparing different social and economic factors that increase an individual's susceptibility will allow researchers and public health officials to be more prepared for future epidemics and distribute assistance and resources to communities that need it most. Additionally, because two relationships would be compared side by side it could cause increased focused on which socioeconomic factors specifically affect which variable.

Opioid misuse is in part due to misleading marketing regarding prescription opioids from large corporations such as Purdue Pharma in the late 1990s and early 2000s. By misleading doctors into believing that opioids were non-addictive, opioids were rapidly prescribed in large quantities resulting in thousands of individuals becoming addicted. This cycle of overprescribing, addiction, and the eventual switch to illicit opioids perpetuated for years, causing the opioid epidemic to spread across large swaths of the country. Similarly, the current COVID-19 pandemic has disrupted lives around the world and will have repercussions for years to come. Scientific consensus indicates that while a vaccine has arrived and the world is learning more every day, there is still little concrete understanding as to what factors make an individual more susceptible to the virus.

Various studies have found a relationship between socioeconomic status and the health of a population. Socioeconomic status includes factors such as income, education, race, and occupation which all contribute to key determinants of health. One's socioeconomic status often determines the level of healthcare available, number of healthy behaviors undertaken, and exposure to environmental factors. Past research appears to mainly focus on socioeconomic factors and overall health. As such, this warrants an investigation of the relationship between socioeconomic vulnerability and mortality.

By comparing the factors affecting deaths due to COVID-19 and deaths due to opioids, we can begin to see which factors span multiple epidemics allowing for policy improvements. A common or universal factor that affects different, diseases, mortality, and overall health would be useful to this line of research. By understanding the socioeconomic factors involved, policymakers are increasingly able to direct resources to areas that need it most and provide a general strategy going forward for other ailments that are influenced by socioeconomic vulnerability. Since the beginning of the COVID-19 pandemic, drug overdoses are higher than normal and socioeconomic vulnerability has increased rapidly for many making this topic even more pressing for society. Socioeconomic level is not inherent to such an event, but instead has given the topic a new highlighted status. As such, the research question this study seeks to answer is "What is the relationship between socioeconomic vulnerability and both deaths due to opioid use disorder and deaths due to COVID-19?"

Literature Review

Introduction

Based on long-standing research, socioeconomic factors play a large role in affecting individual health. Socioeconomic barriers can stop individuals from seeing healthcare providers and therefore affect their health, however there are other more direct measures. Individuals facing additional barriers often live in the same areas making that community, town, city, or county more vulnerable overall. Socioeconomic vulnerability is broadly defined as the degree to which a community exhibits specific socioeconomic conditions that may ultimately affect that community's ability to prevent human suffering and financial loss in the event of disaster (Centers for Disease Control and Prevention, 2014). Socioeconomic vulnerability has been linked to a variety of morbidities and mortalities such as obesity, disabilities, and HIV/AIDS (An & Xiang, 2015; Wallace, Theou, Pena & Rockwood, 2014). This relationship has been found to be accurate across multiple countries in the north, continental, and Mediterranean areas of Europe (Wallace et al., 2014). However, higher levels of vulnerability also limit access to healthcare and makes it less likely to self-report any conditions accurately and have an overall lower life expectancy (Arpey, Gaglioti, & Rosenbaum, 2017). People from lower socioeconomic backgrounds also combat prejudices from healthcare providers themselves. Physicians are less likely to view people from low socioeconomic back grounds as intelligent, responsible, independent, or rational (Arpey et al., 2017). A wide variety of socioeconomic factors explicitly or implicitly affect individual health and the broader healthcare system.

Vulnerability Indexes

However, the question then turns to how society measures socioeconomic levels and ultimately socioeconomic vulnerability. There are multiple indexes that attempt to measure this for a specific area such as a zip code, census tract, or at the county level. The first example is the Centers for Disease Control's Social Vulnerability Index (SVI). Within the index there is a specific theme allotted to socioeconomic vulnerability and the index has data at both the county and census tract level (Centers for Disease Control and Prevention, 2014). Additionally, the index characterizes socioeconomic vulnerability by poverty, employment status, income level, and education level. The other major index is the Social Vulnerability Index (SoVI) created by the University of South Carolina (SoVI). SoVi is available on a county and census tract level across the United States and is an algorithm with twenty-seven variables. Isolating the socioeconomic variables in the SoVI, the four variables are the same as the CDC's SVI (SoVI Evolution). In general, graphical representation of these two indices reveals that they are mostly consistent on which locations are most and least vulnerable (Rufat, Tate, Emrich, & Antolini, 2019). However, based on a case study of Hurricane Sandy, neither the SoVI nor the SVI have a significant correlation with the vulnerability outcomes (Rufat et al., 2019). Additionally, SoVI has been found to be inconsistent and misaligned with theory (Spielman et al., 2020). Both Rufat et al. (2019) and Spielman et al. (2020) suggest that the optimal measure of socioeconomic vulnerability is variable-specific weights constructed by experts. In general, SVI and SoVI models are the most used indices for social vulnerability, and although they appear to agree with each other, it is unclear how accurately they predict the areas most affected by an incident.

Because of the uncertainty on the validity of the indices, some researchers have devised their own methods for quantifying socioeconomic vulnerability. Recently, both Acharya and Porwal (2020) and Amram et al. (2020) separately developed their own vulnerability indices to assist in managing the current COVID-19 pandemic. Acharya and Porwal (2020) created their own index for India and utilized fifteen indicators across five domains with one of them being a socioeconomic domain. The socioeconomic domain in this case includes the same variables as SoVI and SVI: income, poverty, employment, and education levels (Acharya & Porwal, 2020). However, in a review of early Washington state COVID-19 cases, Amram et al. (2020) used different variables to account for any socioeconomic risk factors. The only socioeconomic risk factors used in this study were poverty level and the percentage of people in an area with service occupations (Amram, Amiri, Lutz, Rajan & Monsivais, 2020). Despite disparities in quantifying socioeconomic vulnerability, both vulnerability indices found these factors to be useful and correlated with negative health outcomes indicating that these factors are important parts in creating a valid social vulnerability index.

Socioeconomic Factors and Opioid Use

Beyond a connection between socioeconomic status and overall health, socioeconomic vulnerability has specifically been found to affect opioid misuse and deaths due to opioid use. For example, by analyzing the Mortality Disparities in American Communities Study, Sean Altekruse et al. (2020) found that low socioeconomic status factors, such as low income and unemployment, were associated with fatalities due to opioid use. A separate thorough investigation of data indicates that high opioid mortality rates are associated with economically distressed areas that are more likely to exhibit low socioeconomic status (Monnat, 2019). Through a systematic review of past studies, it was ultimately concluded that "in general, opioid-related mortality rates have been higher … among those with lower SES [socioeconomic status]" (King, Fraser, Boikos, Richardson & Harper, 2014, p. 5). Draanen et al. (2020) also found similar results to King et al. (2014) in her systematic review where low socioeconomic status was associated with higher rates of overdose. Draanen et al. (2020) specifically notes that multiple socioeconomic hardships are positively correlated with overdoses as well. In essence, these studies show socioeconomic vulnerability has been associated with both opioid fatalities and opioid overdoses in several studies.

It is also important to note that it is not just overall survey data that shows a connection between socioeconomic vulnerability and opioid use, but case studies as well. In South Dakota, multiple socioeconomic factors such as unemployment rate, uninsured rate, and poverty rate were associated with drug overdose fatalities, naloxone use, and opioid prescriptions (Wesner et al., 2020). Marynia Kolak et al. (2020, p. 1) researched opioid-related overdoses in rural southern Illinois ultimately finding that "at-risk areas" possessed characteristics of underlying socioeconomic vulnerability. A specific study that King et al. (2014) reviewed was a special analysis of New York City showing methadone-related fatalities were associated with high income inequality and high poverty rates.

In looking at additional socioeconomic factors on their own, race and the ruralness of an area have been found to impact opioid use. Media has often covered the opioid epidemic as a problem largely affecting only white Americans (Netherland & Hansen, 2016). While it may be easy to dismiss this as narrow framing, Pletcher et al. finds that white patients are significantly more likely to be prescribed opioids for all types of pain-related doctor visits (2008). White Americans are not only more likely to be prescribed opioids, they also have seen the highest increases in opioid overdoses from 1999 to 2017, specifically in non-metropolitan areas (Lippold & Ali, 2020). Sam Quinones, in his book Dreamland, describes opioids as a pervasive wave, integrating into America's small rural towns (2015). The characterization of opioids largely affecting rural America is not entirely unfounded as prescription opioid use is more concentrated in "states with large rural populations" such as West Virginia or Kentucky (Keyes et al., 2013, p. 1). Additionally, Mosher et al. concluded that hospitalizations due to prescription opioids were 20-30% higher in rural counties than urban counties until 2012 where the gap slightly narrowed (2017). Even beyond the more specific aspects of socioeconomic vulnerability, past research has shown that lower socioeconomic status is correlated with opioid misuse and overdoses.

Socioeconomic Factors and COVID-19

As previously suggested, a significant number of researchers are examining what factors may cause an individual to be more susceptible to COVID-19 in order to allocate resources most effectively to those who are hardest hit by the virus. Researchers have examined socioeconomic factors during the pandemic, with many of them found to potentially influence COVID-19 cases. In a United Kingdom case study, lower education levels are associated with a higher chance of COVID-19 health risks (Mikolai, Keenan & Kulu, 2020). This analysis determined that economic needs could prevent a household from following health guidelines making people more vulnerable to COVID-19 (Mikolai et al., 2020). A different study by Patel et al. (2020) also on the United Kingdom found that people with low socioeconomic status are more likely to have increased exposure to COVID-19. Additionally, each of the two aforementioned case studies in India (Acharya & Porwal, 2020) and Washington state (Amram et al., 2020) found a connection between socioeconomic status and COVID-19 cases.

There is a broad relationship between socioeconomic disparities and the COVID-19 pandemic. In examining the COVID-19 lockdown in Italy, socioeconomic disparities are made abundantly clear between different communities and neighborhoods (Bonaccorsi et al., 2020). In general, those with lower socioeconomic status are found to have a reduction in connectivity which has negative mental health consequences. A study in Nepal has found an increased burden placed on those with a socioeconomic disadvantage such as job insecurity, or low-income (Poudel & Subedi, 2020). Although COVID-19 is extremely recent and the literature is therefore limited, at this point there are many indicators that socioeconomic vulnerability plays a large role in an individual's susceptibility to COVID-19.

COVID-19 mirrors the opioid epidemic in that both race and rurality have become prominent factors in discussions regarding those most susceptible to the virus. Overall, researchers have found that Black individuals have a disproportionately higher risk of COVID-19 hospitalizations (Karaca-Mandic et al., 2020). Minority communities also have a higher risk of illness from COVID-19 and minority Americans were more likely than their white counterparts to have multiple risk factors (Raifman & Raifman, 2020). Beyond susceptibility to illness, in 22 out of 28 states that were surveyed, Gross et al. found that there was a higher risk of death for Black individuals (2020). However, the disparities that COVID-19 has highlighted in terms of both race and rurality extend beyond the United States. Patel et al. have found that minorities in England have higher mortality rates, and Kumar et al. have found that rural communities in India are struggling with a lack of infrastructure similar to rural America (2020; 2020). Specifically, Hemming-Smith determined that rural areas possess a heightened risk for COVID-19 because of pre-existing inequalities and limited access to healthcare (2020). Expanding further, Peters et al. (2020, p. 1) found that around "33% of rural counties are highly susceptible to COVID-19" due to a variety of factors such as an older population, more uninsured individuals, and fewer physicians.

Conclusion

In reviewing the literature there is clear evidence that socioeconomic factors are known to affect health and there is debate on which factors should be included or emphasized. As such, it is unsurprising that many scholars have attempted to understand both deaths due to opioid misuse and deaths due to COVID-19 through a lens of vulnerability. There are also a variety of vulnerability indexes that have tried to quantify and compare levels of vulnerability across different geographical areas. These indexes have clear methods for evaluation that will be useful moving forward. However, there are clear gaps in the research. Due to the recency of COVID-19, there are significant gaps in knowledge about the virus and its future repercussions. It is also unclear which socioeconomic factors have the biggest effect on health outcomes. Both gaps indicate the need for future research on the subject.

The main gap where this study will fall is in how these variables could be examined together. In comparing how socioeconomic vulnerability affects COVID-19 and opioids, this knowledge would also be conducive both in distributing various public health resources and in aiding general knowledge about the topic. As such, this study proposes a positive relationship between socioeconomic vulnerability and deaths due to both COVID-19 and opioid misuse. A study of this kind could be imperative in further understanding socioeconomic vulnerability and how it relates to morbidities and mortalities.

Methods

Variables

In this research study, the independent variable is socioeconomic vulnerability assessed on a county level because there is a previously established relationship between socioeconomic status and health. The Center for Disease Control's Social Vulnerability Index will be used as the data source for socioeconomic vulnerability. The 2018 Social Vulnerability Index was used for all variables in order to streamline the process as 2000 data was unavailable to download. According to the CDC, socioeconomic vulnerability takes four identifiable factors into account. These factors include the amount of people unemployed or living below the poverty line as well as the income and education level of an individual. In measuring these factors, the CDC used results from the census to aggregate the average of each factor for a given census tract. Each census tract is compared to the others in the state and given a percentile ranking on a scale from 0 to 1 with higher values indicating higher levels of vulnerability. The census tract percentile ranking has then been correlated for of each county. Combining the percentile ranking for each of the four factors for socioeconomic vulnerability provides the overall socioeconomic vulnerability data that will be used. Additionally, race often affects health, so data on the percentage of the population that is white in each county was taken from the American Census Bureau and will be used as a separate measure of vulnerability. The last independent variable is the urban-rural continuum found through the United States Department of Agriculture. Rural areas are more vulnerable to economic disasters than urban areas largely due to the lack of resources.

Both the number of deaths due to opioid misuse and COVID-19 are dependent variables and will also be assessed at the county level and the data will come from the mortality reports of the state departments of health. All drug poisoning deaths are broken down by the drug involved with the death making it simple to identify which deaths are due to opioids. COVID-19 is listed as a separate cause of death as well. Since COVID-19 is a new disease, mortality reports and certificates are not available yet, however due to the global nature of this crisis, information regarding number of deaths per county is easily found through the Johns Hopkins COVID-19 Dashboard.

Data Manipulation

The Centers for Disease Control's Wide-ranging Online Data for Epidemiologic Research (WONDER) provides access to public health information and statistical research data published by the CDC. Data was extracted from the CDC WONDER database for the number of deaths due to opioids in each county for the years 2000 and 2019. The goal was to get data from both before and after the peak of the opioid crisis to get a better understanding. Mortality in the CDC WONDER database is assessed according to ICD-10 codes which are worldwide diagnostic codes for all ailments. In order to appropriately isolate deaths due to opioids, the research followed guidance from Substance Abuse and Mental Health Services Administration (SAMHSA) on which ICD-10 codes are used to classify deaths related to opioid overdoses[1]. The total number of deaths for each county was the divided for the population of that county for that year in order to make data comparable across all counties regardless of population. It is important to note that counties with a raw number of deaths less than 10 are suppressed by the CDC for identification purposes. To adjust, all counties with suppressed data were randomly assigned a number from 0-9 in Excel. Separately, data was pulled on February 3, 2021 from the Johns Hopkins COVID-19 dashboard for all deaths due to COVID-19 up to that day and is also at a county level. The same method for making counties comparable based on population was used on this data as well.

Examining the independent variables, in order to quantify socioeconomic vulnerability, the CDC's Social Vulnerability Index (SVI) was used. The Index shows measures of social vulnerability for every county in the United States. Additionally, the percent of the population that is white per county is available through the American Community Survey and Census data. The most recent data is from 2018. Lastly, the Urban-Rural Continuum is updated every 10 years by the United States Department of Agriculture and the most recent data is from 2013. Counties are broken down into metropolitan and non-metropolitan categories based on population size,

[1] See Appendix 1 for more details.

and then further broken down by the amount of urbanization and proximity to metro areas. All counties in the United States are ranked on a scale from 1-9 with 1 indicating a highly urban area such as New York City, and 9 indicating an extremely rural county. The data for all variables was easily downloaded from their respective websites into Excel spreadsheets for further analysis.

Data Analysis

The first step is to pool the datasets, which was easily accomplished using R by matching the county's FIPS code. During this process, it was discovered that the most recent Census data for Rio Arriba County, New Mexico was calculated improperly and as a result, the Social Vulnerability Index is lacking data. The best way to resolve this issue was to remove the county from the dataset because the data for this county was unusable and incalculable. Throughout this study, the dependent variables are deaths due to opioids in year 2000, deaths due to opioids in year 2019, and deaths due to COVID-19. The independent variables are socioeconomic vulnerability, the percent of white population in a county, and the urban-rural continuum. From here, scatterplots, correlation tests, and models were created in R between all combinations of one dependent variable and one independent variable to determine relationships between the variables. This study mainly modeled linear regressions in the following form:

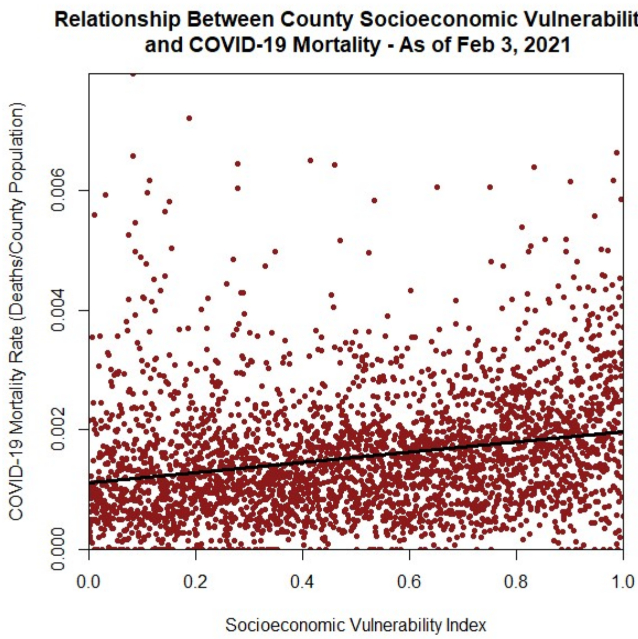
$$Y = \alpha + \beta x + \varepsilon$$

although exponential models were used occasionally if they fit the data better.

Findings and Discussion

This study seeks to find a "universal factor" that affects multiple types of mortality in order to influence how policymakers allocate resources and react to future epidemics. It was hypothesized that there would be a relationship between heightened vulnerability and increased mortality due to both COVID-19 and opioids. Heightened vulnerability includes increased socioeconomic vulnerability, a lower white population, and increased rurality. However, only the COVID-19 mortality rate showed all three hypothesized relationships, and in contrast, both the year 2000 and 2019 opioid mortality rate did not.

Socioeconomic Vulnerability[2]



COVID-19 Linear Model	Socioeconomic Vulnerability
Coefficient	0.0008561
Standard Error	0.00006129
t	13.97
P> |t|	<2e-16 ***
R-Squared	0.05855

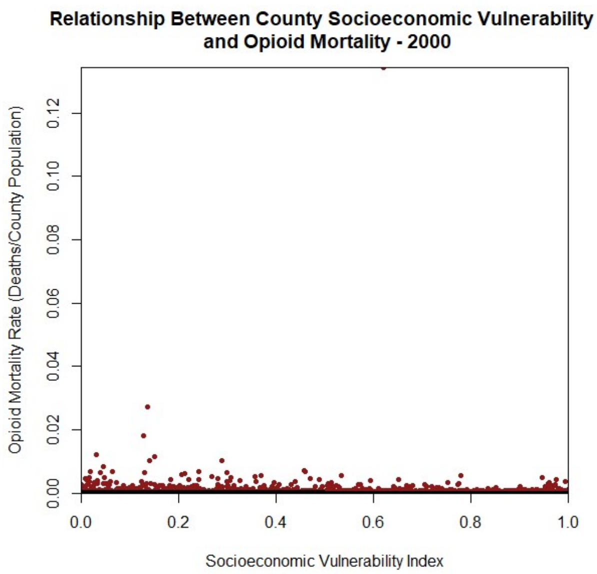
Figure 1: Using data from the CDC's Social Vulnerability Index and Johns Hopkins COVID-19 Dashboard, there is a correlation between increased vulnerability and increased COVID-19 mortality rates. Trendline: Y = 0.00111 + 0.00086x.

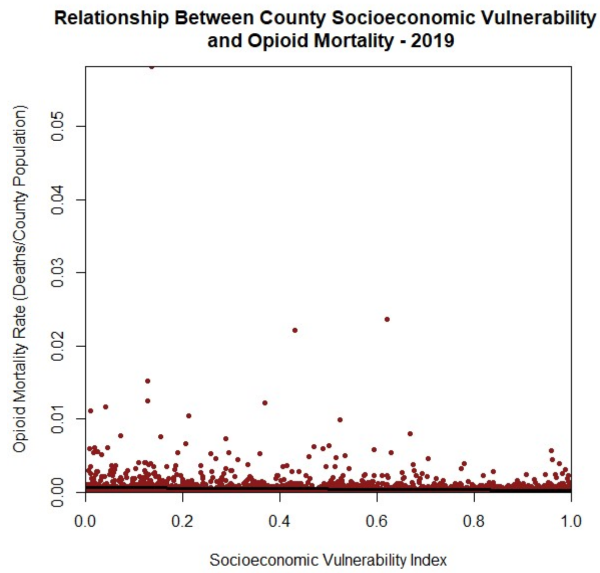
Table 1: Summary of the components of the linear model shown in Figure 1.

In essence, it was hypothesized that as socioeconomic vulnerability increased, mortality rates would increase as well because such vulnerability often indicates both decreased access and funding for healthcare leading to higher mortality. The relationship between COVID-19 and socioeconomic vulnerability is one of the clearest ones throughout the entire analysis (Figure 1). The relationship is highly significant, and the R-squared value is 0.058 indicating that socioeconomic vulnerability is correlated with deaths due to COVID-19, but it is not the primary

[2] Descriptive Statistics available in Appendix 2.

variable for understanding the variance in these deaths (Table 1). As vulnerability increases by 1 unit, we can expect the rate of deaths due to COVID-19 by county to increase by 0.0008561. Although the coefficient is small, so is the scale that this project is working at. By converting the mortality rate into a precise number of deaths, this can be conceptualized further. For example, in a county the size of Monroe County, Indiana (population slightly under 150,000) a 1 unit increase in socioeconomic vulnerability would lead to an additional 13 deaths from COVID-19 every year.





2000 Opioid Linear Model	Socioeconomic Vulnerability
Coefficient	-0.00026
Standard Error	0.00026
t	-1.604
P> |t|	0.1089
R-Squared	0.0005

Figure 2: Using data from the CDC's Social Vulnerability Index and CDC WONDER, there is no relationship between vulnerability and 2000 opioid mortality rates. Trendline: Y = 0.00056 + -0.00026x.

Table 2: Summary of the components of the linear model shown in Figure 2.

2019 Opioid Linear Model	Socioeonomic Vulnerability
Coefficient	-0.00043
Standard Error	0.0015
t	-4.688
P> |t|	2.875e-6***
R-Squared	0.007

Figure 3: Using data from the CDC's Social Vulnerability Index and CDC WONDER, there little correlation between vulnerability and 2019 opioid mortality rates. Trendline: Y = 0.00069 + -0.00043x.

Table 3: Summary of the components of the linear model shown in Figure 3.

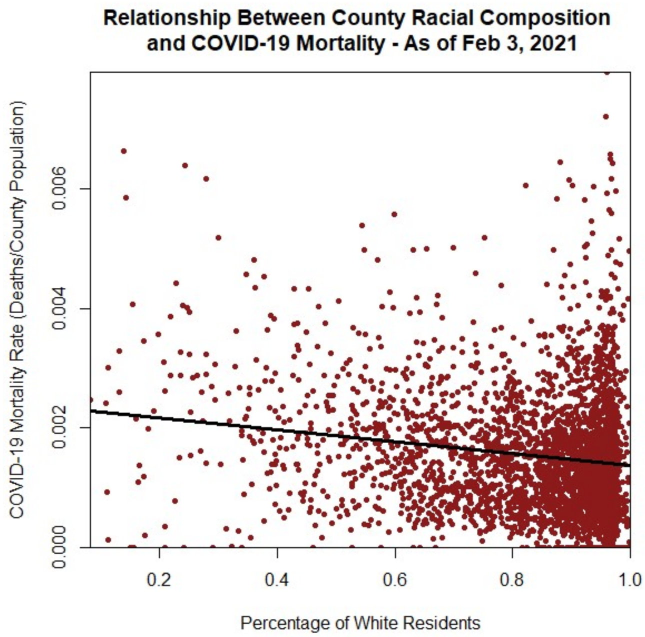
In contrast, the opioid mortality rate in both year 2000 and year 2019 have little to no relationship with socioeconomic vulnerability (Figure 2; Figure 3). In both cases, the R-squared is less than 0.007, or less than one percent, indicating no relationship between the two variables (Table 2; Table 3). However, in 2019 socioeconomic vulnerability is significant and therefore a factor affecting mortality due to opioids, but the relationship is incredibly weak. Additionally, in year 2000 socioeconomic vulnerability is not a statistically significant variable indicating the changes in the rates of deaths due to opioid misuse in this year are not affected by socioeconomic vulnerability. This is surprising for both magnitude and significance because past research has shown that socioeconomic vulnerability influences deaths due to opioids. According to the World Health Organization, individuals with low socioeconomic status are at a higher risk for opioid overdose, but this relationship is not found in this analysis (World Health Organization, 2020). There are multiple reasons this result could have occurred. For example, much of the research already conducted on this topic is at an individual level and does not involve community or county wide generalizations. Additionally, the Social Vulnerability Index ranks counties against each other on a scale from 0 to 1 meaning that there is no exact measure for each county. Even at a county level, fitting 3,139 counties from 0-1 leads to very little leeway for variance or correlation. It is entirely possible that on a more spread-out scale with exact measurements, the analysis would yield differing results.

Racial Composition[3]

Breaking down socioeconomic vulnerability a little further, the percent of a county's population that is white affects both mortality rates for opioids and COVID-19. However, the

[3] Descriptive Statistics available in Appendix 3

percent of white residents has a positive relationship with both years of opioid mortality and a negative relationship with COVID-19. Although it may seem a bit counterintuitive, this analysis is in line with past research showing that opioid fatalities are higher among white Americans and deaths due to COVID-19 are higher in minority communities.

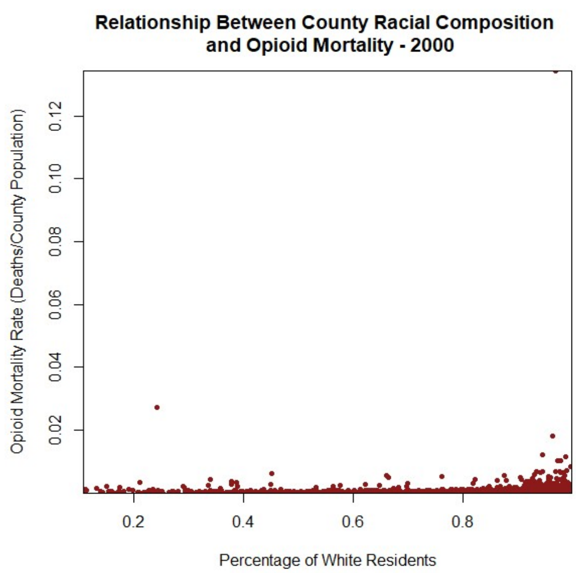


COVID-19 Linear Model	%White
Coefficient	-0.0009809
Standard Error	0.0001072
t	-9.147
P> |t|	<2e-16 ***
R-Squared	0.02598

Figure 4: Using data from the American Community Survey and Johns Hopkins COVID-19 Dashboard, there is a correlation between a higher white county population and lower COVID-19 mortality rates. Trendline: Y = 0.00235 + -0.00098x.

Table 4: Summary of the components of the linear model shown in Figure 4.

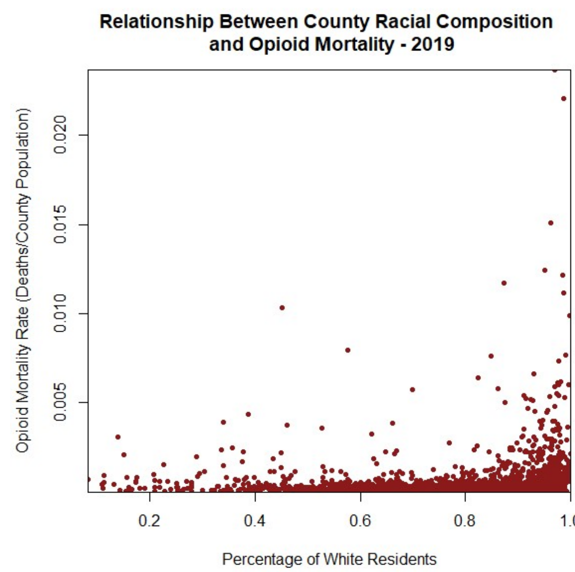
There is a negative relationship between the COVID-19 mortality rate and the percent of the county population that is white (Figure 4). The R-squared for this relationship is 0.026 and all variables are highly significant (Table 4). As vulnerability increases by 1, we can expect the rate of deaths due to COVID-19 by county to decrease by approximately 0.001. Since the scale for COVID-19 mortality rates is from 0 to nearly 0.008, a decrease of 0.001 is quite noticeable. For example, Marion County, Indiana where Indianapolis is located has a population of 964,582. If this county increased its population of white residents by 10% or 0.1, that would lead to a decrease of 95 deaths per year due to COVID-19. However, since the R-Squared is quite small, the percent of the population that is white is not the main factor influencing COVID-19 mortality rates. It is important to note though that the R-squared value was expected to be small because mortality is such a complex issue. The results of the analysis indicate that counties with an increased minority population are more likely to have a higher COVID-19 mortality rate than areas with a majority white population.



2000 Opioid Log Model	%White
Coefficient	1.14
Standard Error	0.1531
t	7.45
P> |t|	1.258e-13***
R-Squared	0.019

Figure 5: Using data from the American Community Survey and CDC WONDER, there is a correlation between a higher white population and increased 2000 opioid mortality rates.
Trendline: $\ln(Y) = -9.6584 + 1.14x$.

Table 5: Summary of the components of the exponential model shown in Figure 5.



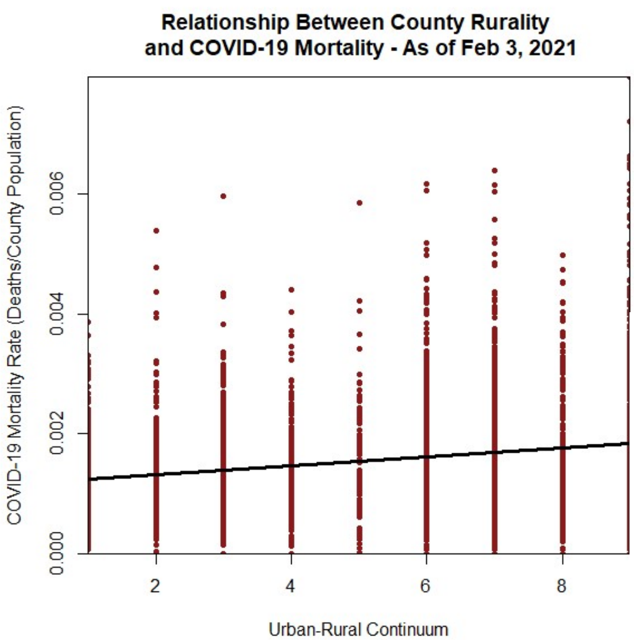
2019 Opioid Log Model	%White
Coefficient	0.6721
Standard Error	1.139
t	5.265
P> |t|	1.51e-7***
R-Squared	0.0095

Figure 6: Using data from the American Community Survey and CDC WONDER, there is a relationship between a higher white population and higher 2019 opioid mortality rates.
Trendline: $\ln(Y) = -8.9331 + 0.6721x$.

Table 6: Summary of the components of the exponential model shown in Figure 6.

In analyzing the opioid mortality rate against the percent of the population that is white, it is clear that a linear relationship is not the best option. Instead, an exponential model more accurately describes the relationship shown (Figure 5; Figure 6). It is important to note that in creating an exponential model, all values of 0 for opioid mortality rates had to be removed from the dataset which was approximately 300-400 counties for each year. Using an exponential model for 2019 opioid mortality doubled the R-squared value from the original 0.005 to 0.01 (Table 6). Additionally, the exponential model contained an extra level of significance compared to the linear model. Through the analysis, it is clear that higher opioid mortality rates are more likely to occur in counties with a higher white population and therefore, a lower minority population. Similarly, examining opioid mortality from the year 2000, the percentage of white residents in a county was found to be statistically significant when using an exponential model (Table 5). The data yields an R-squared value of 0.02. Due to significance at the 0.001 level, it is highly likely that the results of this analysis are accurate and not due to chance or any external factors. Based on past literature, this relationship as expected, although given the narrow framing the media uses, a higher correlation and larger R-squared were expected in both relationships.

Urban-Rural Continuum[4]



COVID-19 Linear Model	Urban-Rural Continuum
Coefficient	0.00007504
Standard Error	0.001001
t	11.38
P> |t|	<2.2e-16 ***
R-Squared	0.03962

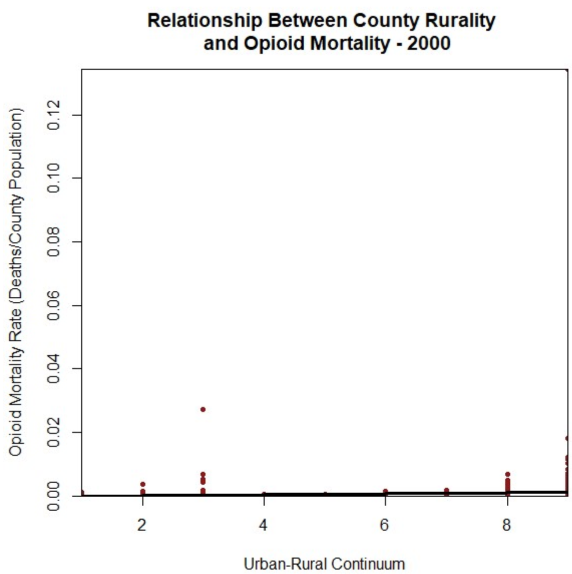
Figure 7: Using data from the United States Department of Agriculture and Johns Hopkins COVID-19 Dashboard, there is a correlation between increased rurality and increased COVID-19 mortality rates. Trendline: Y = 0.00117 + 0.00075x.

Table 7: Summary of the components of the linear model shown in Figure 7.

Analysis involving mortality and the urban-rural continuum yields incredibly interesting results. When examining the relationship between deaths due to COVID-19 and the dynamic

[4] Descriptive Statistics Available in Appendix 4

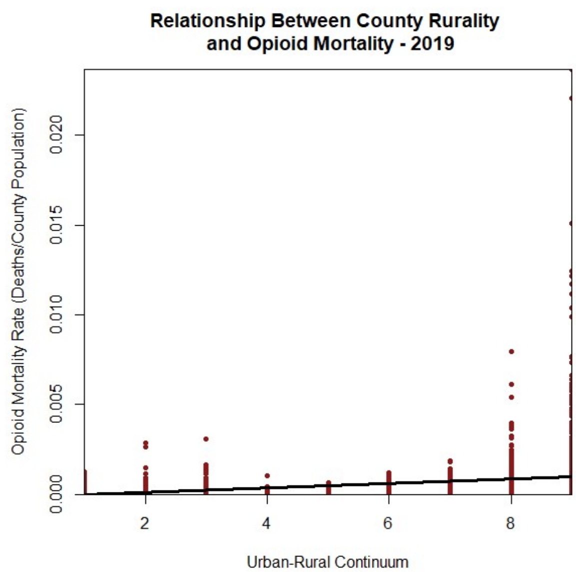
between urban and rural areas, comparatively, non-metropolitan and more rural areas (>5 on the scale) tend to have a higher mortality rate than urban areas (Figure 7). There is an R-squared for this relationship of 0.04, or 4%, and the results are statistically significant (Table 7). For every 1 unit increase on the urban-rural continuum, the mortality rate increases by 0.000075. For a larger county, such as Marion County, Indiana with a population around 964,000, a 1 unit increase in rurality would yield 72 additional deaths per year from COVID-19. Overall, counties with the highest rates of mortality are consistent with increasingly rural areas.



2000 Opioid Linear Model	Urban-Rural Continuum
Coefficient	0.00014
Standard Error	0.00256
t	7.99
P> |t|	1.75e-15***
R-Squared	0.019

Figure 8: Using data from the United States Department of Agriculture and CDC WONDER, there is a correlation between increased rurality and increased 2000 opioid mortality rates.
Trendline: Y = -0.00024 + 0.00014x.

Table 8: Summary of the components of the linear model shown in Figure 8.



2019 Opioid Linear Model	Urban-Rural Continuum
Coefficient	0.00012
Standard Error	0.00102
t	18.358
P> |t|	<2.2e-16***
R-Squared	0.097

Figure 9: Using data from the United States Department of Agriculture and CDC WONDER, there is a correlation between increased rurality and increased 2000 opioid mortality rates.
Trendline: Y = -0.00017 + 0.00012x.

Table 9: Summary of the components of the linear model shown in Figure 9.

Regardless of year, counties in more rural areas clearly have a higher mortality rate due to opioid misuse (Figure 8; Figure 9). In 2019, there is a clear, strong, relationship between rurality and deaths due to opioid misuse. Specifically, the R-squared value is 0.097 which is incredibly high compared to all other relationships in this analysis (Table 9). This indicates that 9.7% of the variance in opioid mortality rates in 2019 is due to the rurality of a county. As previously mentioned, mortality is an incredibly complex topic meaning an R-squared value of nearly 10% is unexpected and shows a great line of investigation for future work. Based on the 2019 data, a 1 unit increase in rurality corresponds with an additional 18 deaths per year for a county the size of Monroe County with around 150,000 people. Additionally, although less strong, there is also a considerable relationship shown above between increased rurality and mortality rate due to opioids in 2000 (Table 8). As the ruralness of a county increases by 1, or changes category on the urban-rural continuum, the opioid mortality rate in 2000 increased by 0.0014. Although the coefficients are small in both cases, there are statistically significant relationships between rural areas and a higher mortality rate due to opioid misuse for both year 2000 and year 2019.

Conclusion

At the beginning of this study, it was hypothesized that areas with higher levels of socioeconomic vulnerability would have increased mortality rates for both COVID-19 and opioid misuse. There was a mix of results regarding this hypothesis. Specifically, for COVID-19, this hypothesis is entirely true. When compared with socioeconomic vulnerability from the Centers for Disease Control, mortality rates rose as vulnerability rose. Areas with a higher white population are in general less vulnerable and this study finds that that areas with a higher white population have lower mortality rates due to COVID-19. Lastly it is clear that increased rurality, another marker of high vulnerability, is correlated with increased COVID-19 mortality. For opioid misuse, the hypothesis was not consistently proven to be correct. In year 2000, mortality rates due to opioid misuse were not affected by socioeconomic vulnerability but are affected the percent of the population that is white and by the rurality of an area. In 2019, opioid mortality rates are affected by all three variables tested. However, despite statistical significance, the relationship between 2019 opioid mortality rates and socioeconomic vulnerability is rather weak. The key takeaway from this analysis is the impact that rurality had on all three dependent variables. Each relationship was statistically significant and showed that increasingly rural areas have increased mortality rates for both COVID-19 and opioid misuse. This finding suggests that rurality may be a common or universal factor among a variety of health disparities.

Limitations

There are several limitations that affected this study. First, socioeconomic data was pulled from 2018 because data from 2000 was not easily available in open-source form. This could help explain why the relationship between the Socioeconomic Vulnerability Index and opioid mortality rates in year 2000 was not significant. Next, due to the aggregation of data at the county level, it is possible that the data is less representative of the population comparatively. Similarly, the use of a vulnerability index instead of a specific measure could have influenced the results. Since the counties were ranked against each other, any differences in data were decreased in magnitude. For example, if County A and County B had corresponding measurements of 0.09% and 0.15% for the unemployed population, they could still be ranked next to one another in the index due to other variables affecting socioeconomic vulnerability. The average distance between the rankings is .0003 while the example unemployed population shows a difference of 0.06%. Using specific measurements could be a way to further investigate the relationship between socioeconomic vulnerability and mortality rates.

Lastly, unexpectedly low rates of opioid mortality are likely affecting the results. Nearly half of counties in 2000 and a third in 2019 had a mortality rate of less than 0.0001. Such universally small rates impact the amount of variation and correlation that can be found. To address this, if counties could be separated into groups based on population, then a rate would be less necessary for comparison as population would be neutralized in a different manner. However, as noted throughout this study, the socioeconomic factors chosen showed much lower correlation and influenced mortality rates less than expected. This could be due to a variety of reasons including county level data, the use of a vulnerability index, and the overall low mortality rates.

Conclusion

This study was designed as a comparison, and there appears to be one main connection between the socioeconomic factors that affect COVID-19 and opioid mortality rates. Overall socioeconomic vulnerability affects COVID-19 mortality rates, but not opioid mortality. Similarly, while the racial composition of a county does affect both forms of mortality, the relationship is in opposite directions. Although this finding is interesting, it does not help pinpoint a common socioeconomic factor that affect epidemics across America. Lastly, there is a positive relationship between rural counties and both forms of mortality rates. This relationship indicates that rurality as a whole is linked with higher mortality rates and therefore, less desirable health conditions and outcomes.

Looking toward future research, studies should examine a more precise understanding of socioeconomic factors and mortality. It would be useful to do a comparison with this mortality between the CDC's Social Vulnerability Index and a different vulnerability index in order to determine if the results found in this study are connected with the index chosen. The results would show if the design of the index is influencing the results and potentially to what magnitude. Research in this field would also benefit from performing a similar study with data at an individual level in order to further ascertain the relationship between socioeconomic status and mortality. Separately, by breaking down the specific factors of the vulnerability indices into individual socioeconomic factors, such as income or education level, there would be greater clarity on exactly which factors are most influential. Lastly, additional research would be needed to establish if the relationships and results identified in this study hold true for other crises and types of mortality.

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Appendices

Appendix 1

The following steps were used to obtain the data for deaths due to opioid misuse from the CDC Wonder database.

1. Go to the Center for Disease Control's WONDER Database (https://wonder.cdc.gov/).
2. Click "Multiple Cause of Death" under "Deaths" > "All Ages".
3. Under "Current Multiple Cause of Death Data" select "Data Request" under "1999-2019."
4. Click "I agree."
5. Change "Group Results By" to "County" in section 1.
6. In section 4, select the year.
    a. Note: For the purposes of this analysis, year 2000 and year 2019 data were accessed and downloaded separately.
7. In section 6 select "UCD-ICD-10 Codes."
8. In section 6 where is says "Browse" select "V01-Y89" and select "Open Fully" below.
    a. Note: The page will refresh when open fully is clicked. Simply scroll back down to section 6 to continue.
9. In section 6 use the control button (or command if using a Mac computer) to select multiple answers and click X40, X41, X42, X43, X44, X60, X61, X62, X63, X64, X85, Y10, Y11, Y12, Y13, and Y14.
    a. NOTE: it is extremely easy to select these codes incorrectly.
10. In section 7 select "MCD-ICD-10 codes."
11. In section 7 where it says "Browse" select "S00-T98" and select "Open Fully" below.

a. Note: The page will refresh when open fully is clicked. Simply scroll back down to section 7 to continue.

12. In section 7 click T40.0, T40.1, T40.2, T40.3, T40.4, T40.6 and click the top “Move Items Over” button to move the codes into the box that says, “Select Records with any of these items”.
13. In section 8, check “Export Results”, show suppressed and zero values, and change precision decimal places to 2.
14. Click “Send” at the very bottom of the request page.

Appendix 2

Socioeconomic Vulnerability	
Mean	0.499667346
Standard Error	0.005151717
Median	0.4997
Mode	0.1844
Standard Deviation	0.288634095
Sample Variance	0.083309641
Kurtosis	-1.19993246
Skewness	6.91762E-05
Range	1
Minimum	0
Maximum	1
Count	3139

Descriptive statistics for the CDC’s 2018 Socioeconomic Vulnerability Index data.

Appendix 3

%White	
Mean	0.829746855
Standard Error	0.002994919
Median	0.895875506
Mode	N/A
Standard Deviation	0.167795682
Sample Variance	0.028155391
Kurtosis	2.674780345
Skewness	-1.68142245
Range	0.916723884
Minimum	0.083276116
Maximum	1
Count	3139

Descriptive statistics for the percent of white residents in a county from the American Community Survey in 2019.

Appendix 4

Urban-Rural Continuum	
Mean	5.007327174
Standard Error	0.048345632
Median	6
Mode	6
Standard Deviation	2.708650041
Sample Variance	7.336785046
Kurtosis	-1.33690151
Skewness	-0.06984923
Range	8
Minimum	1
Maximum	9
Count	3139

Descriptive statistics for United States Department of Agriculture's 2013 Urban-Rural Continuum.

Appendix 5

COVID-19 Mortality Rate	
Mean	0.001541443
Standard Error	1.82267E-05
Median	0.001385027
Mode	0
Standard Deviation	0.001021181
Sample Variance	1.04281E-06
Kurtosis	3.23472635
Skewness	1.357889973
Range	0.007948336
Minimum	0
Maximum	0.007948336
Count	3139

Descriptive statistics for the county-level COVID-19 mortality rate as of Feb 3, 2021 based on data from the Johns Hopkins University COVID-19 Dashboard.

Appendix 6

Opioid Mortality Rate - 2000	
Mean	0.000434148
Standard Error	4.62219E-05
Median	0.000139246
Mode	0
Standard Deviation	0.002589664
Sample Variance	6.70636E-06
Kurtosis	2283.561362
Skewness	44.71685929
Range	0.134328358
Minimum	0
Maximum	0.134328358
Count	3139

Descriptive statistics for the county-level opioid mortality rate in 2000 based on data from the CDC WONDER database.

Appendix 7

Opioid Mortality Rate - 2019	
Mean	0.000472034
Standard Error	2.65989E-05
Median	0.000197824
Mode	0
Standard Deviation	0.00149025
Sample Variance	2.22084E-06
Kurtosis	756.1935667
Skewness	22.26248101
Range	0.058139535
Minimum	0
Maximum	0.058139535
Count	3139

Descriptive statistics for the county-level opioid mortality rate in 2019 based on data from the CDC WONDER database.