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Socioeconomic Determinants of Health and COVID-19 outcomes: A county level study of the United States

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Abstract

A range of medical, policy and socioeconomic factors have played a role in determining the spread of the coronavirus (COVID-19) in different communities. These factors vary largely across the United States, which presents a challenge to centralized planning and policy measures. A county-level analysis can provide deeper insight into the structural inequities that exist within the country and guide strategies that are better equipped to alleviate the public's hardships.

Using publicly available county-level datasets, we identified key socio-economic factors influencing susceptibility of a population to COVID-19. We focused this study on 6 socioeconomic determinants of health: education, unemployment, income, rural-urban classification, access to hospital beds and access to primary care physicians. Education rate, rural-urban classification and unemployment were found to be moderately correlated with COVID cases per 1,000 people and deaths per 1,000 people. The regression analysis found education, unemployment, median household income, rural-urban classification and number of hospital beds to be statistically significant determinants of COVID outcomes. We use the derived insights to propose appropriate policy changes.

We discuss how county level governments could improve health literacy using public engagement and minimizing misinformation. We recommend innovative public health policy reforms to finance better healthcare access for lower income groups. We also recommend a guaranteed employment policy as a preventative measure against future viruses. Finally, although access to healthcare through bed capacity and physicians per capita did not exhibit strong correlation with COVID-19 spread, strategies such as elective surgeries, rapid-response groups, and streamlined patient flow management show promise in dealing effectively with virus spread.

Keywords
COVID-19, socio-economic, rural health, public health, health inequity, policy

1 Introduction

The first case of the novel coronavirus disease (COVID-19) was reported in December 2019, originating from Wuhan, China. In the months that followed, COVID-19 swept the globe and evolved into a pandemic as declared by the World Health Organization (WHO) on March 12, 2020 [1]. The United States of America (USA) has been affected significantly. At the time of this writing (May 31st 2020), the USA has the highest reported impact of COVID-19 in the world with 1,761,503 cases and 103,700 deaths [2]. The spread of COVID-19 within the USA can be attributed to more than just epidemiological factors. Preliminary data suggests that certain demographic groups have been disproportionately affected by COVID-19 [3]. These outcomes can possibly be explained by systemic socio-economic disadvantages that many communities bear. Therefore, an inquiry into these socio-economic determinants is required to understand the inequitable spread of COVID-19 in different communities. This analysis can further be used to guide pragmatic public health policies that can ascertain equitable access to healthcare in future epidemics.

Authors of previous studies have explored the effects of socio-economic indicators on COVID spread and mortality. Stojkoski et al. analyze the impact of 29 socio-economic indicators on COVID outcomes including healthcare infrastructure, societal characteristics, economic performance, demographic structure etc. [4]. Their study focuses on country-level data and presents a model for public health policies to be implemented on a national, centralized scale. We found that many of socio-economic determinants are highly varied within the population of a country. Therefore, county-level studies can be used to guide decentralized public health decisions that affect relatively uniform populations.

Other studies have explored state and county-level data for guiding public policy decisions. Li et al. investigate variables of racial demographics, environmental conditions and underlying health conditions in populations to determine their impact on COVID-19 outcomes in American counties [5]. Souch, et al. found that rural counties in the US are performing tests at a lower rate, leading to under-reporting of cases and possibly unchecked spread in high-risk populations [6].

This study analyzes 6 socio-economic determinants to predict the number of positive COVID-19 cases per 1,000 people in the counties of the USA. These determinants are: household income, post-secondary education, urbanization, unemployment, number of ICU beds per 1,000 people and number of primary-care physicians per 1,000 people.

2 Materials & Methods

2.1 Data Collection

We used the COVID-19 dataset by New York Times which provides cumulative counts of coronavirus cases in the United States, at the state and county level, over time [7]. We aggregated the data to use the total cases and deaths up to 26th May, 2020. The United States has 3,143 counties and county-equivalents in its 50 states and the District of Columbia. We focus our study to counties with at least 50 COVID-19 cases, and at-least 5 deaths. This adjustment has been found to produce better correlations and fits in other studies [5]. This adjustment filtered our study to 728 counties with 'significant' COVID data. We procured datasets on several socio-economic indicators. These datasets are provided to the public by the United States Department of Agriculture [8] via their Economic Research Service. The datasets used in this study are described below.

- **Education**: This dataset provides the percentages of adults, 25 years or older, for each county that attained a minimum level of education. For the purpose of our study, the minimum level was chosen to be "Completing Some College". The latest data available for this measure was the 5-year average over the years 2014-2018.

- **Unemployment and Median Household Income**: This dataset provides the unemployment rate and median household income for each county in the United States. The latest available data on unemployment rate and median household income were from 2019 and 2018 respectively.

- **Population**: We used the county-specific population estimates for 2019 to calculate the number of COVID-19 cases and deaths per 1,000 people in each county.

- These 3 datasets also include a **Rural-Urban Continuum Code (RUC)** variable, which provides a classification scheme to distinguish metropolitan counties from non-metropolitan counties. Table 1 describes the classification scheme in more detail.

We also gathered county-level data on 2 indicators that determine access to healthcare.

- **Availability of Healthcare Providers**: This dataset provides the total number of primary care physicians and mental health professionals present within each county in the United States, along with the number of healthcare providers per 100,000 people for each county.

- **Hospital Capacity**: This dataset provides the total number of licensed beds and ICU beds within each county. This distinction between licensed beds and ICU beds is required because depending on the severity of the case, the patient may/may not require a ventilator.

All datasets were cleaned manually and programmatically in python using pandas. We combined the datasets into a single dataframe for the purpose of our study. This was done using the Federal Information Processing Standard Publication (FIPS) code, which is a unique code assigned to each county in the United States.

RUC	Description of county
1	Metro - Population 1 million or more
2	Metro - Population 250,000 to 1 million
3	Metro - Population of less than 250,000
4	Nonmetro - Urban population of 20,000 or more, adjacent to a metro area
5	Nonmetro - Urban population of 20,000 or more, not adjacent to a metro area
6	Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area
7	Nonmetro - Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area

Table 1: Rural-Urban Continuum Code Classification

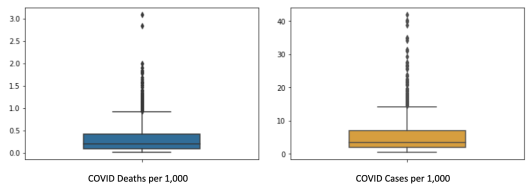

Figure 1: Distribution of COVID-19 cases and deaths per 1,000 people (N=728). This shows that COVID outcomes per county are mostly clustered in the range of 0 to 10 cases per 1,000 and 0 to 0.5 deaths per 1,000. However, the outliers variance shows much higher infection and fatality rates in some counties.

2.2 Statistical Analysis

We performed Pearson's correlation test to analyze the correlation between the collected attributes, as outlined above. The coefficients used were further analyzed in models to determine the contribution of these factors in predicting the spread of COVID cases in a county. We used a Multiple Linear Regression model to investigate the influence of these variables in predicting COVID outcomes. Fitting regression lines with higher order functions causes overfitting due to the amount of COVID data, and there is no evidence yet about the direct relation of such variables in predicting COVID outcomes [9]. Therefore, a linear regression model is best for comparing population demographics and county-level policies. We define the COVID-19 outcome of a county as the number of positive cases per 1,000 people living in that county. The regression model can be defined as follows.

$$y = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6$$

Here, y is the dependent variable, which was chosen to be the COVID-19 outcome of a county. The independent variables $\{x_i\}_{i=1}^6$ are defined as:

- x_1: Percentage of population that completed some college education (range: $[11.4, 40.7]$)
- x_2: Unemployment level (range: $[0, 1]$)
- x_3: Median household income (range: $[25000, 141000]$)
- x_4: Rural - Urban category (range: $[1, 9]$)
- x_5: Number of primary care physicians per 1,000 people (range: $[4, 227]$)
- x_6: Number of hospital beds per 1,000 people (range: $[0, 34]$)

We opted not to use an intercept, because a situation with $\{x_i = 0\}_{i=1}^6$ (ie. a county with 0 education, unemployment, income, etc.) is impossible and, hence, irrelevant for our analysis. We define $\{a_i\}_{i=1}^6$ as the corresponding coefficients of these variables. All statistical analyses were performed in python. We used seaborn for visualizations and the statsmodels library for the regression analyses.

3 Results

We studied our output dataset of COVID-19 cases per 1000 people and COVID-19 deaths per 1000 people by using a box plot as depicted in Figure 1.

3.1 Correlation Analysis

We performed Pearson's correlation analysis on the variables in our dataset. Figure 2 shows the results from this analysis in the form of a heatmap. Several moderately strong correlations were established. Education rate had a correlation coefficient of -0.29 with cases per 1,000 people and -0.32 with deaths per 1,000. Rural-Urban continuum code had a correlation of 0.14 with cases per 1,000 and 0.19 with deaths

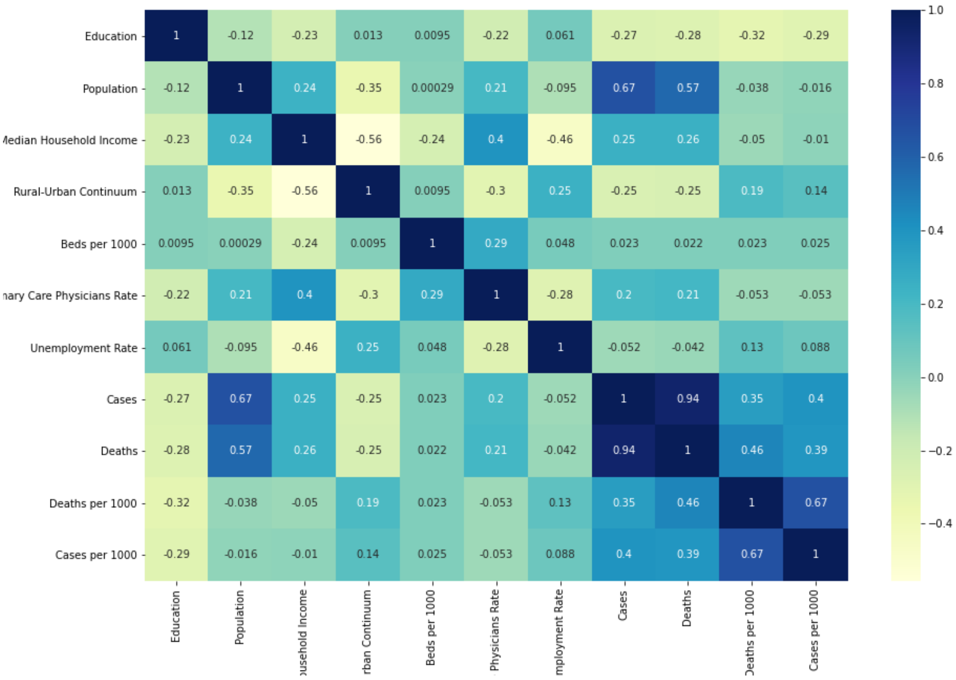

Figure 2: Correlation matrix heatmap of the data set (N=728). It compares COVID-19 cases, deaths, cases per 1,000 people and deaths per 1,000 people with the socio-economic determinants of health.

per 1,000. Other variables were relatively weakly correlated with our dependent variable. These results were investigated further using linear regression analysis to establish statistical significance in their predictive capacities.

It is also worth highlighting that median household income, primary-care physician rate, mental health provider rate and educational attainment were all factors that showed moderate-to-strong correlations with the number of cases and deaths (unadjusted for population). Of these, median household income (correlation coefficient: 0.25) is a feature of interest because it is not directly influenced by the population of a county.

3.2 Linear Regression Analysis

We ran a multiple linear regression model with Ordinary Least Squares estimation method. In the initial version of the model, we used the unadjusted variables to obtain an adjusted R-squared value of 0.51. This means that for a given county with a sample of the chosen socioeconomic variables $\{x_i\}_{i=1}^{6}$, this model can predict the mean value of the COVID-19 cases per 1,000 people with 51% accuracy. However, this unadjusted model was not robust owing to the condition number $49,300$. This indicated strong multicollinearity between the independent variables and poor scaling of the data [10].

We normalized the attributes in our data to the range of 0 to 1 to improve the robustness of the model. Table 2 displays the results of the adjusted regression model. The adjusted model had a condition number of 13.1, and R-squared value of 0.465. While the R-square value suggests that the adjusted regression model provides a slightly less accurate fit as compared to the unadjusted model, it is significantly more robust and accurate as a predictive model.

From the p-value analysis of the attributes, we found that **educational attainment, unemployment rate, median household income, rural-urban index and number of hospital beds** were statistically significant determinants of COVID outcomes. On the other hand, availability of healthcare providers turned out to be statistically insignificant.

4 Discussion

The results that we obtained by correlating socioeconomic factors at the county level to COVID-19 cases and deaths are largely consistent with expected trends and related literature. Apart from the healthcare provider attribute, all other factors exhibited statistical significance in

Variable	Attribute	Coeff	Std. Error	t-value	p-value
x_1	College Education	-0.1123	0.024	-4.605	4.88e-06
x_2	Unemployment Rate	0.3570	0.064	5.543	4.17e-08
x_3	Household Income	0.3115	0.039	7.995	5.13e-15
x_4	Rural-Urban Cont.	0.1819	0.024	7.478	2.2e-13
x_5	Physicians Rate	-0.0476	0.043	-1.106	0.269
x_6	Beds Per Capita	0.2830	0.079	3.582	3.636e-04

Table 2: Multiple Linear Regression of COVID cases per 1,000 people using 6 socio-economic indicators. Significance Level for all variables: 0.05

their relation to COVID-19 cases and deaths. The following section evaluates the results we obtained for each variable in the model against COVID-19 cases, proposing potential solutions and policy changes.

Education: Education measured using the percentage of college graduates conclusively shows a negative correlation to COVID-19 cases per 1,000 (coefficient: -0.1086). Studying education as a key determinant of health in Europe, Albert et al. inferred that education is associated with the pursuit of social and financial welfare, and discuss how more qualified individuals are proven to perform better in self provision of health [11]. Education also improves an individual's ability to understand healthcare information and guidance, and strongly correlates to health literacy [12]. Our results also align with previous studies that show how limited health literacy exacerbates health disparities[13]. Individuals with higher education levels have also shown to be connected more with social media for preventive measures [14]. Furthermore, increased social media activity allows people to adopt preventative practices earlier than others. Education also decreases people's susceptibility to fake news. We see there is strong evidence of multifaceted role education in times of epidemic, and thus strongly recommend county level policy change to improve health literacy. County-level governments should improve their public outreach programs to tackle the spread of misinformation and improve health literacy. Further free public secondary education can eliminate low income as a barrier to better health literacy.

Rural - Urban Classification: The regression model indicates a disadvantage to rural counties in terms of COVID-19 cases per 1,000 people (regression coeff: 0.127). The correlation between COVID cases per 1,000 is and rural urban continuum is 0.13, positive yet very small to make a conclusive inference. Our results differ from a study done by Philip Cohen which highlight urban counties have higher COVID-19 cases per capita[15]. Cohen and similar studies consider all counties in the United States(3144 counties), including most rural counties that have less than 5 cases in the county. To make our regression model more robust, we eliminated outlier counties with less than 50 cases and 5 deaths[16]. However we do observe a relatively strong negative correlation between rural counties and education. This ties into our argument about the crucial role health literacy and education can play in improving public health [17].

Income: Our regression model shows a positive contribution of higher median household income and the number of COVID-19 cases per 1,000 people. However the correlation is not very conclusive. There can be multiple possible justifications for these results. A paper studying the impact of income inequality on COVID-19 cases among countries concluded that although richer countries are often associated with better population health; high economic activity and trade in such countries also enhance transmission of diseases [4]. Another research speculates that socialization, dining out and similar elastic income behaviours heighten infection risk of well-off groups[18]. These results are contradictory to the widely studied impact of income inequality as a social determinant of health and life expectancy[19]. Our findings don't necessarily negate these results, but suggest that such outcomes might differ in the case of epidemics of viral pathogens. Although our study does not find conclusive evidence to claim the direct impact of low income in susceptibility to COVID-19, there is strong proof of income as a key determinant of health. This could imply low income groups might be at a disadvantage in terms of preexisting health conditions, thereby making them more at risk if they contracted COVID-19. America should strongly consider policies that use Sin Tax to finance healthcare for low income groups to improve their access to healthcare [20].

Unemployment Rate: Unemployment serves as an important socioeconomic determinant because of its interconnectedness with similar factors that determine the quality of life. The jointness test developed by Hofmarcher et al. and implemented by Stojkoski et al. show how unemployment relates closely to income inequality, government spending, and population [4]. Our study demonstrates that unemployment rate is a statistically significant factor in predicting the spread of COVID-19. As depicted by the heat map, unemployment has a strong negative correlation with median household income, explaining that counties where fewer adults are employed will suffer from lower household incomes. COVID-19 cases per 1,000 has a positive correlation (0.3605) with unemployment rates. This can be attributed to the fact that regions where unemployment rates are higher may lower the quality of life, due to poorer access to information for practices on sanitation and hygiene. Unemployed individuals also tend to have more unstructured daily schedules, which may expose them to a wider range of people or places that could expose them to the virus [21]. Other studies have supported the notion that previously unemployed groups who are also historically marginalized have been disproportionately affected due to their inability to advocate for basic benefits and job conditions [21].

With our study showing that the virus spread is more pronounced within unemployed populations, it is crucial to look into public policies that prevent such groups being more vulnerable to diseases. A study by Tcherneva draws parallels between unemployment and an epidemic; explaining how unemployment spreads like an infectious disease, magnified by a ripple effect of job loss leading to more job loss [22]. Geographical areas hit particularly hard by unemployment seem to never fully recover, suggesting that the best way to combat such an issue is through preparedness and prevention. Guaranteed employment policies have exhibited promising results which counter cyclically unstable labour markets that are largely influenced by private sector activity. While government aid programs such as Unemployment Insurance (UI) and Assistance to Needy Families (ATNF) may bring temporary relief to affected groups, they fail to facilitate pro-employment growth [23]. Guaranteed employment also leads to higher job satisfaction, which improves happiness, mental health, and places individuals in a better position to combat future illnesses [24].

Beds per 1,000 people: Availability of hospital beds is an important indicator of health infrastructure in a county. It gives information about the hospital's capacity to treat patients, especially for COVID-19 where individuals may require ventilators in ICUs. The availability of hospital beds in hospitals during COVID-19 has been a critical factor that has affected how counties have responded to the virus [25]. There is a positive correlation of 0.2867 between the beds per 1,000 and the COVID-19 cases thus demonstrating that hospital preparedness is a critical factor to determine effective handling of pandemics [26]. This shows that counties were aware of the risks and understood that certain areas were high risk zones, allowing them to have more beds available to prepare for the virus.

Health policy officials and medical professionals have outlined a few strategies to mitigate future shortages in hospital beds during outbreaks. One study suggests prioritizing equipment use, cancelling elective surgeries, and maximising the use of physical hospital space. [27].

Primary Care Physicians Rate (PCPR): PCPR describes the availability of health care professionals per 100,000 people that can help combat COVID-19. PCPR is another important factor that outlines the ability of a county to handle COVID-19 spread depending on their healthcare workforce capacity, as a smaller workforce experiences higher levels of physical and mental stress [28]. Our model produced an interesting correlation of just -0.0003 between PCPR and COVID-19 cases. Furthermore, the p-value proved to be statistically insignificant at 0.488 indicating that there is weak evidence against the conjecture. Therefore, our model yields an inconclusive result since it is possible to reason that PCPR rates are one of the many covariables involved in mitigating the spread of the virus, making it difficult to isolate and analyze through our model. This could be explained by understanding that urban counties with a high PCPR rate may still be overburdened and unable to contain COVID-19 spread simply due to the overwhelming population in the county itself.

The evidence of the impact of these social determinants of healthcare desperately call for public health and economic policy reform. Some wider systemic changes may include rapid-response groups and revisions of patient flow management strategies to streamline treatment [25].

A limitation of our study is that there is very limited public data available on the socio-economic demographics of COVID patients. Because of this, the only way to conduct a county-level analysis was to procure each determinant from individual datasets. The available datasets are limited in the availability of the recent data. Most of the demographic county level data was obtained from 2018-2019, when COVID-19 did not exist in any of the regions. So, our model does not imply direct relations between the data points of demographic information and COVID-19 outcomes.

Furthermore, we acknowledge that this pandemic and the subsequent lockdowns have had a huge impact on socio-economic conditions. For example, within the USA, unemployment is now at an all time high with over 3.3 million unemployment insurance claims being filed weekly [29]. We leave the analysis of the resulting changes in employment patterns created by COVID-19 and their impact on populations to future studies.

Conclusions

The purpose of this study was to understand the socio-economic determinants of public health and their effect on the spread of COVID-19. We investigated 6 such factors to examine how the COVID-19 pandemic affected different demographic groups. We found reasonable correlation for education levels and unemployment with COVID-19 spread. Other factors such as rural-urban distribution, household income levels, and healthcare workers per 100,000 people showed inconclusive correlations with the datasets we used.

Our study has provided insights at the county level, which combined with our suggestions may assist public health officials implement policy changes at the grassroots level. This study was limited to the US, but the methodology can be applied to countries around the world helping smaller jurisdictions worldwide paint a better picture of the situation.

The impact of COVID-19 is compounded, and it will be worthwhile for further research to look into how socio-economic factors and COVID-19 affect each other to determine how to make more informed public policy decisions. Governments and institutions worldwide can make this possible by making datasets more publicly accessible and detailed for deeper insights.

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