Analyzing the Relationship of Economic Indicators on COVID-19 Outcomes

Michael Lewis* Aarushi Sahejpal† Katherine Prince‡

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Abstract

This is our informative abstract of fewer than 200 words. It describes what we investigate, how we investigate it, and what we find.

1 Introduction

In this section, we introduce the reader to the phenomenon we investigate. We describe the way in which our analysis contributes to an important intellectual debate, or how it answers a pressing political or social question. We introduce our hypotheses, data, and results. We signpost for the reader what's coming in the rest of the paper.

We remember that our paper is not a mystery novel. We note our core results early and often.

Throughout our paper, we use active, first-person language and avoid the passive voice. For example, we write "we examine the relationship between X and Y"; we do not write "the relationship between X and Y was examined." Where we do the analysis, we speak about it transparently.

2 COVID-19 Driven Disparities

This paper and project came about as a result of the increasing amount of scholarly and peer-reviewed literature that sheds light on the ever-present and visible economic, social, and medical disparities that resulted directly from the COVID-19 pandemic. Among this literary discourse, there is overwhelming agreement that strong disparities are present within the American population as a result of individuals who contracted and/or died from COVID-19. Not only are there existing risk factors that make certain marginalized members of populations more susceptible to impact from contraction of COVID-19 but the harms of contraction are further exacerbated (Abedi et al. 2021). With evidence that a large burden of the brute impacts of COVID-19 are felt by the country's essential workers, low-income populations, and by those who found healthcare inaccessible, our research question and variable selection is informed with this insight in mind (Kantamneni 2020). Even in some of the more basic health instructions administered by the United States government during the COVID-19 pandemic, such as social distancing, there are severe disparities by levels of commute and income level in individuals being able to adhere to those restrictions (Garnier et al. 2021). From the American Community Survey, one the country's leading resources for measuring impacts among populations in the United States, we select economic, social, and health indicators to further evaluate the nature of the impact that COVID-19 truly had within the population of the United States.

*SIS/CAS, American University
†CAS, American University
‡SPA, American University

With a large portion of the scholarly conversation surrounding the interdisciplinary human impact of COVID-19 being centered around the United States, we decide to take a micro approach to see its specific impact in our communities of DC, Maryland, and Virginia.

3 Data and Methods

3.1 Data Sources

This project sources two data sets in order to investigate the relationship between certain economic and social variables American Community Survey (ACS) and COVID-19 data in the DC, Maryland, and Virginia. The American Community Survey (ACS) is acquired from the US Census Bureau's API and COVID-19 Data is acquired from Covid ActNow's API.

Our final combined data set, with both ACS and COVID-19 data, has 158 total observations with 13 variables of interest.

The American Community Survey is a perpetual survey run by the United States Census Bureau that provides the United States government, and the American population, access to information surrounding different economic and social characteristics such as jobs, income, and education on a yearly basis. The ACS contacts over 3.5 million households every year for participation in this survey, where all individuals contacted are legally obligated to answer all the questions in the survey. The sample is selected at random by the Census Bureau, where no address is chosen more than once every 5 years.

Data surrounding the spread and impact of COVID-19 in the United States is sourced from COVID ActNow. This organization is a collection of scientists, pandemic experts, engineers, and public health experts who collect COVID-19 data in the United States, and then subsequently assess its quality. Their works supports federal, state, and local government agencies and their data sets are considered some of the most-trusted regarding the COVID-19 pandemic.

In determining the variables of interest that we want to investigate from the American Community Survey, we are most interested in the number of working individuals aged 16 years and older that commute to work, the total mean household earnings, the number of individuals that have health insurance coverage, and the percent of working individuals aged 16 years and older that are employed in an essential worker capacity. The specific independent variables and their official ACS codes are below:

- DP03_0018 Estimate, **Commuting to Work**, Workers 16 years and over
- DP03_0065 Estimate, Income and Benefits (in 2021 inflation adjusted dollars), **Total households, With earnings, Mean earnings** (dollars)
- DP03_0095 Estimate, **Health Insurance Coverage**, Civilian noninstitutionalized population
- DP03_0042P Percent, Industry, Civilian **employed** population 16 years and over, **Educational services, and health care and social assistance** (Note: we classify this variable as "essential employees", however, we recognize that this term is imperfect in encapsulating varying definitions of "essential" across three states and 150 plus counties. Nonetheless, we believe that these occupations generally represent what can be considered "essential" occupations during the pandemic)

With the variables selected from the ACS, we first start out with time series COVID-19 data for Maryland, DC, and Virginia. We only select the year 2021 for COVID-19 data in order to match the ACS data from 2021. We are able to get a daily cumulative case and death count from COVID ActNow, but in order to ensure that our analysis is on the same level as ACS data, we create two new variables – average cases from 2021 and average deaths from 2021. The specific dependent variables of interest from this data set are:

- Average Cases

- Average Deaths

For the purpose of building a model to assess the significance of the relationship between multiple economic and social indicators and the spread of COVID in DC, Maryland, and Virginia, we combine both data sets to prepare it for analysis. We are able to load in both Census ACS data and COVID-19 data from COVID ActNow through their respective APIs, and then subsequently clean the source data.

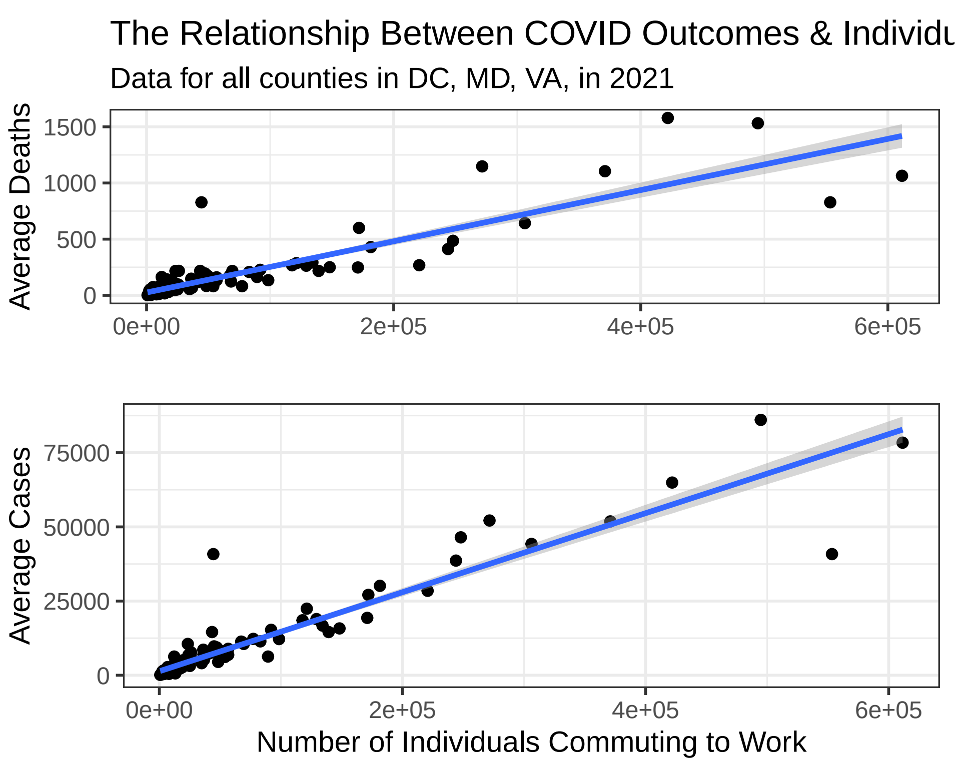
For cleaning the COVID-19 data, we parse out DC, Maryland, Virginia from our complete time series data from COVID ActNow, then create a separate data set with just these three geographic locations, and compute average cases and deaths for each county during 2021. Then we merge both data sets to combine variables from both individual source sets.

We conduct our analyzing using R version 4.2.2 (R Core Team 2022). To clean our data we primarily used the `tidyverse` (Wickham et al. 2019) packages as well as `janitor` and `lubridate`. Data collection is aided by the `tidycensus` package, which allows us to pull direct data from the ACS/US Census Bureau. Data analysis/visualization is conducted using `ggplot2` from the Tidyverse, as well as `stargazer` to create tables (Hlavac 2018). Finally, we use the `keyring`, `httr`, and `jsonlite` packages for API imports from the respective sources.

This project aims at investigating the relationship, and its subsequent significance, between certain economic and social indicators and COVID-19 average cases and deaths in different locales within DC, Maryland, and Virginia. Because of this goal, a linear model is the best fit to further analyze our research question.

3.2 Methods

We conduct a Ordinary Least Squares (OLS) regression model to explore the relationship between the aforementioned economic indicators and average COVID outcomes in 2021. We chose this method after examining the raw data and noticing patterns which indicated that a linear model may be appropriate. The below figure illustrates this phenomenon with individuals commuting to work and mean COVID deaths. While there is more variability in cases at the upper-ends, on balance the data follows a linear pattern.



Other variables also show evidence of a linear relationship. In our exploratory data analysis we found a positive association between health insurance coverage (or number of individuals in a given county with health insurance) and COVID deaths and cases. This finding seems counter-intuitive and was something we wanted to examine more closely after controlling for the effect of other predictors.

This exploratory data analysis leads us to pursue linear regression as a method for analyzing multiple economic indicators and mean COVID outcomes. Specifically, we arrive at three research questions: (1) is health insurance coverage still positively associated with worse COVID outcomes even after controlling for the effects of other predictors, (2) what variables had the largest effect on mean COVID cases and deaths, and (3) how important is wealth in predicting COVID outcomes? The next section will discuss our model and results.

4 Findings

We begin by estimating an Ordinary Least Squares (OLS) model that predicts average cases and deaths (in 2021) for all counties in DC, Maryland, and Virginia. In our model, we consider: the percent of workers that could be considered essential, the number of individuals that have health insurance, the number of workers that commute to work, and the mean individual earnings. Since state and local vaccination efforts were underway for the duration of 2021, we also control for average vaccinations administered. The ultimate goal of our analysis is to ascertain which economic indicators were significant in predicting COVID outcomes.

Overall, our models explain about 80-90% of variation in both average cases and deaths for all counties in DC, MD, VA in 2021. The following paragraphs will dive deeper into each model and elucidate the significance of our results.

Table 1: Two Regression Models Predicting Variation in 2021 COVID Outcomes

	For all counties in DC, MD, VA	
	Average Cases	Average Deaths
Percent Essential Workers	128.566^{**} (62.578)	2.880^{**} (1.272)
Number of Individuals with Health Insurance	0.103^{**} (0.042)	0.003^{***} (0.001)
Number of Individuals Commuting to Work	−0.121 (0.081)	-0.004^{**} (0.002)
Mean Earnings (USD)	−0.015 (0.014)	-0.001^{*} (0.0003)
Average Vaccinations Administered	0.037^{***} (0.004)	0.0003^{***} (0.0001)
Intercept	−887.164 (2,021.619)	−4.595 (41.079)
Corrected AIC	2611	1551.2
R^2	0.895	0.805
F Statistic (df = 5; 130)	221.441^{***}	107.624^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

4.1 Average Cases

Our baseline model explains about 89% of the variance in average cases, however, only three of the five predictors were statistically significant. To account for this, we estimate another linear model using just the variables identified from a forward stepwise selection at $\alpha = .05$. The results are shown in Table 2 and below.

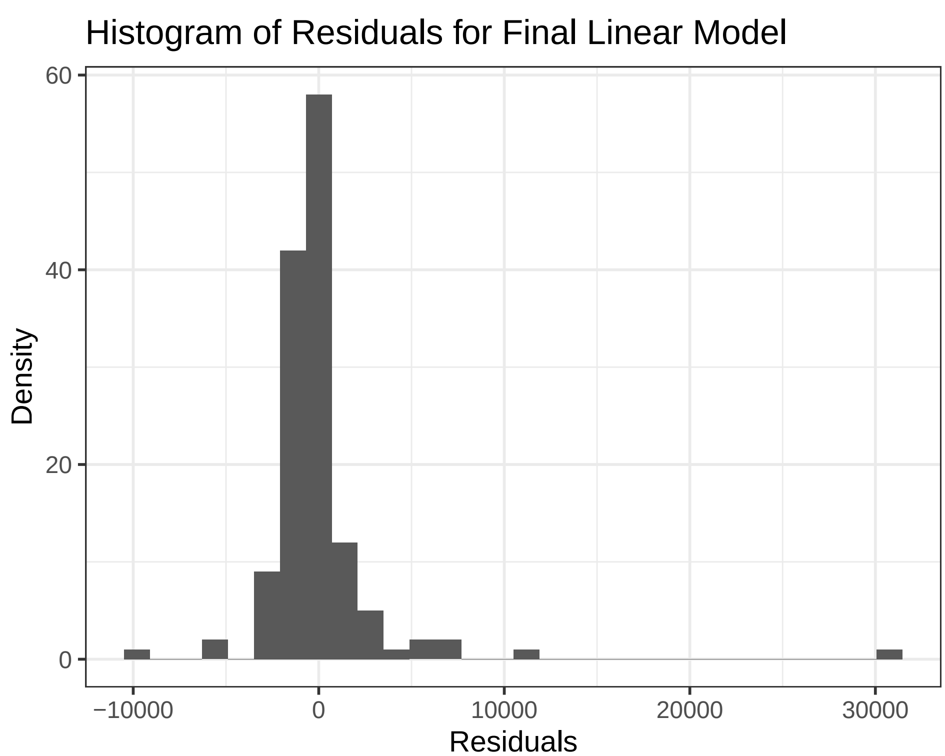
$$\begin{aligned}\widehat{Average\ Cases}_i = \beta_0 + \beta_2(Percent\ Essential\ Workers_i) + \beta_2(Number\ of\ Individuals\ with\ Health\ Insurance_i) \\ +\beta_3(Average\ Vaccinations\ Administered_i) + \epsilon_i\end{aligned}$$

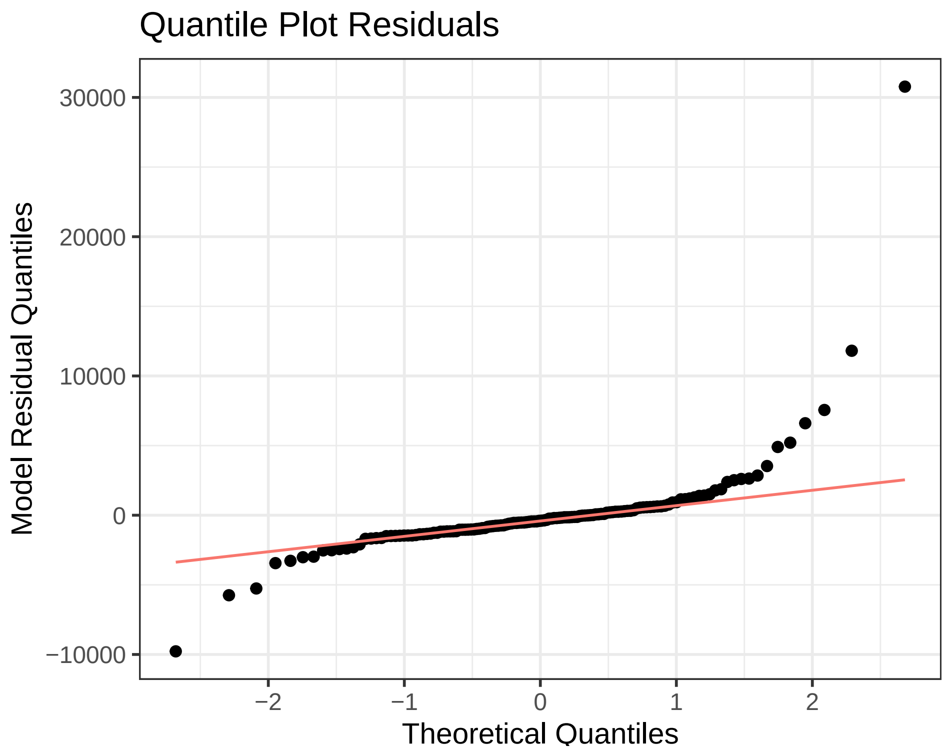
Table 2: Only Significant Variables for Predicting Variation in Average Cases

	For all counties in DC, MD, VA
	Average Cases
Percent Essential Workers	164.734*** (60.682)
Number of Individuals with Health Insurance	0.039*** (0.003)
Average Vaccinations Administered	0.035*** (0.004)
Intercept	−2,691.905* (1,509.005)
Corrected AIC	2611.1
R^2	0.891
F Statistic	361.109*** (df = 3; 132)
Note:	*p<0.1; **p<0.05; ***p<0.01

Notably, the percent of essential workers in a given county has by far the largest effect on average cases. Indeed, for every percent of workers in a county that could be classified as essential average cases will increase by about 164. The estimates for number of individuals with health insurance and average vaccinations administered are both much lower at .039 and .035, respectively. Despite being statistically significant, the estimates for these variables are small enough that they largely lack practical significance in the context of our analysis.

The model assumptions are generally satisfactory. A histogram of the residuals shows that the residuals follow a normal distribution despite some outlying values on both the upper and lower tails. This is also confirmed by the normal Q-Q plot which shows that most of the residuals follow a normal pattern.





Our data has multiple extreme outlying values, however, only two have a relatively high leverage and only three have a Cooks' Distance above our threshold of three times the mean of all distances. Thus, of our sample of 158 observations only three are extreme and/or influential. After dropping these values and re-running our model our test statistic did not change drastically. As a result we retained these values in our final model.

Cooks' Distances Above Threshold
30.824135
1.361435
8.950398

In the next section, we will repeat our analysis against average deaths using the same predictors.

4.2 Average Deaths

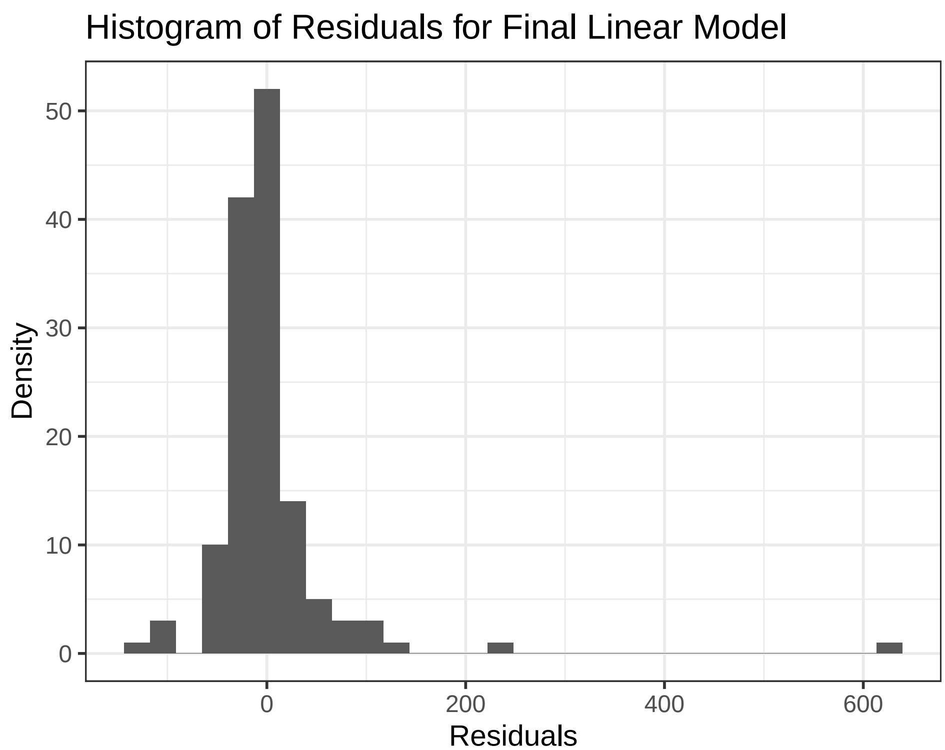
Our baseline model explains about 80% of the variance in average deaths. Every predictor was statistically at least at $\alpha = .1$, however, most were significant at lower alpha values. Our final model is estimated below:

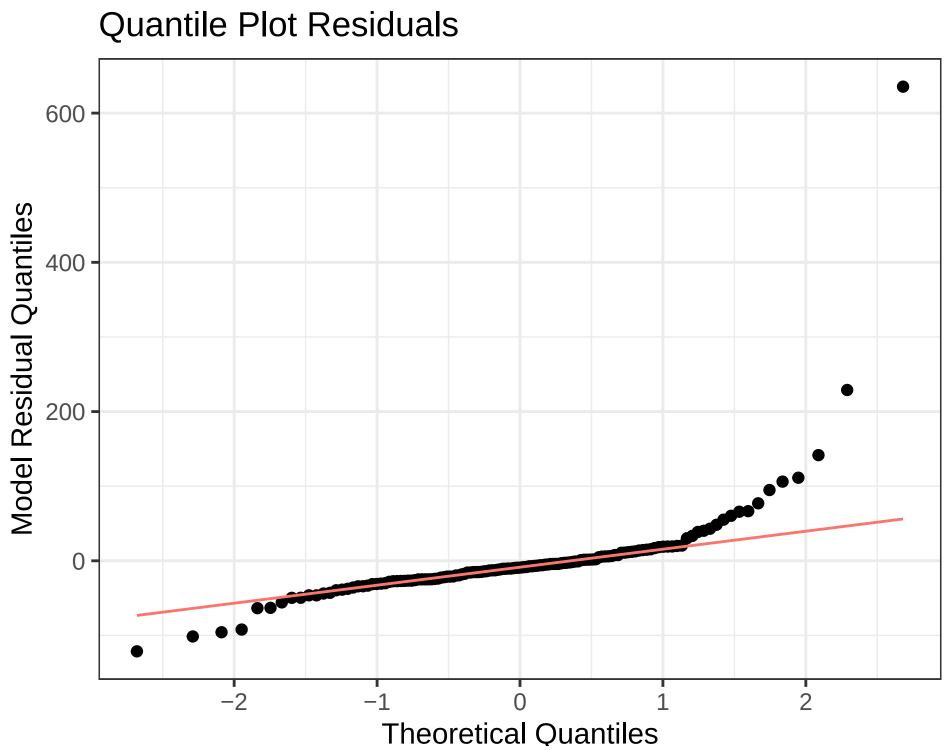
$$\widehat{Average\ Deaths} = \beta_o + \beta_1(Percent\ Essential\ Workers) + \beta_2(Number\ of\ Individuals\ with\ Health\ Insurance)$$
$$+\beta_3(Number\ of\ Individuals\ Commuting\ to\ Work) + \beta_4(MeanEarnings)$$
$$+\beta_5(Average\ Vaccinations\ Administered) + e_i$$

Between the two models, this one performs better, with a comparable R-sq at .8 and lower AIC. Notably, we find that for every additional percent in essential workers we estimate average deaths to increase by about 2.8, while holding other variables constant. We also find that as mean earnings increases, we can expect average deaths to decrease. Specifically, an increase of $10,000 in mean earnings (for a given county) is predicted to result in a decrease of ten for mean deaths, while holding other predictors constant. While we cannot say this relationship is causal – it does highlight the importance of wealth and resources in impacting public health outcomes. Indeed, counties with higher earnings likely have better hospitals and public services, factors which one can reasonably assume have a positive impact on public health outcomes.

In our check for multi-collinearity we find that the number of individuals with health insurance and number of individuals commuting to work are highly correlated as indicated by the VIF and Pearson's R-sq. Thus, we do not place much emphasis on the coefficients for these predictors. While multi-collinearity does make it difficult to disaggregate the effect of one predictor from another, it does not diminish the overall predictive power of a model. The next section will consider some possible explanations for this collinearity.

In checking the model assumptions we again see evidence of outlying values, however, for the most part the residuals are normally distributed. In this model, only four observations had Cooks' Distances above our threshold. Again, we retained these values due to insufficient changes to the test statistic after dropping them.





Cooks' Distances Above Threshold
6.1221131
1.1474881
0.5007913
1.7874811

5 Discussion

The COVID-19 pandemic has renewed conversations about health equity disparities. As data becomes more abundant, literature has emerged seeking to understand health outcomes, policy interventions, and disparities (Thornton and Yang 2023). This research project aims to contribute to this growing body of literature by examining the relationship between socio-economic factors and mean COVID outcomes for all counties/wards in Virginia, Maryland, and the District of Columbia.

Notably, we find strong evidence that suggests that counties with a higher percent of essential workers are predicted to have more cases and deaths on average. The effect, however, is substantially greater for average cases. This finding is consistent with what we would expect, as well as existing theoretical explanations. Indeed, Rosengren et al. (2022), Rhodes et al. (2022), Do and Frank (2021), and Welsh (2022) all underscore the elevated risks that essential workers face(d) during the pandemic and outbreaks. Our analysis, however, considers the larger implications of this by estimating how many more cases and deaths a local county could possibly expect based on the percentage of essential workers. While these findings cannot be generalized beyond the mid-Atlantic – and specifically DC, Maryland, and Virginia – it does provide and important contribution in measuring this phenomenon at the local level.

We also find a puzzling positive association between worse COVID outcomes and health insurance coverage. This finding – while strange – is not novel Cuadros et al. (2023) document a similar association between insurance coverage and a higher burden of disease. Importantly, the authors note that there isn't a "negative impact of insurance on health status" – rather a series of factors which may be at play. First, insured individuals may be more likely to seek care than uninsured individuals – something which is well documented in the consistent and pervasive under-diagnosis of diseases/conditions in the uninsured population. Second, population size may play an intervening role. Larger counties/locales which are predisposed to having more cases could plausibly have a greater raw number of individuals who are insured. Finally, our analysis reveals that health insurance coverage and the number of individuals who commute to work were highly associated. This collinearity makes it difficult to estimate the true effect of health insurance coverage on average COVID outcomes. In short, we don't place much emphasis on the effects of health insurance (and by extension the number of individuals commuting to work). The literature over overwhelmingly suggests that health insurance plays a positive role in health status Uninsurance (2002), however, statistical results like ours are possible Cuadros et al. (2023) for a variety of reasons. Thus, these results likely indicate there are other factors at play that our model doesn't adequately capture.

Our final research question is aimed at understanding the role of earnings on average COVID outcomes. We found that as mean earnings increased counties could expect less cases and deaths on average. On average, an increase of $10,000 (USD) for a county is predicted to result in a decrease of ten deaths in our model. This measure should not be generalized beyond DC, Maryland, and Virginia and should be used with caution. The relationship between wealth and health disparities has been well-documented in both the COVID-19 pandemic and beyond (Tai et al. 2022; Khayat, Teron, and Rasoulyan 2022). However, there are likely many variables which we did not include due to project time-constraints, that would enhance our estimate. Specifically, mean earnings vary by location, industry, and population size – all things which future research should consider as factors when estimating the relationship between earnings and health outcomes. Despite this, our estimate contributes to this growing research body and provides a baseline for future analysis.

Our research aims at exploring the intersection of economic indicators and average COVID outcomes. To date, much research has been done on the role of socio-economic factors and health outcomes. Our research builds on this by examining this for three states in the mid-Atlantic. Overall, we discover that the percent of essential workers and mean earnings (at the county level) were important variables when estimating average COVID outcomes. Our models explain between 80-90% of the variation in average COVID outcomes within our sample. Moving forward, future research should be aimed at expanding both the temporal and spatial scopes we employed as well as consider more socio-economic variables which we didn't have the chance to incorporate. Additionally, future research should consider other methods – such as an ordinal probit model – which may do a better job at modeling the relationship between socio-economic indicators and health outcomes.

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