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A Model to Explain Statewide Differences in COVID-19 Death Rates

By

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Abstract

COVID-19 death rates per 100,000 vary widely across the nation. As of September 1, 2020, they range from a low of 4 in Hawaii to a high of 179 in New Jersey. Although academic research has been conducted at the county and metropolitan levels, no research has rigorously examined or identified the demographic and socioeconomic forces that explain state-level differences. This study presents an empirical model and the results of regression tests that help identify these forces and shed light on the role they play in explaining COVID-19 deaths.

A stepwise regression model we tested exhibits a high degree of explanatory power. It suggests that two measures of density explain most of the state-level differences. Less significant variables included the poverty rate and racial/ethnic differences. We also found that variables relating to health, air travel, and government mandates were not significant in explaining COVID-19 deaths at the state level.

This study also examines the elasticities of those variables we found significant. We measured both average and constant elasticities to determine the relationship between changes in COVID-19 deaths and percentage changes in the relevant explanatory variables. In an analysis of residuals, we found that the unexplained variation was found to be related mainly to factors site-specific to individual states.

Unlike the empirical results of several academic studies, our model found that the density of a state is the most important factor explaining COVID-19 deaths. The role that density plays in the transmission of COVID-19 has important policy implications in responding to the challenges posed by the coronavirus and future pandemics.

Introduction

A number of academic studies have studied the impact of demographic and socioeconomic forces on the incidence of COVID-19. These studies have focused attention on counties and metropolitan statistical areas (Hamidi, Sabouri, and Ewing, 2020; Liu et al., 2020; Wheaton and Thompson, 2020). No academic research, however, has examined or identified the variables that explain state-level differences in COVID-19 death rates. Although the print and electronic media have extensively reported on differences among states (Tavernise and Mervosh, *New York Times*, 2020; Olsen, *Washington Post*, 2019; Rosenthal, *New York Times*, 2020), these reports are largely anecdotal and lack academic rigor.

State-level COVID-19 death rates vary widely. As shown in the rank ordering of Table 1, cumulative death rates per 100,000 people as of September 1, 2020, range from a low of 4 in Hawaii to a high of 179 in New Jersey. The mean cumulative death rate for all 50 states was 44.9, with a standard deviation of 39.84. Figure 1 shows that the mean death rate for all 50 states has increased in a linear-like manner from April 1, 2020, to September 1, 2020.

FIGURE 1
Cumulative Average Number of COVID19 Deaths in the Unites States per 100,000 in Population

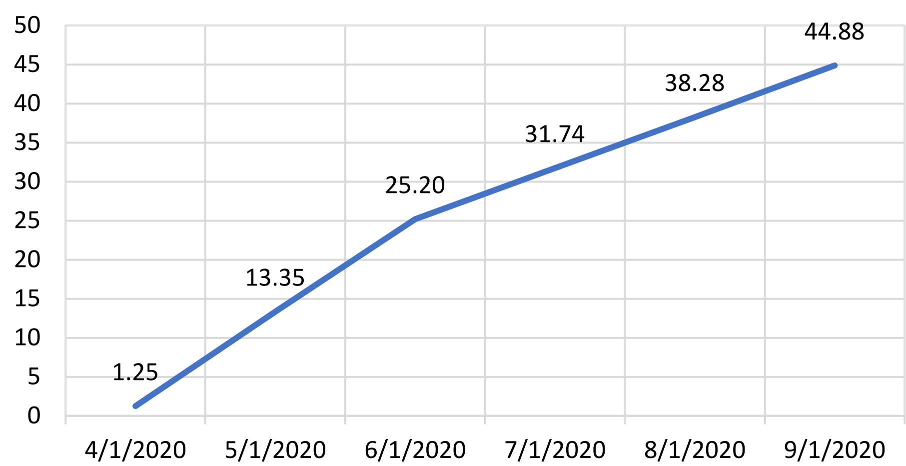


TABLE 1

As of September 1, 2020

Rank	State	COVID Death Rates per 100,000 people
1	Hawaii	4
2	Alaska	5
3	Wyoming	6
4	Vermont	9
5	Maine	10
6	Montana	10
7	Oregon	11
8	West Virginia	12
9	Utah	13
10	Kansas	15
11	North Dakota	19
12	South Dakota	19
13	Wisconsin	19
14	Idaho	20
15	Nebraska	20
16	Oklahoma	20
17	Kentucky	21
18	Missouri	25
19	Washington	25
20	Arkansas	26
21	North Carolina	26
22	Tennessee	26
23	Virginia	30
24	New Hampshire	32
25	California	33
26	Minnesota	33
27	Colorado	34
28	Iowa	35
29	Ohio	35
30	New Mexico	37
31	Nevada	42
32	Alabama	44
33	Texas	44
34	Indiana	49
35	Florida	52
36	Georgia	53
37	South Carolina	53
38	Pennsylvania	60
39	Delaware	62
40	Maryland	62
41	Illinois	65
42	Michigan	68
43	Arizona	69
44	Mississippi	82
45	Rhode Island	99
46	Louisiana	106
47	Connecticut	125
48	Massachusetts	131
49	New York	169
50	New Jersey	179

Although no state-level studies for COVD-19 have been published, a survey of SSRN showed 4,334 studies dealing with the coronavirus. Of those, 2,531 papers relate to public health, legal, economic, societal, and fiscal implications.

Several of these studies focus attention on the impact of density on COVID-19 infection and death rates. Hamidi, Sabouri, and Ewing (2020), for example, conclude that their most important finding is "that density is unrelated to confirmed virus infection rates and inversely related to confirmed virus death rates" (page 11). They conclude that "COVID-19 death rates are lower in dense counties and higher in less dense counties (page 12). Wheaton and Thompson's (2020) findings reveal that density and the total number of infections are inversely related, but that density has no significant effect when the infection rate serves as the dependent variable.

Given the commonly accepted view that greater social interaction leads to higher COVID-19 infections and deaths, the fact that these peer-reviewed studies do not empirically support that view seems anomalous.

These findings have important implications for socioeconomic planning and policies. As Hamidi, Sabouri, and Ewing (2020) conclude:

> *The fact that density is unrelated to confirmed virus infection rates and inversely related to confirmed death rates is important, unexpected and profound. It has important implications for community design, ... and nearly every other front-burner issue important to planners. (2020, page 12)*

In the study to follow, we hope to shed light not only on how density and other factors are associated with the COVID-19 death rate, but also why our findings differ from the conclusions reached in previous studies.

We present an empirical model and the results of regression tests to explain these differences in death rates at the state level. The tests regress state-level COVID-19 death rates against hypothesized demographic and socioeconomic explanatory variables. Those variables found to be significant in this study will also shed light on the role these variables play in explaining COVID-19 deaths.

The Model

We selected the cumulative COVID-19 death rate per 100,000 people by state as of September 1, 2020, to serve as our dependent variable. A death is defined as a person dying that tested positive for the coronavirus no matter a person's preexisting health conditions. COVID-19 virus infection rates were not included in our study because of potential biases due to state-level differences in testing methodologies and people's varying access to such tests. For that reason, we focused on the death rate. The structural form of our model is shown below in equation(1).

$$D_i = b_0 + b_1(x_{1,i}) + b_2(x_{2,i}) + \ldots + b_n(x_{n,i}) \quad (1)$$

where:

D_i = Cumulative COVID-19 death rates per 100,000 in state i as of September 1, 2020.

$x_1 \ldots x_n$ = 1 … n independent variables in state i

$b_0, b_1 \ldots b_n$ = n parameters to be estimated and error terms are suppressed

Equation (1) can also be estimated in exponential form using natural logs (ln).

In order to control and test for the factors that explain COVID-19 death rates by state, we selected demographic and socioeconomic variables, as shown in Table 2 and below in equation (2).

$$\begin{aligned} \text{Deathrate}_i = b_o \textstyle\sum_{d=1}^{3} b_d \text{ Density}_i + \sum_{y=1}^{2} b_y \text{ Income}_i + \ldots \\ + \ldots \textstyle\sum_{r=1}^{3} b_r \text{ Racial/Ethnic}_i + \sum_{h=1}^{4} b_h \text{ Health}_i + \ldots \\ + \ldots \textstyle\sum_{a=1}^{2} b_a \text{ Air Travel}_i + \sum_{m=1}^{3} b_m \text{ Mandates}_i \quad (2) \end{aligned}$$

where:

Deathrate_i = Cumulative COVID-19 deaths per 100,000 in state_i as of September 1, 2020

$b_o, b_d \ldots b_m$ = Parameters to be estimated

error terms are suppressed, and the independent variables are as shown in Table 2.

Table 2. Dependent and independent variables used in the study

Description	Name	Mean	SD	CV	Min	Max	Obs.	Source
Dependent variable								
Death rates from coronavirus (COVID-19) in the US as of 09/01/20, by state (per 100,000 people)	deathrate	44.88	39.84	88.77	4.00	177.00	50	https://www.statista.com/statistics/1109011/coronavirus-covid19-death-rates-us-by-state/
Independent variables								
I. Density variables								
Population density per square mile	density	202.65	266.24	131.38	1.30	1207.80	50	https://worldpopulationreview.com/state-rankings/state-densities
Super density per square mile	sdensity	342.98	1610.69	469.62	0.00	11076.00	50	https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density
Urban population as a percentage of the total population	urbanpop	0.74	0.15	20.27	0.39	0.95	50	https://en.wikipedia.org/wiki/Urbanization_in_the_United_States
II. Income variables								
Per Capita Personal Income (000)	py	54.50	8.80	16.15	39.36	79.09	50	https://fred.stlouisfed.org/release/tables?rid=151&eid=257197
Poverty rate	poverty	0.14	0.04	28.57	0.07	0.27	50	https://en.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_poverty_rate
III. Racial/Ethnic variables								
Black or African American Population as a percent of the total population	afram	10.51	9.55	90.87	0.40	37.60	50	https://worldpopulationreview.com/states/states-by-race
Hispanic population as a percentage of the total population	hispanic	11.74	10.34	88.07	1.50	48.54	50	https://worldpopulationreview.com/state-rankings/hispanic-population-by-state
Asian population as a percentage of the total population	asian	4.18	5.53	132.30	0.76	37.75	50	https://worldpopulationreview.com/state-rankings/asian-population
IV. Health related variables								
Percentage of population aged 65 or over	age65	16.49	1.88	11.40	11.10	20.60	50	https://www.prb.org/which-us-states-are-the-oldest/
Obesity rate, percent of obese adults (BMI of 30+)	obesity	30.75	3.73	12.13	22.60	38.10	50	https://worldpopulationreview.com/state-rankings/obesity-rate-by-state
Diabetes mortality rate, number of deaths per 100,000 total population	diabetes	21.95	4.39	20.00	14.60	36.20	50	https://www.cdc.gov/nchs/pressroom/sosmap/diabetes_mortality/diabetes.htm
Smoking Rate, percent of persons who smoke	smokers	17.33	3.50	20.20	8.90	26.00	50	https://worldpopulationreview.com/state-rankings/smoking-rates-by-state
V. Air Travel								
Domestic passenger air traffic arrivals to top 40 US gateway cities from June 2018 to March 2019 as a percent of the total population	darrival	2.10	4.29	204.29	0.00	19.00	50	https://www.transportation.gov/policy/aviation-policy/us-international-air-passenger-and-freight-statistics-report
Foreign passenger air traffic arrivals to top 40 US gateway cities from June 2018 to March 2019 as a percent of the total population	farrival	2.29	6.09	265.94	0.00	31.94	50	https://www.transportation.gov/policy/aviation-policy/us-international-air-passenger-and-freight-statistics-report
VI. Mandates								
Number of days from March 12 to Sept. 1 before state-level mandates on wearing masks were imposed	mask	123.60	43.98	35.58	35.00	171.00	50	https://www.aarp.org/health/healthy-living/info-2020/states-mask-mandates-coronavirus.html
Number of categories (gathering, schools, restaurants, non-essential business, and stay-at-home orders) from 0 to 5 where states enacted restrictions within 30 days of March 12, 2020	enact	3.44	1.16	33.72	1.00	5.00	50	https://www.medrxiv.org/content/10.1101/2020.03.30.20046326v1
Social distancing index that represents the extent residents and visitors practiced social distancing where "0" indicates no social distancing while "100" indicates all residents stayed at home.	distance	30.12	9.51	31.57	17.00	57.00	50	https://data.covid.umd.edu/

Empirical Findings

The results of the regression tests are presented in Table 3. A stepwise model was used to add demographic and socioeconomics independent variables to the regression tests arranged in groupings from I to VI, as shown in Tables 2 and 3. In most cases, variables were removed if not significant at the $p < 0.10$ level (one-tailed).

Analyses of the explanatory power of the variables included in groupings I to VI are presented below.

I. Density Variables

We added a super density variable (sdensity) to our regression tests because density, as generally measured, does not adequately control for its impact on a state-level basis. A state's density (density) is defined as the population of that state divided by its total geographic area in square miles or as shown in Table 2: "population density per square mile." That measure is relevant for most states but not for those states where a highly populated metropolitan area exhibits extremely high density. In those instances, the true nature of a metropolitan area's density is obscured when dividing by the entire land area of a state. For example, New York City's density is the ratio of its population of 8.2 million (2010 census) and its land area of 302.6 square miles. The resulting density of New York City of 27,016 compares to New York state's density of 169. Using a state-level density of 169 for New York state would miss the impact of the extraordinarily high rate of density for the city.

In order to capture that impact on a state-level basis, we selected all metropolitan areas in the nation with a population of 300,000 or more that had a population density of at least 10,000 people per square mile. We then took the population of those metropolitan areas as a ratio of each state's total population. The resulting ratio, in turn, was multiplied by the density of the metropolitan areas that met the selection criteria presented above.

As shown in Table 3, both density variables (density and sdensity) were highly significant. The urbanization variable (urbanpop) had the expected positive sign of association but was not significant. That result is not surprising since urbanization is defined to measure the proportion of people who live in geographic clusters of 50,000 or more population. No distinction is made in that definition regarding density. Since the spread of COVID-19 is expected to increase when there is close contact, urbanization is too broadly defined to adequately account for virus transmission. Our reason for adding it as a variable in our tests is because the print and electronic media continue to use urbanization as a major factor in explaining the spread of the coronavirus (Wharton, 2020; and Klaus, 2020). Our regression results suggest its use should be curtailed. Not only did we find that the coefficient for urbanpop insignificant, but when it was removed as an explanatory variable from the regression equation, the R^2 term remained virtually unchanged at 0.73.

Table 3. Regression results, dependent variable: Deathrate (COVID-19 deaths per 100,000 people by state)

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5	Equation 6
R-squared	0.73	0.79	0.83	0.83	0.83	0.84
Constant	14.54	-40.23	-8.91	19.13	-8.96	-34.52
I. Density variables:						
density	0.10	0.10	0.10	0.10	0.1	0.1
	(7.63) ***	(8.06) ***	(9.90) ***	(8.33) ***	(9.22) ***	(9.06) ***
sdensity	0.01	0.01	0.01	0.01	0.01	0.01
	(4.75) ***	(4.48) ***	(5.58) ***	5.17 ***	(4.60) ***	(5.02) ***
urbanpop	8.59					
	(0.35)					
II. Income variables						
py		0.37				
		(0.75)				
poverty		295.25	149.4	174.82	148.94	169.57
		(3.35) ***	(1.95) **	(1.94) **	(1.87) **	(2.16) **
III. Racial/Ethnic variables						
afram			0.75	0.74	0.75	0.75
			(2.41) ***	(2.07) **	(2.33) ***	(2.39) ***
hispanic			0.39	0.32	0.39	0.29
			(1.46) *	(0.96)	(1.39) **	(1.05)
Asian			-0.88	-0.99	-0.82	-1.24
			(-1.81) **	(-1.84) **	(-0.81)	(-2.05) *
IV. Health related varibles						
age65				-0.95		
				(-0.60)		
obesity				-0.11		
				(0.28)		
diabetes				-0.08		
				(-0.69)		
smoker				0.24		
				(0.17)		
V. Air travel variables						
darrival					520881	
					(-0.42)	
farrival					1090947	
					(-0.08)	
VI. Mandates						
mask						0.05
						(0.65)
enact						2.31
						(0.84)
distance						0.38
						(0.98)

Notes: t statistics in parentheses. *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

What is particularly noteworthy about the two highly significant density variables is that they explain most of the variation in state-level COVID-19 death rates. Even for statistical outliers like New Jersey and New York, the regression equation (not reported here) with only density and sdensity as independent variables explains most of the variation (actual of 179 for New Jersey versus predicted of 149) and (actual of 169 for New York versus predicted of 167).

These results suggest that the extremely high density of New York City explains its high death rate rather than whether its crisis planning or containment policies were effective. This observed significance of the density variables is in sharp contrast to the results of the studies cited earlier. The reason for these contrasting empirical results is likely related to different methodological approaches as well as the timeliness of the data. Our study, for example, is at the state level and covers COVID-19 deaths through September 1, 2020, while all other academic studies focus at the county and/or MSA levels over earlier time periods.

Perhaps a more important factor that accounts for the differences in how density affects COVID-19 is model specification. When Wheaton and Thompson (2020) added population as an explanatory variable to the regression equation that also includes density, the density variable is no longer significant. That does not necessarily mean that density is not a significant factor in explaining COVID-19 infections (cases). More likely, the population serves as a proxy for density at the MSA and county levels. As a result, collinearity between population and density may account for the loss of density's explanatory power. Indeed, the explanatory power of density is robust ($p < .01$) in the Wheaton and Thompson (2020) study when the population variable is not included in their equation.

Hamid, Sabouri, and Ewing (2020) examined the impact of population and density on COVID-19 infection and deaths at the county level. The regression results suggest that density at the county level is not significant, while population at the MSA level is significant in explaining infection rates. The density variable is significant in explaining the death rate, but its sign is negative instead of positive, suggesting that higher density decreases rather than increases COVID-19 death rates. The authors suggest that this may be due to "better access to health facilities and easier management of social distancing interventions such as sheltering in place." (Hamidi, Sabouri and Ewing, 2020, page 12)

We believe the insignificance of density in explaining infections and the significant negative relationship in explaining death rates in Hamidi, Sabouri, and Ewing's findings are the result of their model's construct. In their regression tests of the impact on the rate of COVID-19 infections by county, the density of a county is used as well as the population of the MSA within which the county is located as another explanatory variable.

We concur that the demographic characteristics of the MSA are more important in explaining COVID-19 infection and death rates than county-level characteristics. But in their structural equation model (SEM), MSA population likely serves as a proxy for density at the MSA level. Hamidi. Sabouri and Ewing's conclusion that density is not significant in explaining COVID infection rates may be due to the collinear relationship between population and density at the MSA level. This possibility can be tested by replacing the population variable with density at the MSA level.

In their SEM tests of COVID-19 deaths, Hamidi, Sabouri, and Ewing test both the infection rate and death rate. They initially measure the virus infection rate. Then in measuring the death rate, they use the infection rate as an independent variable in explaining the death rate. But when the infection rate is included as a variable in explaining COVID-19 deaths, its explanatory power is so significant (coefficient = 0.97 and measured t ratio = 35.39), little unexplained variable is left for the density variable. As a result, we believe their conclusion that higher (lower) county density results in lower (higher) COVID-19 deaths is suspect.

Even though our findings are at the state rather than county level and our empirical approach uses ordinary least squares rather than SEM, we believe that replacing population with density at the MSA level in the Hamidi, Sabour, and Ewing tests will restore density as a significant variable in positively explaining COVID-19 infection and death rates.

This view is supported by subsequent regression tests in our formulation. When our density variables are replaced by population at the state level, the population variable is significant but at a lower level than density. In addition, the explanatory power of the equation drops sharply.

The lower significance of the population as compared to density in our tests is not surprising. The states of Maryland and Missouri, for example, have virtually the same population of 6.1 million. But since Missouri is seven times larger than Maryland, its density of 89.3 p/m^2 is much lower than Maryland's 622.9 p/m^2. One would expect that in spite of their equal populations, Maryland is more vulnerable to the coronavirus than Missouri because of its higher relative density. That expected vulnerability will not be captured if population rather than density serves as the explanatory variable.

Similarly, this problem also exists at the county and MSA levels. If two MSA's have the same population but different densities, the use of population in place of density as the relevant explanatory variable would suggest that both MSA's are equally vulnerable to the coronavirus. Given that one of the MSA's has a higher density, that is not likely to be the case.

But before meaningful conclusions can be reached about the relationship between density and the COVID-19 death rate, it is necessary to control for the impact of other socioeconomic factors. We do that in our stepwise methodological approach by initially adding the "Income Variables" grouping (see Table 2) to our regression tests.

II. Income Variables

Our findings, as shown in Table 3, show that per capita personal income (py) is not significant but that the poverty rate (poverty) is. The poverty variable also had the expected positive sign of association.

The fact that the poverty variable is significant while the personal income variable is not can be explained by the collinear relationship between the two. The Pearson correlation between poverty and personal income is -0.50 ($p < 0.01$). Separate regression tests not reported here with only one of the variables included reveal that personal income has the expected negative sign of association but was not significant. When poverty serves as the explanatory variable in place of personal income, it is positive, as expected, and is highly significant.

These empirical results suggest that the poverty rate at the state level is a more important variable than personal income levels in explaining COVID-19 death rates. This is consistent with literature that points to higher poverty rates as increasing the number of confirmed COVID-19 deaths (Finch and Finch, 2020; Ridgwell, 2020).

With respect to the per capita income variable (py), our results run counter to those studies that point to income as a significant positive or negative factor in explaining the coronavirus. Hamidi, Sabouri, and Ewing's empirical results, for example, show that counties with a higher percentage of college-educated have significantly lower infection rates. They do not, however, include any variable representing poverty in their tests. Since higher education undoubtedly serves as a proxy for personal income, they may simply be picking up a spurious inverse association between higher education and infection rates because of the collinear relationship between income and poverty that we observed in our empirical findings.

Unlike Hamidi, Sabouri, and Ewing's findings of an inverse relationship between the percentage of college-educated and COVID-19 infections, Wheaton and Thompson found a significant positive relationship between per capita income and coronavirus cases at the county and MSA levels. The authors were surprised by this result and state, "It is tempting to suggest that perhaps dining out, entertaining, and socialization are all income elastic consumption items – items that also generate higher infection risk. But we need further direct research before drawing that conclusion" (Wheaton and Thompson, 2020, page 9).

Alternatively, our findings suggest that the collinear relationship between income and poverty should be taken into account in order to more accurately assess the impact of personal income.

III. Racial/Ethnic Variables

Most of the reported findings on the relationships between racial (ethnic) variables point to higher infection and death rates for African-Americans and Hispanics (Magnier, 2020; APM Research, 2020), but the findings on Asians are mixed. Several studies point to higher rates of COVID-19 infections and fatalities (McKinsey & Company, 2020; Health Affairs, 2020), while others (Magnier, 2020; APM Research, 2020) point to significantly lower rates. These studies, however, do not control for the causal relationships of other demographic or socioeconomic variables like density and poverty.

The empirical findings shown in Table 3 point to a highly significant positive association between the percentages of African-American populations and COVID-19 death rates at the state level. The relationship is also positive for Hispanics but only marginally significant.

Our findings of an inverse association between Asians and COVID-19 deaths support those studies that pointed to higher (lower) percentages of Asians leading to lower (higher) rates of COVID-19 deaths at both the age and age-adjusted levels (Magnier, 2020; APM Research, 2020). These inverse associations are consistent with anecdotal reports that Asians have healthier diets and consider the risks of COVID-19 more seriously, leading Asians to be more inclined to self-administer social distancing measures.

We believe a more compelling argument for the lower death rates for Asians is related to their lower poverty rates. This received empirical support in our study by the drop in explanatory power for the poverty variable when the racial/ethnic variables were added to the model. Although the poverty variable is still significant, Table 3 shows that adding race and ethnicity to the regression tests reduced the measured t statistic for the poverty coefficient from 3.35 in equation (2) to 1.95 in the current equation (3).

In light of the positive correlation between African- American and poverty and Hispanics and poverty and the negative association between Asians and poverty as shown in Table 4, it should not be surprising that adding racial/ethnic variables to our equation reduced the explanatory power of the poverty variable. What is more revealing, however, is that racial/ethnic variables in affecting COVID-19 death rates are still significant even after holding density and overall poverty rates constant. This finding suggests that other racial/ethnic characteristics besides density and poverty are associated with the coronavirus.

TABLE 4
Pearson Correlation Coefficients between Poverty and Racial/Ethnic Composition

Race/Ethnicity	Poverty	Measured t
African- American	0.37	2.78 ***
Hispanic	0.18	1.27
Asian	-0.10	-0.70

*Notes: *** indicates two-tailed significance at the 0.01 level.*

It should be noted that in our regression tests (Equation (3) to (6) in Table 3), we excluded the White racial category (white) in our racial/ethnic grouping because adding it would bring the equation close to a singular matrix.

Many have argued that the significant positive relationship between African-Americans and Hispanics with COVID-19 deaths and the inverse association with Asians is because Asians have better health (lower rates of diabetes, obesity, and smoking) and diets. That possibility suggests those variables need to be held constant before reaching any definitive conclusions about the relationship between race/ethnicity and the coronavirus.

IV. Health-Related Variables

None of the four health-related variables added to our equation tested as significant. As shown in Table 3, all measured t's were below one.

The high degree of collinearity between obesity, diabetes, and smokers is reflected by Pearson correlation coefficients that range between 0.67 to 0.78. Because of this high degree of correlation, we tested regression equations that added obesity, diabetes and smoking rates individually as separate explanatory variables. Even in these equations (findings not reported here), the coefficients for each of the individual health-related variables showed no significance.

What is most surprising in these results is the lack of significant explanatory power for the variable representing the percentage of the population over 65. We also tested the percentage of the population over 80 (not reported here) and obtained similar results that showed no significance between age and death rates.

As shown in Table 5, 79 percent of all COVID-19 deaths occurred in age cohorts of 65 and above. With COVID-19 death rates disproportionally affecting those in older cohorts, one would expect that the age 65 variable would exhibit a significant positive relationship. The fact that our empirical results reveal no significance seems anomalous, especially in light of findings in the Hamidi, Sabouri, and Ewing (2020) study. Unlike our findings, their SEM tests for the impact of the percentage of population aged 60+ on both the virus rate and the death rates resulted in highly significant coefficients ($p < .0001$).

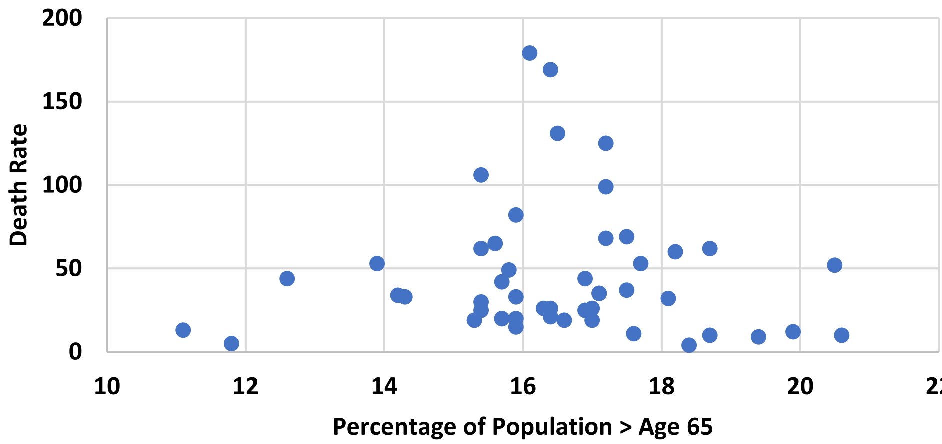
TABLE 5
Deaths Associated with COVID-19 by Age Group in the U.S.
(September 23, 2020)

Age Group	**No. of Deaths**	**Percent of all Deaths**	**Death Rate per 100,000 People in Age Cohort**
All ages	188,470	100.00	57.61
Under 1 year	20	0.01	0.52
1 – 4 years	15	0.01	0.09
5 – 14 years	31	0.02	0.08
15 – 24 years	353	0.19	0.82
25 – 34 years	1,457	0.77	3.19
35 – 44 years	3,809	2.02	9.23
45 – 54 years	10,057	5.34	24.16
55 – 64 years	23,991	12.73	56.75
65 – 74 years	40,613	21.55	133.19
75 – 84 years	49,871	26.46	323.96
85 years and over	58,253	30.91	890.11

Source: https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htm

Closer examination of the data, however, offers an explanation for the differing findings. The scatter diagram in Figure 2 shows that the death rates at the state level occurred with mean state-level ages concentrated near the national average rather than at outlying values.

FIGURE 2
Death Rate for Aged 65 or Over Population at the State-Level



These findings suggest there is not enough age dispersion in the state-level data for the regression equation to pick up any significant explanatory power. At the county and metropolitan levels, however, the dispersion is greater, as reflected by a coefficient of variation (cv) of 21.6 in the Hamidi, Sabouri, and Ewing (2020) study for their age 60+ variable. The cv for our 65+ variable (age65) at the state level is a lower 11.4. That cv of 11.4, as shown in Table 2, is the lowest cv value for any of the variables we tested.

These results suggest that while age is clearly a significant factor in explaining county and metropolitan COVID-19 death rates, there is not enough age dispersion to accurately measure its impact in regression tests at the state level.

V. Air Travel

Foreign and domestic travel is expected to increase the transmission of epidemics as greater connectivity leads to a faster spread of diseases from their originating locales (Neiderud, 2015). Yet, Hamidi, Saboudi, and Ewing (2020) found that higher enplanement rates (annual enplanements in metropolitan area per 10,000 population) led to significantly lower rates of COVID-19 infections. The authors explain these puzzling findings by suggesting that more globally connected metropolitan areas recognized the greater risks of viral transmission and consequently imposed travel restrictions earlier than they otherwise would. In our tests, we separated enplanements to distinguish between the rate of domestic and foreign travelers. Neither variable, however, was significant in our tests.

It is interesting to note that the Asian variable was no longer significant with the addition of enplanement rates. This likely occurred because of the significant correlation between the Asian and the farrival variable. Pearson's correlation coefficient between the two variables is an extremely high 0.84. This suggests that those states with a higher proportion of Asians also have a greater rate of foreign arrivals.

Although our results suggest that domestic and foreign passenger enplanements do not appear to have a significant impact on COVID-19 deaths at the state level, we believe more research is needed, especially in light of the limitations of our data. The most current data we were able to obtain for both the rate of domestic and rate of foreign passenger arrivals are totals for the entire June 2018 to March 2019 period. A more relevant period for testing would be the January 2020 to March 2020 period. In addition, data that reflects the national origin of the international flight arrivals would provide helpful micro-oriented data.

VI. Mandates

A great deal of controversy has arisen over the efficacy of governmental mandates that imposed various restrictions in order to control the spread of COVID-19. An article in the *New York Times* (Erdbrink, *New York Times*, 2020) suggests that Sweden's recent low caseload supports its relatively lax approach in responding to the coronavirus. Others argue that lower cumulative infections and death rates in neighboring Denmark and Norway, two nations that are responding with more aggressive government mandates, support the use of publicly imposed restrictions (*Boston Review*, 2020; Healthline, 2020).

We attempted to measure the effects of mandates on COVID-19 deaths in our model by testing the impact of three variables. Those included, as shown in Table 2, the number of days from March 12 to September 1 before state-level measures were imposed on wearing masks (mask); a variable (enact) that represents the cumulative number (0 to 5) of state-level mandates imposed within a 30-day period following March 12, 2020, a date where no mandates had yet been imposed; and a social distancing index (distance) that measures the degree to which people self-administered social distance practices.

If these measures were effective, one would expect when a state took longer to impose mask requirements (mask), it would result in a higher COVID-19 death rate. In the early days, when the coronavirus began to be considered a serious health crisis, it might be expected that states that responded quickly by imposing restrictive measures would have a lower COVID-19 death rate. And greater use of social distancing (distance) would also be expected to reduce the transmission, infection, and death from the disease.

Equation (3) presents these hypothesized signs of association in functional form:

$$Deathrate_i = f\,(\overset{+}{mask_i},\ \overset{-}{enact_i},\ \overset{-}{distance_i}) \qquad (3)$$

The empirical results of testing the above hypothesis in Equation 6 are shown in Table 3. All three variables in the Mandate variables grouping are insignificant, with only the variable representing the number of days it took before a state-imposed mask requirement (mask) exhibiting the hypothesized positive sign of association.

But as in the case of the high degree of correlation among the health-related variables, the three mandate variables tested here also exhibit significant correlation. The absolute value of Pearson's correlation coefficients for these three variables ranges between 0.41 and 0.49.

Rather than test each of the variables separately in regression tests as we did for the health-related grouping, we constructed a "mandate score." This score is comprised of eight different mandates. In addition to the three mandate variables shown in equation (3), we added variables relating to the number of days from March 12 it took for each state to place restrictions on social/religious gatherings, schools, restaurants, and establishing stay-at-home orders. We also added a variable that measures the number of days from March 12 it took for each state to reopen (remove its mandates) (Lee, J. et al., *New York Times,* October 7, 2020). In this case, it would be expected that keeping the mandates in place longer by reopening later would increase the mandate score. Because some of these mandate variables are expressed in different units, it was necessary to construct standard normal values (z scores) with higher values reflecting more stringent mandates. It should be noted that we equally weighted all eight mandate variables included in the final mandate score.

The resulting mandate scores are shown in Table 6. Note in analyzing Table 6 that states with rates of COVID-19 deaths exceeding 100 per 100,000 people all occurred in states that imposed more restrictive mandates. This, of course, does not necessarily mean that mandates led to more deaths. Simultaneity bias may be obscuring the real impact that mandates have on the coronavirus.

In a regression test (not reported here) where we replaced the three independent variables representing mandates (see equation 6 in Table 3) with the single-mandate score variable shown in Table 6, it was insignificant.

It may be that mandates are effective in reducing COVID-19 deaths, but that effectiveness is not revealed in regression tests because of reverse causation between the dependent variable and the independent variables. Namely, state governments are likely to respond more aggressively in imposing mandates when higher rates of infections and deaths are observed. The resulting simultaneity means that the measured coefficients are biased and no longer reflective of the causality postulated in our regression model.

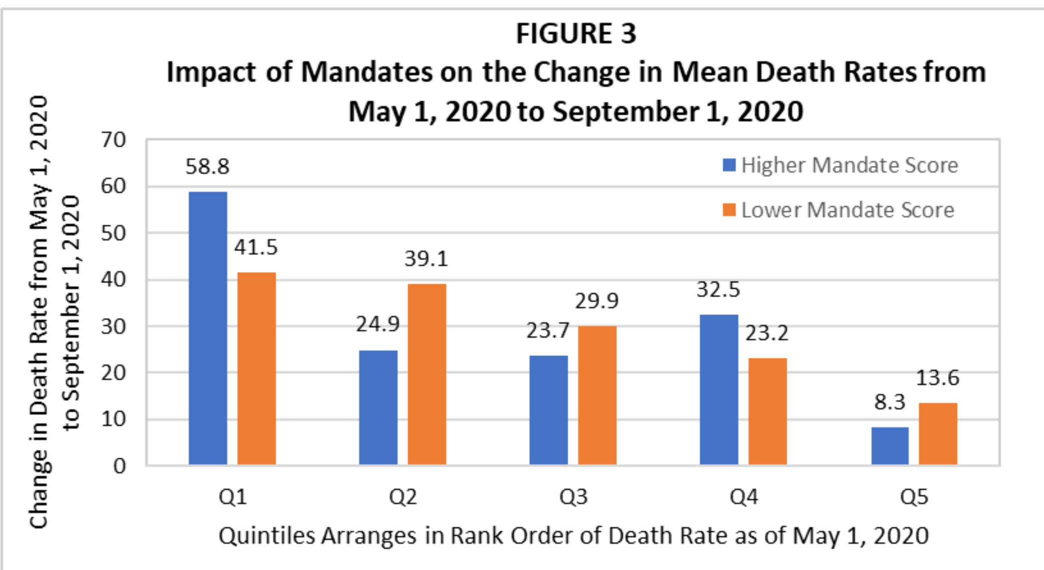
TABLE 6
Ranking of Mandates Scores by State

Rank	State	Mandate Score	COVID-19 Deaths per 100,000 as of 9/1/20
1	New York	1.50	169
2	California	1.47	33
3	Hawaii	1.18	4
4	Illinois	1.15	65
5	Delaware	1.13	62
6	New Jersey	1.13	179
7	Washington	1.07	25
8	Connecticut	1.02	125
9	Michigan	0.98	68
10	Oregon	0.98	11
11	Massachusetts	0.82	131
12	Louisiana	0.66	106
13	Pennsylvania	0.57	60
14	Nevada	0.54	42
15	New Mexico	0.48	37
16	Ohio	0.46	35
17	Vermont	0.42	9
18	West Virginia	0.34	12
19	Maryland	0.26	62
20	Rhode Island	0.24	99
21	Virginia	0.22	30
22	Minnesota	0.15	33
23	Indiana	-0.04	49
24	Kentucky	-0.07	21
25	North Carolina	-0.10	26
26	Maine	-0.12	10
27	Colorado	-0.12	34
28	Wisconsin	-0.25	19
29	Utah	-0.25	13
30	Arizona	-0.28	69
31	New Hampshire	-0.29	32
32	Florida	-0.37	52
33	Montana	-0.39	10
34	Alaska	-0.46	5
35	Alabama	-0.53	44
36	Texas	-0.56	44
37	Kansas	-0.57	15
38	Arkansas	-0.58	26
39	North Dakota	-0.60	19
40	Wyoming	-0.77	6
41	Iowa	-0.81	35
42	Nebraska	-0.86	20
43	Oklahoma	-0.86	20
44	Idaho	-0.99	20
45	South Carolina	-1.00	53
46	Missouri	-1.03	25
47	South Dakota	-1.10	19
48	Tennessee	-1.12	26
49	Georgia	-1.32	53
50	Mississippi	-1.32	82

In order to control for the effects of simultaneity, we conducted a test where states exhibiting similar death rates at a particular point in time impose different mandates. The resulting change in the death rates from that point in time to some future period would more likely exhibit one-way causation between the independent and dependent variables.

The empirical results shown in Figure 3 were obtained by arranging states in quintiles of 10 each based on the rank order of death rate as of May 1, 2020 (Figure 1 shows that May 1, 2020, was the first month that death rates by the state reached sizable numbers). We then ranked the ten states within each quantile based on the level of each state's mandate score. Finally, we calculated the mean in the death rate from May 1, 2020, to September 1, 2020, within each quintile for the five states that had higher mandate scores and the five states with lower scores.

Notice in Figure 3 that in quintiles Q1 and Q4, states with higher mean mandate scores experienced higher increases in mean death rates. But quintiles Q2, Q3, and Q5 show that states with lower mandate scores had higher increases in mean death rates. The fact that there is no general tendency for states with higher (lower) mandate scores to exhibit lower (higher) death rates suggests that, at least at the state level, the efficacy of impairing mandates is not empirically supported.



Elasticities

The average elasticity, $\overline{\mathrm{E}}$, of the death rate with respect to density in our model is given by

$$\overline{\mathrm{E}} = \left(\frac{\partial \mathrm{deathrate_i}}{\partial \mathrm{density_i}}\right)\left(\frac{\overline{\mathrm{density_i}}}{\overline{\mathrm{deathrate_i}}}\right)$$

In the structural form of our model, this can be derived by

$$\overline{\mathrm{E}} = \mathrm{b_d}\left(\frac{\overline{\mathrm{density_i}}}{\overline{\mathrm{deathrate_i}}}\right)$$

where b_d is the estimated coefficient for density, as shown in equation 3 in Table 3, and the mean values of density and death rate are as shown in Table 2.

$\overline{\mathrm{E}}$ represents average elasticity and is therefore relevant only at the mean values of the dependent and independent variables.

When the functional form of the structural equation is in exponential form such as

$$\mathrm{Deathrate_s} = \mathrm{b_0}\,(\mathrm{density_s})^{\mathrm{b_d}}\ ,$$

It can be shown that the constant elasticity, E, can be expressed in the double logarithmic form (Doti and Adibi, 2019, page 385) as

$$\mathrm{E} = \frac{\partial \mathrm{deathrate_s}}{\partial \mathrm{density_s}} * \frac{\mathrm{density_s}}{\mathrm{deathrate_s}} = \frac{\mathrm{b_1 b_0 (density_s)^{b_d - 1}}}{\mathrm{deathrate_s}} = \mathrm{b_d}$$

The calculated average elasticities, E, and constant elasticities, $\overline{\mathrm{E}}$ for density and the other variables estimated in equation 3 are present in Table 7.

TABLE 7

Independent Variable	Average Elasticity $\overline{\mathrm{E}}$	% Change in Deathrate with respect to a +10% change in Independent Variable Based on $\overline{\mathrm{E}}$	Constant Elasticity E	% Change in Deathrate with respect to a +10% change in Independent Variable Based on E
density	0.45	+4.5	0.32	+3.2
sdensity	0.07	+0.7	0.05	+0.5
poverty	0.46	+4.6	0.27	+2.7
afram	0.17	+1.7	0.25	+2.5
Hispanic	0.10	+1.0	0.34	+3.4
asian	-0.08	-0.8	-0.33	-3.3

The double logarithmic form of the regression equation upon which the constant elasticities shown in Table 7 are based has an R^2 value of 0.70 versus the higher R^2 value of 0.83 in the linear form of the equation (Equation 3 in Table 3). In spite of the lower explanatory power of the double ln form of the equation, elasticities based on that equation have the advantage of being constant across different values of the independent variables.

Their drawback is that the estimated coefficients are not as reliable, given the lower explanatory power of the regression equation in double ln form. Nonetheless, the fact that the $\overline{E}$ and E values are fairly close suggests that the $\overline{E}$ values do not change appreciably at different values of the independent variable and, therefore, can serve as proxies for E.

Analysis of Residuals

The actual and estimated death rates and residuals for all 50 states based on Equation 3 in Table 3 are presented in Table 8. The high degree of the equation's explanatory power is shown in Figure 4 that compares quartiles of the actual mean death rates with the corresponding regression mean "fitted" rates arranged from the highest to the lowest quartile.

FIGURE 4
A Comparison of Actual Versus Regression Estimates of Mean Death Rates by Quartile

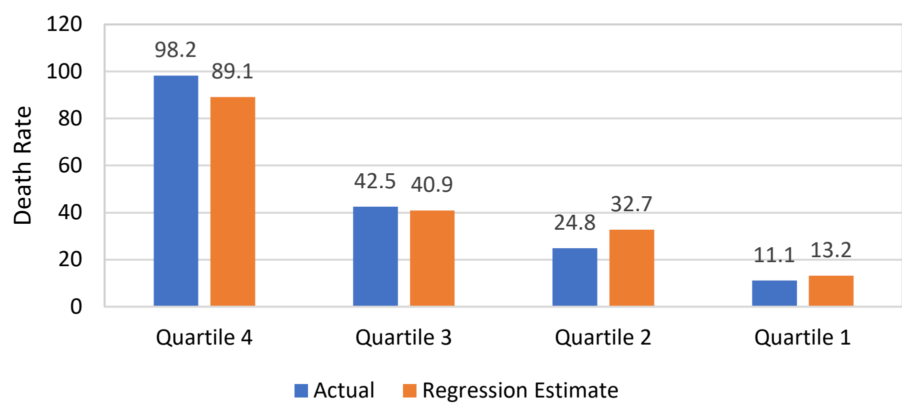
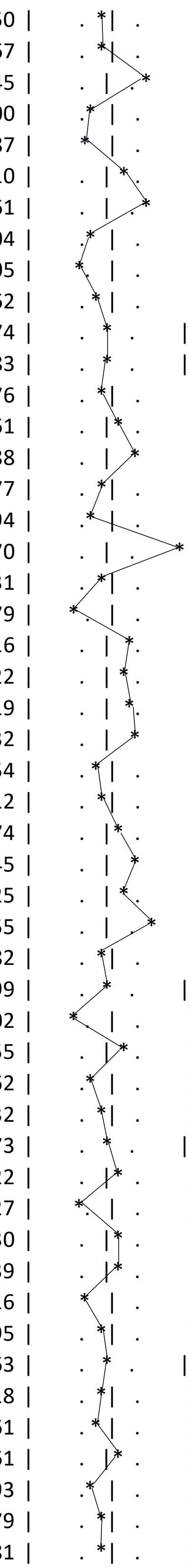


TABLE 8
Actual Mean Death Rates Versus Regression Mean Estimates

Obs	State	Actual	Fitted	Residual
1	Alabama	44.0000	46.6550	-2.6550
2	Alaska	5.0000	8.9567	-3.9567
3	Arizona	69.0000	42.1055	26.8945
4	Arkansas	26.0000	38.7600	-12.7600
5	California	33.0000	52.3787	-19.3787
6	Colorado	34.0000	24.0690	9.9310
7	Connecticut	125.0000	93.6639	31.3361
8	Delaware	62.0000	78.2704	-16.2704
9	Florida	52.0000	76.0205	-24.0205
10	Georgia	53.0000	61.7662	-8.7662
11	Hawaii	4.0000	5.1574	-1.1574
12	Idaho	20.0000	18.2117	1.7883
13	Illinois	65.0000	69.2476	-4.2476
14	Indiana	49.0000	42.8239	6.1761
15	Iowa	35.0000	15.9712	19.0288
16	Kansas	15.0000	21.9477	-6.9477
17	Kentucky	21.0000	34.5494	-13.5494
18	Louisiana	106.0000	48.2430	57.7570
19	Maine	10.0000	13.5731	-3.5731
20	Maryland	62.0000	90.8079	-28.8079
21	Massachussetts	131.0000	116.6884	14.3116
22	Michigan	68.0000	60.3778	7.6222
23	Minnesota	33.0000	18.9281	14.0719
24	Mississippi	82.0000	60.8768	21.1232
25	Missouri	25.0000	32.2854	-7.2854
26	Montana	10.0000	13.1112	-3.1112
27	Nebraska	20.0000	14.2926	5.7074
28	Nevada	42.0000	24.2155	17.7845
29	New Hampshire	32.0000	21.1675	10.8325
30	New Jersey	179.0000	146.7645	32.2355
31	New Mexico	37.0000	41.2282	-4.2282
32	New York	169.0000	168.8001	0.1999
33	North Carolina	26.0000	56.1802	-30.1802
34	North Dakota	19.0000	10.5045	8.4955
35	Ohio	35.0000	49.7762	-14.7762
36	Oklahoma	20.0000	24.1632	-4.1632
37	Oregon	11.0000	8.9327	2.0673
38	Pennsylvania	60.0000	57.7678	2.2322
39	Rhode Island	99.0000	125.0627	-26.0627
40	South Carolina	53.0000	50.7270	2.2730
41	South Dakota	19.0000	15.1061	3.8939
42	Tennessee	26.0000	46.4216	-20.4216
43	Texas	44.0000	48.7495	-4.7495
44	Utah	13.0000	13.9963	-0.9963
45	Vermont	9.0000	12.8418	-3.8418
46	Virginia	30.0000	42.1161	-12.1161
47	Washington	25.0000	21.1239	3.8761
48	West Virginia	12.0000	25.3393	-13.3393
49	Wisconsin	19.0000	23.8279	-4.8279
50	Wyoming	6.0000	9.4481	-3.4481

Residual Plot



The states whose estimated death rates deviated more than ±1.5 standard errors (±26.4) from the actual values are shown in Table 9.

TABLE 9

Estimated COVID-19 Death Rates Deviating More than 1.5 Standard Errors (±26.4) from the Actual Values

State	Actual	Estimate	Residual
Arizona	69.0	42.1	-26.8
Connecticut	125.0	93.7	+31.3
Louisiana	106.0	48.2	+57.8
Maryland	62.0	90.8	-28.8
New Jersey	179.0	146.8	+32.2
North Carolina	26.0	56.2	-30.2

One might question why the actual death rates in the states shown in Table 9 deviated more sharply from the regression estimates. Although this rigorous examination of question is beyond the scope of this study, several observations are in order.

It has been argued, for example, that Arizona's high rate is largely due to that state reacting slowly in mandating precautionary measures and then removing them too quickly after they had (Vox, 2020). But our findings suggest that the various mandates we tested on a national basis were not significant explanatory variables in explaining COVID-19 deaths. In addition, Arizona's mandate score, as shown in Table 6, ranked 30th. While that was below the mean and median, it hardly indicates a lax response, at least relative to all 50 states. Some have argued that a more viable rationale for Arizona's high death rate is that relatively high temperatures in Arizona kept people inside their homes where close contact and poor ventilation helped transmit the virus (Vox, 2020).

The fact that Connecticut and New Jersey experienced higher unexplained COVID-19 deaths is almost certainly due to a large percentage of their populations commuting to New York (*Hartford Current*, May 1, 2020). While our regression equations were able to capture New York's high death rate as a result of adding a variable that measured its extraordinarily high density (sdensity), that variable was not relevant for contiguous states that were closely connected to New York City's urban core.

In the case of Louisiana, many have suggested that its high COVID-19 death rate is due to its relatively high share of African Americans who disproportionately suffered from the coronavirus (*The Advocate*, April 24, 2020) as well as the state's higher incidence of diabetes and obesity. Our model, however, held these factors constant in our regression tests. In light of this, we believe it is more likely that the higher transmission during the early stages of the coronavirus was due to its celebration of Mardi Gras in late February. Following the celebration, Louisiana experienced the fastest growth in COVID-19 infection rates in the world (Katy Reckdahl et al., *New York Times*, updated April 13, 2020).

We have no explanations for the low rate of COVID-19 deaths as compared to our estimates for Maryland and North Carolina. But in analyzing the residuals, we found a curious geographic pattern. In addition to Maryland and North Carolina experiencing lower than expected death rates, we found, as shown in Table 10, the contiguous states of Delaware, West Virginia, and Virginia also had negative residuals.

TABLE 10

Estimated COVID-19 Death Rates as Compared to Actual Rates

State	Actual	Estimate	Residual
Maryland	62.0	90.8	-28.8
Delaware	62.0	78.3	-16.3
West Virginia	12.0	25.3	-13.3
Virginia	30.0	42.1	-12.1
North Carolina	26.0	56.2	-30.2

The low probability of negative residuals being geographically clustered together in a region of five states warrants further investigation.

Conclusion

A great deal of attention has been given to the actions taken by state governments and their governors to control the spread of COVID-19 and reduce its death toll. These actions have engendered much controversy over their efficacy. In spite of this, no academic papers have been published that examine and explain statewide differences in COVID-19 infections and deaths. This study hopes to fill that gap by presenting a stepwise regression model that measures the impact of hypothesized explanatory variables on each state's COVID-19 death rate.

Perhaps our most important finding is that the density of a state's population is clearly the most important factor explaining a state's death rate. This finding may seem intuitively obvious. It runs counter, however, to several important quantitative studies that focus on counties and metropolitan statistical areas. In contrast to our findings, these studies found that population is more important than density in explaining infections and deaths from the coronavirus.

The fact that we reached different conclusions, we believe, is not because our study is more macro in scope. More likely, they stem from different research and methodological designs.

Given the significance of our finding relating to the powerful role that density plays in explaining COVID-19 death rates, we conclude that density at the state and local levels needs to be given serious attention in planning and public policy considerations and formulations. Although less significant than density, our empirical results also suggest that higher poverty rates are associated with higher COVID-19 death rates. Specifically, we found in our elasticity calculations that a 10 percent increase in the poverty rate leads to a 2.7 to 4.6 percent increase in the death rate.

Race and ethnicity also play a role. A 10 percent increase in the proportion of the state's African-American and Hispanic populations are associated with increases in COVID-19 deaths that range between 1.0 to 3.4 percent. A greater proportion of Asians, on the other hand, leads to lower death rates.

We were initially surprised that government mandates issued by state governments appear to have no significance in changing the likelihood of dying from COVID-19. Simultaneity bias, however, may be clouding our results. While additional research is needed to reach more definite conclusions, it should be noted that we found no compelling evidence that government mandates were effective in reducing the COVID-19 death rate.

An examination of the residuals from our best-fit equation suggests that the widest differences between estimated and actual death rates are mainly due to unique circumstances in various states. The fact that our model identified those states opens interesting lines of future research.

With respect to this research, we look forward to tracking and updating our regression findings as more data become available. More importantly, we will test whether our methodology and model structure are applicable at the county and MSA levels.

References

Alirol, E., Getaz, L., Stoll, B., Chappuis, F., & Loutan, L. (2011). Urbanization and infectious diseases in a globalized world. *The Lancet Infectious Diseases, 11*(2), 131–141. https://doi.org/10. 1016/S1473-3099(10)70223-1

APM Research Lab Staff (2020). The Color of Coronavirus: COVID-19 Deaths by Race and Ethnicity in the U.S. *APM Research Lab*. https://www.apmresearchlab.org/covid/deaths-by-race

Baniamin, Hasan Muhammad and Rahman, Mizanur and Hasan, Mohammad Tareq (2020). The COVID-19 Pandemic: Why are Some Countries More Successful than Others? Available at SSRN: https://ssrn.com/abstract=3575251 or http://dx.doi.org/10.2139/ssrn.3575251

Béland, Louis-Philippe and Brodeur, Abel and Wright, Taylor (2020). The Short-Term Economic Consequences of Covid-19: Exposure to Disease, Remote Work and Government Response. IZA Discussion Paper No. 13159, Available at SSRN: https://ssrn.com/abstract=3584922

Blumenshine, P., Reingold, A., Egerter, S., Mockenhaupt, R., Braveman, P., & Marks, J. (2008). Pandemic influenza planning in the United States from a health disparities perspective. *Emerging Infectious Diseases, 14*(5), 709–715. https://doi.org/ 10.3201/eid1405.071301

Brotherhood, Luiz and Kircher, Philipp and Santos, Cezar and Tertilt, Michèle (2020). An Economic Model of the Covid-19 Epidemic: The Importance of Testing and Age-Specific Policies. CESifo Working Paper No. 8316, Available at SSRN: https://ssrn.com/abstract=3618840

Cascella, M., Rajnik, M., Cuomo, A., Dulebohn, S. C., & Di Napoli, R. (2020). Features, evaluation and treatment coronavirus (COVID-19). *In StatPearls [Internet].* StatPearls Publishing.

Centers for Disease Control and Prevention (CDC). (2020c*).* *Coronavirus disease 2019 (COVID-19): Cases in the U.S.* https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/ cases-in-us.html

Chowell, G., Bettencourt, L. M., Johnson, N., Alonso, W. J., & Viboud, C. (2008). The 1918–1919 influenza pandemic in England and Wales: Spatial patterns in transmissibility and mortality impact. *Proceedings of the Royal Society B: Biological Sciences, 275*(1634), 501–509. https://doi.org/10.1098/rspb.2007.1477

Dang, E., Huang, S., Kwok, A., Lung, H., Park, M., and Yueh, E. (2020). COVID-19 and advancing Asian American recovery. *McKinsey & Company Public & Social Sector*. https://www.mckinsey.com/industries/public-and-social-sector/our-insights/covid-19-and-advancing-asian-american-recovery

Doti, J., Adibi, E. (2019). *Econometric Analysis with EViews, 3rd Edition.* McGraw Hill Education.

Ewing, R., & Hamidi, S. (2015a). Compactness versus sprawl: A review of recent evidence from the United States. *Journal of Planning Literature, 30*(4), 413–432. https://doi.org/10.1177/ 0885412215595439

Ferguson, N., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, k., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green,W., Hamlet, A., Hinsley, W., Okell, L., van Elsland, S., Thompson, H., Verity, R., Volz, E., Wang, H., Wang, Y., Walker,P., Walters, C., Winskill, P., Whittaker, C., Donnelly, C., Riley, S., Ghani, A. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. *Imperial College London*. https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-9-impact-of-npis-on-covid-19/

Francke, Marc and Korevaar, Matthijs (2020). Housing Markets in a Pandemic: Evidence from Historical Outbreaks. Available at SSRN: https://ssrn.com/abstract=3566909 or http://dx.doi.org/10.2139/ssrn.3566909

Garrett, G. (2020). The Post-COVID-19 World Will Be Less Global and Less Urban. Wharton, University of Pennsylvania. https://knowledge.wharton.upenn.edu/article/post-covid-19-world-will-less-global-less-urban/

Garrett, T. A. (2010). Economic effects of the 1918 influenza pandemic: Implications for a modern-day pandemic. Working paper CA0721.2007. Federal Reserve Bank of St. Louis. https:// www.stlouisfed.org/—/media/files/pdfs/community-development/research-reports/pandemic_flu_report.pdf

Giagheddu, Marta and Papetti, Andrea (2020) The Macroeconomics of Age-Varying Epidemics. Available at SSRN: https://ssrn.com/abstract=3651251 or http://dx.doi.org/10.2139/ssrn.3651251

Glaeser, E. L. (2011). Cities, productivity, and quality of life. *Science (New York, N.Y.), 333*(6042), 592–594. https://doi.org/ 10.1126/science.1209264

Hamidi, S., Sabouri, S. & Ewing, R. (2020): Does DensityAggravate the COVID-19 Pandemic?, *Journal of the American Planning Association*, DOI:10.1080/01944363.2020.1777891 https://doi.org/10.1080/01944363.2020.1777891

Hamidi, S., Ewing, R., Tatalovich, Z., Grace, J. B., & Berrigan, D. (2018). Associations between urban sprawl and life expectancy in the United States. *International Journal of Environmental Research and Public Health, 15*(5), 861. https:// doi.org/10.3390/ijerph15050861

Hamidi, S., Zandiatashbar, A., & Bonakdar, A. (2019). The relationship between regional compactness and regional innovation capacity (RIC): Empirical evidence from a national study. *Technological Forecasting and Social Change, 142,* 394–402. https://doi.org/10.1016/j.techfore.2018.07.026

Harris, J. E. (2020). The subways seeded the massive coronavirus epidemic in New York City. *National Bureau of Economic Research Working Paper w27021*.

Johnson, U.S. Congresswoman Eddie Bernice and Trautman, Lawrence J. (2020). The Demographics of Death: An Early Look at COVID-19, Cultural and Racial Bias in America. Available at SSRN: https://ssrn.com/abstract=3677607 or http://dx.doi.org/10.2139/ssrn.3677607

Kahn, D. (2020, March 27). California saw dense housing near transit as its future. What now? *Politico.* https://www.politico.com/states/california/story/2020/03/27/california-saw-densehousing-near-transit-as-its-future-what-now-1269263

Katz, R., Vaught, A., & Simmens, S. J. (2019). Local decision making for implementing social distancing in response to outbreaks. *Public Health Reports (Washington, D.C.: 1974), 134*(2), 150–154. https://doi.org/10.1177/0033354918819755

Klaus, I. (2020). Pandemics Are Also an Urban Planning Problem. Bloomberg CityLab. https://www.bloomberg.com/news/articles/2020-03-06/how-the-coronavirus-could-change-city-planning.

Kumar, S., Quinn, S. C., Kim, K. H., Daniel, L. H., & Freimuth, V. S. (2012). The impact of workplace policies and other social factors on self-reported influenza-like illness incidence during the 2009 H1N1 pandemic. *American Journal of Public Health, 102*(1), 134–140. https://doi.org/10.2105/AJPH.2011.300307

Lebano, A. (2020, May 8). Sweden's Relaxed Approach to COVID-19 Isn't Working. *Boston Review*. http://bostonreview.net/politics/adele-lebano-sweden%E2%80%99s-relaxed-approach-covid-19-isn%E2%80%99t-working

Liu, W., Tao, Z. W., Lei, W., Ming-Li, Y., Kui, L., Ling, Z., & Ming, Y. (2020). Analysis of factors associated with disease outcomes in hospitalized patients with 2019 novel coronavirus disease. *Chinese Medical Journal, 133*(9), 1032–1038. https://doi. org/10.1097/CM9.0000000000000775

Lowcock, E. C., Rosella, L. C., Foisy, J., McGeer, A., & Crowcroft, N. (2012). The social determinants of health and pandemic H1N1 2009 influenza severity. *American Journal of Public Health, 102*(8), e51–e58. https://doi.org/10.2105/AJPH. 2012.300814

Magnier, Mark (2020). Asians in the U.S. least likely to get coronavirus infection despite racist assumptions of many, data suggests. *South China Morning Post.* https://www.scmp.com/news/china/article/3084947/asians-us-least-likely-get-coronavirus-infection-data-suggests

Neiderud, C. J. (2015). How urbanization affects the epidemiology of emerging infectious diseases. *Infection Ecology & Epidemiology, 5*(1), 27060. https://doi.org/10.3402/iee.v5. 27060

Nguyen, D. (2010). Evidence of the impacts of urban sprawl on social capital. *Environment and Planning B: Planning and Design, 37*(4), 610–627. https://doi.org/10.1068/b35120

Olsen, H. (2020, March 19). The United States might have a secret weapon against coronavirus. *The Washington Post.* https://www.washingtonpost.com/opinions/2020/03/19/unitedstates-might-have-secret-weapon-against-coronavirus/

Parmet, W. E., & Rothstein, M. A. (2018). The 1918 influenza pandemic: Lessons learned and not. *American Journal of Public Health, 108*(11), 1435–1436.

Radcliffe, S. (2020, June 4). Why Sweden's COVID-19 Strategy Can't Work in the U.S. *Healthline*. https://www.healthline.com/health-news/heres-what-happened-in-sweden-and-you-cant-compare-it-to-u-s

Ridgwell, H. (2020). Poverty Dramatically Increases COVID-19 Death Risk, Researchers Say. *VOA News.* https://www.voanews.com/covid-19-pandemic/poverty-dramatically-increases-covid-19-death-risk-researchers-say

Rosenthal, B. (2020, March 23). Density is New York City's big "enemy" in the coronavirus fight. *The New York Times.* https:// www.nytimes.com/2020/03/23/nyregion/coronavirus-nyccrowds-density.html

Skiera, Bernd and Jürgensmeier, Lukas and Stowe, Kevin and Gurevych, Iryna (2020). How to Best Predict the Daily Number of New Infections of COVID-19. Available at SSRN: https://ssrn.com/abstract=3571252 or http://dx.doi.org/10.2139/ssrn.3571252

Stojkoski, Viktor and Utkovski, Zoran and Jolakoski, Petar and Tevdovski, Dragan and Kocarev, Ljupco (2020). The Socioeconomic Determinants of the Coronavirus Disease (COVID-19) Pandemic. Available at SSRN: https://ssrn.com/abstract=3576037 or http://dx.doi.org/10.2139/ssrn.3576037

Tellis, Gerard J. and Sood, Nitish and Sood, Ashish (2020). Why Did U.S. Governors Delay Lockdowns Against COVID-19? Disease Science vs Learning, Cascades, and Political Polarization. USC Marshall School of Business Research Paper, Available at SSRN: https://ssrn.com/abstract=3575004 or http://dx.doi.org/10.2139/ssrn.3575004

Wheaton, W. C., & Thompson, A. K. (2020). *The geography of COVID-19 growth in the U.S.: Counties and metropolitan areas.* Available at SSRN 3570540.

World Health Organization (WHO). (2014). Ebola virus disease in West Africa: The first 9 months of the epidemic and forward projections. *New England Journal of Medicine, 371*(16), 1481–1495.

W. Holmes and Maria E, Hernandez Finch. (2020). Poverty and Covid-19: Rates of Incidence and Deaths in the United States During the First 10 Weeks of the Pandemic. *Frontiers in Sociology*. https://doi.org/10.3389/fsoc.2020.00047

Yan, B., Ng, F., Chu, J., Tsoh, J., Nguyen, T. (2020). Asian Americans Facing High COVID-19 Case Fatality. *Health Affairs Blog.* https://www.healthaffairs.org/do/10.1377/hblog20200708.894552/full/