Health in America:
What Explains the Variation in COVID-19 Mortality Rate Across the United States

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Summary

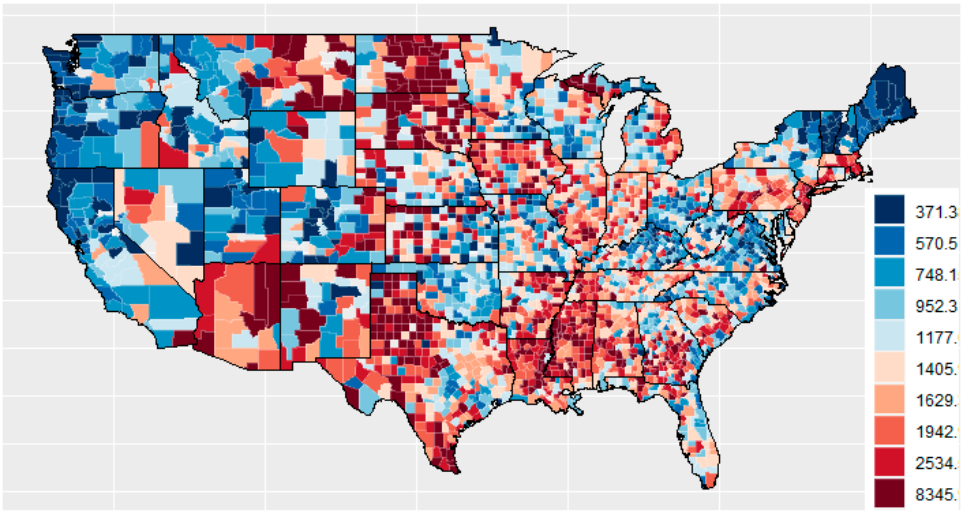
There is wide variation in COVID-19 mortality rates across the U.S. Using a multivariate regression model, we suggest the following variables are associated with county death rate.

- Positively correlated variables: age above 75 years; minority ethnicity; poverty rate; commuting using public transportation; nursing home exposure; excess drinking; and high comorbidity risks.
- Negatively correlated variables: high education; having disability insurance or public insurance; vote percentage for Democrats; working from home; and having access to a computer.

The U.S. has been disrupted by COVID-19 for more than a year. The pandemic has caused more than 520,000 deaths in the U.S. Besides the horrific scale of devastation, we notice that there is a wide variation of death rates across the country. Figure 1 shows the COVID mortality rate per 1 million county residents as of January 23, 2021. We can see some counties with lower death rates (in blue color) while others have higher fatality (red color). For instance, Clallam County in Washington State has a mortality rate of 65 per 1M population while McKinley County in New Mexico has 5,600 deaths per 1M, or a death rate equal to 0.56%. What explains the widely varying casualty rate in the face of this novel virus?

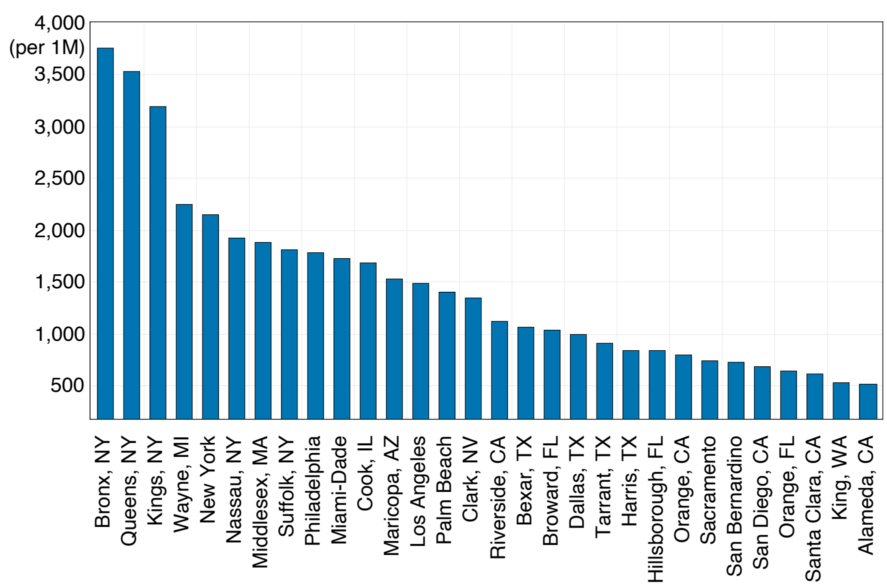
Some might argue these small counties cannot represent the whole picture of public health outcomes. Therefore, Figure 2 presents the COVID-19 death rate (per 1M) for the 30 most populous counties (above 1.3M population) in the United States. Bronx County (3,756 deaths per 1M) and other counties in New York are the ones most devastated by the pandemic. L.A. County ranks 13th (1,484 deaths per 1M), near the middle, while Alameda County has the lowest death rate (512 deaths per 1M). If we examine what factors are driving or correlating to this variation in death rate, we might be able to reduce the mortality risk when the next public health crisis hits our land.

Figure 1 Cumulative COVID-19 Deaths per 1 Million Population by County as of January 23, 2021



Source: USA Facts

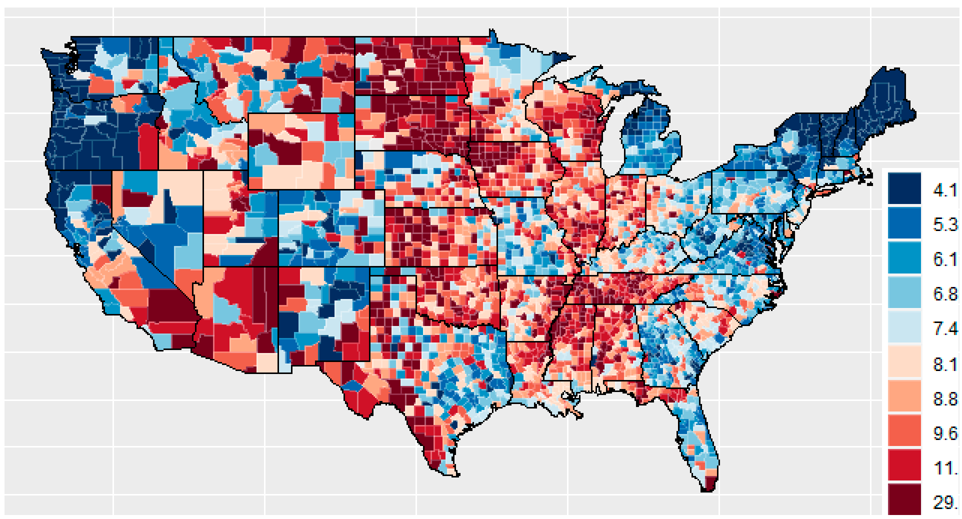
Figure 2 Cumulative COVID-19 Deaths per 1 Million Population for the 30 Largest Counties as of January 23, 2021



Source: USA Facts

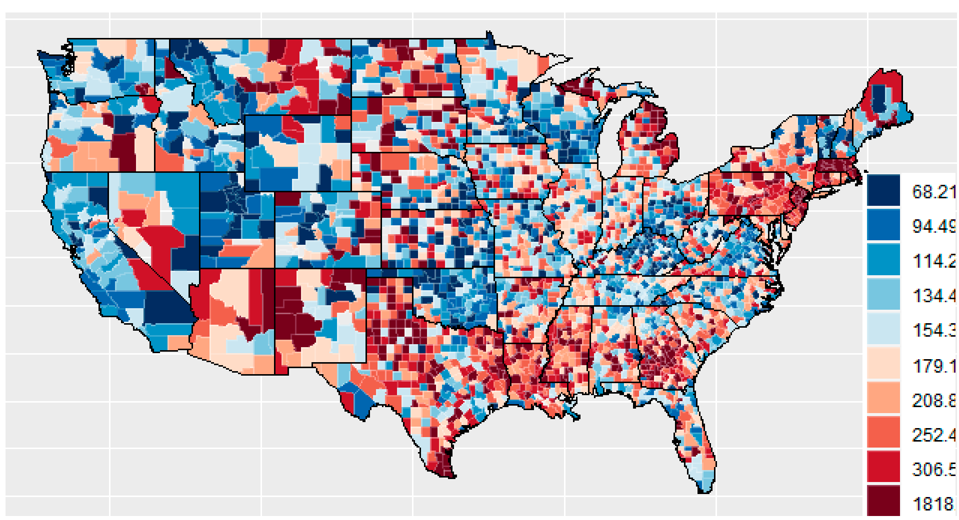
Figure 3 displays the COVID-19 confirmed cases per 100 population by county as of January 23, 2021. Figure 4 illustrates the COVID-19 case fatality rate (CFR) by county, calculated as a percentage of deaths over confirmed cases. Note that there might be a measurement error of confirmed cases because some Americans could have been without symptoms and have never been tested. Figure 5 indicates the strong correlation between COVID-19 confirmed case rate and mortality rate. The blue dots above the red line represent counties with higher CFR.

Figure 3 Cumulative COVID-19 Confirmed Cases per 100 Population by County as of January 23, 2021



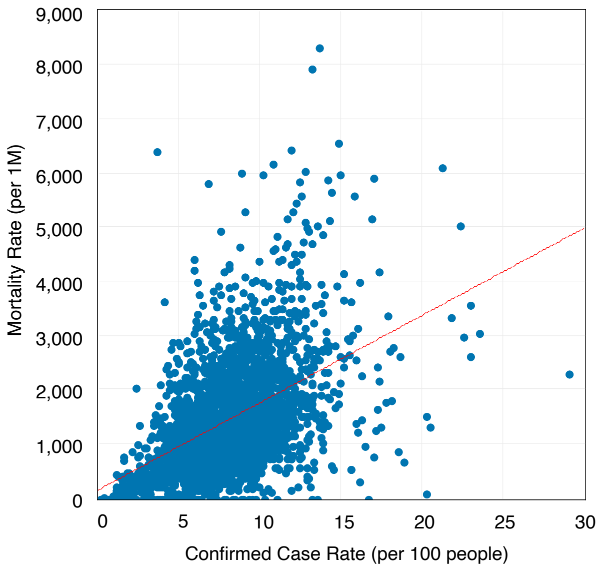
Source: USA Facts

Figure 4 Cumulative COVID-19 Case Fatality Rate (CFR) per 10,000 Population by County as of January 23, 2021



Source: Author's Calculation

Figure 5 Correlation Between COVID-19 Confirmed Case Rate and Mortality Rate



Source: USA Facts

Multivariate Regression Analysis

The best way to analyze the risk factors of COVID-19 is to examine the background of those who have died with the disease and directly compare that to the background of those who have recovered or have never been sick. For example, Asch et al (2020)[1] studied 38,500 adults admitted with COVID-19 to 955 hospitals from January 2020 to June 2020. They suggested several individual risk factors are strongly associated with mortality rates. They found that men had odds 1.3 times higher than women of dying, patients older than 85 years had odds 14.5 times higher than those aged 18 to 45 years, patients transferred from a nursing facility had odds 2.4 times higher than those admitted from the community, and patients with metastatic cancer had odds 1.9 times higher than those without. They also pointed out that good-ranking hospitals have a lower risk standardized event rate, or case mortality rate.

A different approach is to look at the geographic average data in various demographic, socioeconomic, and health variables and see how they are associated with their local/regional mortality rates. For example, Sorci et al. (2020)[2] analyzed how comorbidity, demographics, economics and political factors are associated with the fatality rate of each country during the first half of 2020. They found that countries with high disability-adjusted life years (DALYs)[3] due to cardiovascular, cancer and chronic respiratory diseases had the highest COVID-19 case fatality rate (CFR). CFR is positively associated with a country's share of population over 70 and is negatively associated with the number of hospital beds. Our Anderson Forecast colleague Edward Leamer analyzed the early data on COVID-19 confirmed cases from 58 California counties up to late April 2020.[4] Desmet and Wacziarg (2020)[5] analyze the correlates of COVID-19 cases and deaths across counties up to June 29, 2020. They found that population density, public transportation, age structure, nursing home residents, connectedness to source countries, political preference, and share of minority groups are important predictors.

Research and Data

Here, we adopt a similar approach using a multivariate regression model to analyze what county-level factors are associated with county population mortality rate as of January 23, 2021 in the U.S. Note that the current sample period might provide a more comprehensive view than earlier studies on COVID-19 because the pandemic has persisted across four seasons with three waves and has left no area of the U.S. untouched. The sample period was in the initial stage of vaccination, so the efficiency of vaccination is less relevant in this report.

Our target variable (dependent variable) is the cumulative deaths per 1 million county population (as shown in Figures 1 and 2) as well as case rate (as shown in Figure 3) and CFR (Figure 4) from USA Facts.[6] Based on the literature and news reports, we collect possible factors which could be correlated with COVID-19 fatality. Most of our demo-

1. *Asch et al., "Variation in U.S. Hospital Mortality Rates for Patients Admitted with COVID-19 During the First 6 Months of the Pandemic," JAMA (Journal of the American Medical Association) Internal Medicine, December 2020.*
2. *Gabriele Sorci, Bruni Faivre, and Serge Morand, "Explaining Among-Country Variation in COVID-19 Case Fatality Rate," Scientific Reports 10, 18909 (2020). https://doi.org/10.1038/s41598-020-75848-2*
3. *DALY is a measurement of overall disease burden, expressed as the number of years lost due to ill-health, disability or early death.*
4. *Edward Leamer (2020), "What Explains the Large Differences in Rates of COVID-19 Infections Across California Counties?"*
5. *Klaus Desmet and Romain Wacziarg (2020), "Understanding Spatial Variation in COVID-19 Across the United States, 2020, NBER Working Paper 27329.*
6. *https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/*

graphic and socioeconomic variables by county are from the 5-year American Community Survey (2015 to 2019). We use industry employment data by NAICS code over the county population as an industry density data point from the Quarterly Census of Employment and Wages (QCEW) in 2019. We collect the following county employment percentage data:

- NAICS 7211: Traveler accommodation, e.g. hotels
- NAICS 481111: Scheduled passenger air transportation, e.g. international airports
- NAICS 311612: Meat processed from carcasses, e.g. meatpacking factories
- NAICS 623110: Nursing care facilities, skilled nursing, e.g. nursing homes
- NAICS 445310: Beer, wine, and liquor stores, as a proxy of alcohol supply and demand
- NAICS 621111: Offices of physicians, as a proxy as health care capacity
- NAICS 713940: Fitness and recreational sports centers, as a proxy of access and demand for physical exercise
- NAICS 445110: Supermarket and other grocery stores, as a proxy of access to healthy produce

For a variable to reflect local governmental policies on mitigation and residents' reaction to them, we calculate the percentage of votes for Democrats over total votes by county for the 2016 presidential election. The data is from MIT Election Data and Science Lab.[7]

We collect 11 variables from the 2020 County Health Rankings and Roadmaps program[8] as follows:

- Premature death: Years of potential life lost before age 75 per 100,000 population from National Center for Health Statistics, 2016 to 2018
- Low birthweight: % of live births with low birthweight (less than 2,500 gram), 2012-2018
- Poor or fair health: % of adults reporting fair or poor health, 2017
- Poor physical health days: Average number of physically unhealthy days reported, 2017
- Adult smoking: % of adults who are current smokers
- Adult obesity: % of adult population that reports a BMI greater than 30
- Excessive drinking: % of adults reporting binge or heavy drinking from Behavioral Risk Factor Surveillance System, 2017
- Food environment index: Index of factors that contribute to a healthy food environment from USDA Food Environment Atlas, 2015 and 2017
- Physical inactivity: % of adults age 20 and above reporting no leisure-time physical activity
- Access to exercise opportunities: % of population with adequate access to locations for physical activity
- Primary care physicians: Ratio of primary care physicians to population

7. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ
8. https://www.countyhealthrankings.org/about-us. It is a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

Model	Dependent Variable	Explanatory Variables	Adj. R-Squared	Appendix
1	Death rate	Age, Race, Socioeconomic, Health factors	0.35	1
2	Case rate	Age, Race, Socioeconomic, Health factors	0.33	2
3	Case fatality rate = Death / Case	Age, Race, Socioeconomic, Health factors	0.25	3
4	Death rate	Age, Socioeconomic, Health factors	0.32	4
5	Death rate	Age, Race, Socioeconomic, Health factors, State fixed effect	0.48	5
6	Death rate	Case rate, Age, Race, Socioeconomic, Health factors	0.44	6
7	Death rate	Death rate on May 31, 2020, Age, Race, Socioeconomic, Health factors	0.42	7

Models and Results

We put all these variables together and run the multivariate regression with the following seven models. The statistical detailed outcomes are shown in the appendices.

We use Models 1-3 as the benchmark models to explain the regression findings.

Age

It is consistent to the literature and what we have known from the CDC and news reports that a person aged above 85 years (a85a; code in the regression) has an extremely high-risk (Model 1) of COVID-19 mortality compared with people aged 35 to 54. They are also more likely to be reported as confirmed cases (Model 2). If they are infected, they are more likely to die (Model 3). The results are consistent in Models 4 to 7. People aged between 75 and 84 (a7584) are also a high-risk group but their mortality rate is less than half of those aged 85 and above. It is surprising to see that people aged between 65 and 74 (a6574) have a lower death rate than the middle-age group (Model 1). The main reason is that they are less likely to contract COVID-19 because most of them have retired and therefore they have less chance to be infected in workplaces (Model 2). Their case fatality rate (CFR) is no different from the middle-age group (Model 3). People aged 55 and 64 are no different from those aged 35 to 54 in terms of mortality. On the other hand, young people (aged 20 to 34, a2034) have a marginally lower mortality rate (Model 1), even though they have a higher risk of contracting COVID-19 (Model 2). But young people's CFR is lower than middle-age people (Model 3) due to a stronger immune system.

Demographics and Ethnicity

Population density (pdensity), which is calculated as county population divided by county land mass, has no predictive power at all. Perhaps we could have guessed that from Figure 1 already. Population (pop) is not associated with mortality or infection either. In other words, COVID-19 devasted big, small, urban and rural counties equally.

We have heard various stories from the news that the pandemic hit minority groups especially hard. Unfortunately, this is true. Three minority groups: Native American (aindian), African American (black), and Latino (latino) have statistically significant higher mortality rates than the White and Asian groups (Model 1). Native Americans seem to have a higher infection rate of COVID-19, while African Americans and Latinos have comparable infection rates to the White group (Model 2). In Model 3, we see that Native Americans have a comparable CFR to the White group, but African Americans and Latinos have higher CFRs. Single-parent households (sparent) also have a marginally higher mortality rate.

Why do these minority groups associate with high COVID-19 mortality rate? Table 1 might reveal some information. The value is a simple correlation between the ethnicity % and socioeconomic and health factors of a county. The green color indicates a healthy and good environment while the yellow indicates a risky environment. The bold numbers mean a stronger correlation. We can see that Asians are mostly in the green zone but Native Americans and African Americans are mostly in the yellow zone. If green means higher health capital and yellow means lower one. A low level of health capital among these ethnicity groups could partially explain their high mortality risk.

Table 1 Simple Correlation between Ethnicity % and Socioeconomic and Health Factors

Simple Correlation	Native American	African American	Latino	Asian
Death Rate	0.11	**0.25**	0.1	-0.15
Case Rate	0.17	0.04	0.13	-0.16
CFR	-0.02	**0.25**	0.03	-0.08
CHCI	-0.05	-0.13	-0.12	**0.46**
Median Income	-0.09	**-0.27**	0.08	**0.51**
Single Parent	0.14	**0.6**	0.19	-0.01
Poverty	**0.22**	**0.47**	0.1	**-0.2**
No Health Insurance	**0.33**	**0.2**	**0.38**	-0.14
Low Birth Weight	-0.07	**0.73**	-0.06	-0.12
Healthy Food Access	**-0.28**	**-0.55**	0.01	0.17
Poor Health	0.12	**0.48**	**0.2**	**-0.23**
Excess Drinking	-0.01	**-0.38**	0.04	0.22
Premature Death	**0.3**	**0.37**	-0.18	**-0.34**
Obesity	0.08	**0.32**	-0.19	**-0.34**
Physical Inactivity	0	**0.31**	-0.17	**-0.36**
Unhealthy Days	0.16	**0.3**	-0.03	**-0.28**
Exercise Opportunity	-0.05	**-0.22**	0.16	**0.38**
Smoking	**0.25**	**0.28**	**-0.31**	**-0.35**
Primary Care Physicians	-0.01	-0.06	-0.01	**0.35**

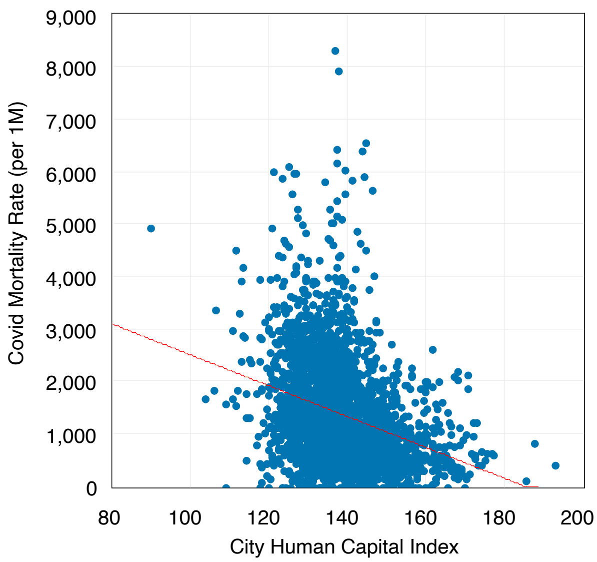
Socioeconomics

Surprisingly, the median household income (mincome) is not a significant factor to explain variation in mortality. Not surprisingly, the poverty rate (poverty) is, in particular for the CFR (Model 3). City Human Capital Index (chci) is the weighted average of the educational attainment of local residents.[9] Since it captures the entire distribution of education level, it is a better measurement of human capital than a typical indicator, such as percentage of people with a bachelor's or higher degree. People having higher education is associated with a lower mortality rate (Model 1). This is mostly from their much-reduced chance of getting COVID-19 in the first place (Model 2). One possible reason is that high-educated/skilled people are more likely to work from home during the pandemic via computer and Zoom and therefore to reduce their chance of infection. Once highly educated people contract the virus, however, the CFR is the same as for less educated people (Model 3). Figure 6 shows a simple negative correlation between human capital and COVID-19 death rate.

People being in the labor force (lcp) or not is not associated with mortality rate (Model 1). Model 2 suggests that people in the labor force are more likely to contract COVID-19 (Model 2) but they have lower CFR. So, the two effects erase the net impact. Unemployed people (ur) have the opposite story, which yields the same effect. People who are unemployed are less likely to contract the virus (Model 2), but this group has a higher CFR if they do get it. Therefore, being employed or unemployed is not significantly correlated with mortality rates.

9. https://www.anderson.ucla.edu/centers/ucla-anderson-forecast/projects-and-partnerships/city-human-capital-index

Figure 6 Correlation Between CHCI and COVID-19 Mortality Rate



Source: USA Facts, American Community Survey, and Author's Calculation

Policy and Politics

People with disability insurance (disable) have had a lower mortality rate during the pandemic. People with public insurance versus without insurance (hi_pub) seem to also have a lower mortality rate, mostly driven by a lower CFR.

After controlling all other factors, counties with higher Democrat vote percentage in the 2016 presidential election (demv) have a lower mortality rate (Model 1) and they are for both reasons: those counties tend to have a lower confirmed case rate (Model 2) and also have lower CFR (Model 3). There are two possible reasons: (1) Democrat governments' policies tend to prioritize public health while Republican policies try to balance economic and public health concerns. Our results suggest that more stringent policies do reduce the confirmed cases and mortality rates. (2) Democrat voters tend to be more concerned about health issues than freedom issues, so they are more likely to follow rules of mask wearing and social distancing, and therefore reduce the health risk.

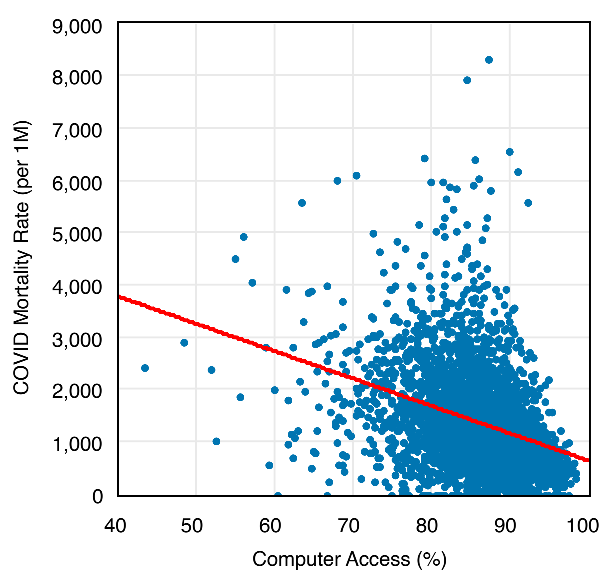
Note that if we remove ethnicity factors from the regression as shown in Model 4, the democrat vote percentage becomes an insignificant predictor. Why? Because higher percentage of these minority groups prefer voting Democrat. So, their higher mortality rate offsets the reasons aforementioned. Desmet and Wacziarg (2020) also provided a similar finding.

Infrastructure and Industry

People who use public transportation to commute (commute_p) have a higher mortality rate. This makes sense. People who work from home (wfh) have a lower mortality rate, which also makes sense. The most interesting thing is that people with a computer and broadband (computer) have significantly lower mortality rates, both in case rates and CFR. The possible explanations are that they are more likely to access COVID-19 information, they are more likely to make appointments with doctors or even do telehealth, they are more able to order groceries and all deliveries online, and to be able to work from home. Figure 7 shows a simple negative correlation between computer access and COVID-19 death rate.

All of the above has examined the variables collected from the American Community Survey. Now let's turn to the variables (sector employment percentage) from QCEW as mentioned before. Among the 8 sectors we suspected might be associated with mortality, only two were statistically significant: (1) Nursing home industry contact (p_nursehome) and (2) Liquor stores (p_liquor). There are many tragic stories and reports over the past year that many elder patients died in nursing homes. That is very true and supported by our regression results. The liquor stores finding is more surprising. We find that counties with more liquor stores have a higher mortality rate, mainly from higher CFR (Model 3).

Figure 7 Correlation Between Computer Access and COVID-19 Mortality Rate



Source: USA Facts, American Community Survey

Health Factors

Finally, among the 11 health indicators we examined, only two variables are significant predictors of high mortality: (1) People with excess drinking behavior have higher COVID-19 mortality rate, mainly via higher CFR, and (2) Counties with higher premature deaths (in 2016 to 2018) related to other diseases are correlated with higher COVID mortality in 2020/21. This is consistent with the literature that suggests the comorbidity risk is an important factor to COVID-19 deaths.

Early State Shocks

When the pandemic spread rapidly in New York region in March, 2020, the country got caught off guard by this novel virus. We did not know the best practice to treat the patient, which caused extremely high mortality rates. To control this early state shock, we add the death rate by county on May 31, 2020 as the first wave factor shown in Model 7. Most of the results are consistent except that one variable turns to insignificant: residents commuting via public transportation. Indeed, New York and Boston metros are in early high fatality region, also with high usage of publica transportation.

Conclusions

The take-aways of the report are as follows:

There is wide variation of COVID-19 mortality rate across the U.S. Using a multivariate regression model, we suggest the following variables are associated with county death rate.

- Positively correlated variables: age above 75 years; minority (Native American, African American, or Latino) ethnicity; poverty rate; commuting using public transportation; nursing home exposure; excess drinking; and high comorbidity risks.
- Negatively correlated variables: high education; having disability insurance or public insurance; vote percentage for Democrats; working from home; and access to a computer and the Internet.

Appendix 1-2

Model 1 **Dep Var: Death Rate**

coefficient	estimate	std error	t statistic	p value
(Intercept)	4189.45	590.1	7.10	0.00
a85a	288.47	24.02	12.01	0.00
a7584	122.95	18.80	6.54	0.00
a6574	-50.16	15.91	-3.15	0.00
a5564	-18.32	15.58	-1.18	0.24
a2034	-16.72	8.40	-1.99	0.05
pdensity	-0.02	0.02	-1.14	0.26
pop	0.00	0.00	-0.09	0.92
aindian	20.17	2.75	7.32	0.00
black	15.30	1.99	7.70	0.00
latino	11.92	1.45	8.19	0.00
asian	-6.74	7.07	-0.95	0.34
sparent	23.26	10.27	2.26	0.02
mincome	0.00	0.00	0.12	0.90
poverty	12.23	5.96	2.05	0.04
chci	-12.28	3.08	-3.98	0.00
lcp	1.76	3.62	0.49	0.63
ur	1.04	8.11	0.13	0.90
disable	-22.41	5.98	-3.75	0.00
hi_pub	-10.24	3.55	-2.89	0.00
demv	-9.32	1.82	-5.11	0.00
commute_p	41.13	8.78	4.68	0.00
wfh	-30.35	6.70	-4.53	0.00
computer	-22.24	4.04	-5.50	0.00
p_nursehome	184.52	31.10	5.93	0.00
p_liquor	903.72	316.9	2.85	0.00
drinking	27.94	6.52	4.29	0.00
prematured	0.04	0.01	3.71	0.00
lowbirthw	21.61	12.30	1.76	0.08
Observations:	**2799**		**Adj. R2:**	**0.35**

Model 2 **Dep Var: Confirm Case Rate**

coefficient	estimate	std error	t statistic	p value
(Intercept)	22.14	1.93	11.46	0.00
a85a	0.74	0.08	9.38	0.00
a7584	0.26	0.06	4.22	0.00
a6574	-0.39	0.05	-7.58	0.00
a5564	-0.16	0.05	-3.08	0.00
a2034	0.07	0.03	2.43	0.01
pdensity	0.00	0.00	-1.10	0.27
pop	0.00	0.00	1.95	0.05
aindian	0.10	0.01	11.10	0.00
black	0.01	0.01	1.83	0.07
latino	0.01	0.00	2.93	0.00
asian	-0.09	0.02	-3.88	0.00
sparent	0.04	0.03	1.27	0.21
mincome	0.00	0.00	-1.12	0.26
poverty	-0.02	0.02	-1.07	0.28
chci	-0.05	0.01	-5.33	0.00
lcp	0.03	0.01	2.31	0.02
ur	-0.15	0.03	-5.52	0.00
disable	-0.03	0.02	-1.62	0.11
hi_pub	-0.01	0.01	-0.88	0.38
demv	-0.03	0.01	-5.37	0.00
commute_p	0.02	0.03	0.71	0.48
wfh	-0.04	0.02	-1.91	0.06
computer	-0.05	0.01	-4.09	0.00
p_nursehome	0.31	0.10	3.08	0.00
p_liquor	0.82	1.04	0.79	0.43
drinking	0.01	0.02	0.59	0.56
prematured	0.00	0.00	-0.42	0.67
lowbirthw	0.15	0.04	3.60	0.00
Observations:	**2799**		**Adj. R2:**	**0.33**

Appendix 3-4

Model 3 **Dep Var: Case Fatality Rate**

coefficient	estimate	std error	t statistic	p value
(Intercept)	255.32	71.87	3.55	0.00
a85a	19.63	2.93	6.71	0.00
a7584	13.96	2.29	6.10	0.00
a6574	0.88	1.94	0.45	0.65
a5564	3.44	1.90	1.81	0.07
a2034	-2.07	1.02	-2.03	0.04
pdensity	0.00	0.00	0.42	0.68
pop	0.00	0.00	-0.45	0.66
aindian	0.33	0.34	0.97	0.33
black	1.92	0.24	7.93	0.00
latino	1.26	0.18	7.12	0.00
asian	1.04	0.86	1.20	0.23
sparent	1.85	1.25	1.48	0.14
mincome	0.00	0.00	0.77	0.44
poverty	1.94	0.73	2.67	0.01
chci	-0.62	0.38	-1.64	0.10
lcp	-0.96	0.44	-2.18	0.03
ur	3.35	0.99	3.39	0.00
disable	-2.15	0.73	-2.95	0.00
hi_pub	-1.50	0.43	-3.48	0.00
demv	-0.84	0.22	-3.79	0.00
commute_p	4.50	1.07	4.21	0.00
wfh	-3.00	0.82	-3.68	0.00
computer	-1.62	0.49	-3.29	0.00
p_nursehome	17.55	3.79	4.63	0.00
p_liquor	154.83	38.59	4.01	0.00
drinking	3.46	0.79	4.36	0.00
prematured	0.00	0.00	3.19	0.00
lowbirthw	-0.75	1.50	-0.50	0.61
Observations:	**2799**		**Adj. R2:**	**0.25**

Model 4 **Dep Var: Death Rate**

coefficient	estimate	std error	t statistic	p value
(Intercept)	6296.18	557.29	11.30	0.00
a85a	288.64	24.38	11.84	0.00
a7584	138.10	19.05	7.25	0.00
a6574	-45.48	16.14	-2.82	0.00
a5564	-51.21	14.99	-3.42	0.00
a2034	-23.51	8.47	-2.78	0.01
pdensity	-0.02	0.02	-1.13	0.26
pop	0.00	0.00	-0.13	0.89
sparent	46.79	9.97	4.69	0.00
mincome	0.00	0.00	0.51	0.61
poverty	19.45	5.96	3.26	0.00
chci	-21.86	2.70	-8.09	0.00
lcp	-4.37	3.60	-1.22	0.22
ur	14.31	8.12	1.76	0.08
disable	-36.75	5.93	-6.20	0.00
hi_pub	-19.39	3.47	-5.59	0.00
demv	0.34	1.47	0.23	0.82
commute_p	39.56	8.83	4.48	0.00
wfh	-21.40	6.64	-3.22	0.00
computer	-21.89	4.02	-5.45	0.00
p_nursehome	147.32	31.52	4.67	0.00
p_liquor	879.14	320.88	2.74	0.01
drinking	23.06	6.40	3.61	0.00
prematured	0.05	0.01	5.69	0.00
lowbirthw	38.64	10.60	3.64	0.00
Observations:	**2799**		**Adj. R2:**	**0.32**

Appendix 5

Model 5 **Dep Var: Death Rate**

coefficient	estimate	std error	t stat	p value
(Intercept)	5083.36	906.02	5.61	0.00
a85a	266.17	23.67	11.24	0.00
a7584	105.36	17.93	5.88	0.00
a6574	-38.78	15.48	-2.50	0.01
a5564	-29.51	15.19	-1.94	0.05
a2034	-18.19	8.21	-2.22	0.03
pdensity	0.00	0.01	0.11	0.91
pop	0.00	0.00	0.08	0.94
aindian	16.25	2.89	5.62	0.00
black	11.00	2.38	4.62	0.00
latino	11.29	2.17	5.20	0.00
asian	6.68	8.39	0.80	0.43
sparent	20.63	9.41	2.19	0.03
mincome	0.00	0.00	-0.98	0.33
poverty	9.04	5.63	1.61	0.11
chci	-14.04	3.12	-4.50	0.00
lcp	-4.39	3.54	-1.24	0.21
ur	-7.37	7.60	-0.97	0.33
disable	-3.27	5.82	-0.56	0.57
hi_pub	-20.08	5.04	-3.98	0.00
demv	-5.70	2.06	-2.77	0.01
commute_p	30.70	8.49	3.62	0.00
wfh	-22.40	6.47	-3.46	0.00
computer	-10.06	3.87	-2.60	0.01
p_nursehom	164.44	28.74	5.72	0.00
p_liquor	-42.75	321.7	-0.13	0.89
drinking	-8.89	12.43	-0.72	0.47
prematured	0.04	0.01	4.18	0.00
lowbirthw	0.16	12.08	0.01	0.99
AL	-118	643	-0.18	0.86
AR	162	639	0.25	0.80
AZ	397	656	0.61	0.54
CA	-490	636	-0.77	0.44
CO	181	641	0.28	0.78
CT	513	669	0.77	0.44
DC	-321	915	-0.35	0.73
DE	-31	728	-0.04	0.97
DE	-31	728	-0.04	0.97
FL	-287	640	-0.45	0.65

coefficient	estimate	std error	t statistic	p value
GA	-76	640	-0.12	0.91
HI	-850	729	-1.17	0.24
IA	343	636	0.54	0.59
ID	-269	646	-0.42	0.68
IL	179	636	0.28	0.78
IN	107	637	0.17	0.87
KS	-403	640	-0.63	0.53
KY	-438	636	-0.69	0.49
LA	461	641	0.72	0.47
MA	795	654	1.22	0.22
MD	-169	645	-0.26	0.79
ME	-691	652	-1.06	0.29
MI	252	636	0.40	0.69
MN	-100	636	-0.16	0.87
MO	-441	638	-0.69	0.49
MS	432	644	0.67	0.50
MT	305	643	0.47	0.64
NC	-511	638	-0.80	0.42
ND	568	646	0.88	0.38
NE	-417	642	-0.65	0.52
NH	-214	662	-0.32	0.75
NJ	721	646	1.12	0.26
NM	-8	649	-0.01	0.99
NV	-421	657	-0.64	0.52
NY	-61	637	-0.10	0.92
OH	-285	636	-0.45	0.65
OK	-882	643	-1.37	0.17
OR	-468	642	-0.73	0.47
PA	240	637	0.38	0.71
RI	433	691	0.63	0.53
SC	-27	643	-0.04	0.97
SD	904	642	1.41	0.16
TN	137	640	0.21	0.83
TX	-34	639	-0.05	0.96
UT	-635	660	-0.96	0.34
VA	-474	636	-0.75	0.46
VT	-337	654	-0.51	0.61
WA	-381	640	-0.60	0.55
WI	-85	640	-0.13	0.89
WV	-405	643	-0.63	0.53
WY	-57	650	-0.09	0.93
Observations:	**2799**		**Adj. R2:**	**0.48**

Appendix 6-7

Model 6 — Dep Var: Death Rate

coefficient	estimate	std error	t statistic	p value
(Intercept)	1696.74	561.36	3.02	0.00
casep	112.59	5.37	20.98	0.00
a85a	205.44	22.68	9.06	0.00
a7584	93.67	17.54	5.34	0.00
a6574	-5.70	14.94	-0.38	0.70
a5564	-0.64	14.51	-0.04	0.96
a2034	-24.27	7.82	-3.10	0.00
pdensity	-0.01	0.01	-0.79	0.43
pop	0.00	0.00	-0.87	0.38
aindian	8.90	2.62	3.40	0.00
black	13.96	1.85	7.55	0.00
latino	10.35	1.35	7.64	0.00
asian	3.39	6.60	0.51	0.61
sparent	18.47	9.55	1.93	0.05
mincome	0.00	0.00	0.58	0.57
poverty	14.59	5.54	2.63	0.01
chci	-6.22	2.88	-2.16	0.03
lcp	-1.32	3.37	-0.39	0.69
ur	17.56	7.58	2.32	0.02
disable	-18.84	5.57	-3.39	0.00
hi_pub	-9.09	3.30	-2.75	0.01
demv	-5.71	1.70	-3.35	0.00
commute_p	38.83	8.16	4.76	0.00
wfh	-25.63	6.24	-4.11	0.00
computer	-16.14	3.77	-4.28	0.00
p_nursehome	149.24	28.96	5.15	0.00
p_liquor	811.32	294.64	2.75	0.01
drinking	26.53	6.06	4.38	0.00
prematured	0.04	0.01	4.16	0.00
lowbirthw	5.28	11.46	0.46	0.65
Observations:	**2799**		**Adj. R2:**	**0.44**

Model 7 — Dep Var: Death Rate

coefficient	estimate	std error	t statistic	p value
(Intercept)	3826.87	558.25	6.86	0.00
deathp520	0.94	0.05	18.26	0.00
a85a	259.92	22.76	11.42	0.00
a7584	116.65	17.78	6.56	0.00
a6574	-41.81	15.05	-2.78	0.01
a5564	-26.16	14.74	-1.77	0.08
a2034	-14.07	7.95	-1.77	0.08
pdensity	-0.02	0.01	-1.30	0.20
pop	0.00	0.00	-0.59	0.55
aindian	17.50	2.61	6.71	0.00
black	11.54	1.89	6.11	0.00
latino	13.02	1.38	9.46	0.00
asian	-1.95	6.69	-0.29	0.77
sparent	16.20	9.72	1.67	0.10
mincome	0.00	0.00	-1.71	0.09
poverty	8.71	5.64	1.54	0.12
chci	-8.06	2.92	-2.76	0.01
lcp	3.18	3.42	0.93	0.35
ur	1.38	7.67	0.18	0.86
disable	-16.62	5.67	-2.93	0.00
hi_pub	-11.85	3.36	-3.53	0.00
demv	-9.80	1.72	-5.68	0.00
commute_p	9.24	8.48	1.09	0.28
wfh	-22.64	6.35	-3.57	0.00
computer	-22.83	3.82	-5.97	0.00
p_nursehome	149.15	29.47	5.06	0.00
p_liquor	348.98	301.12	1.16	0.25
drinking	31.65	6.17	5.13	0.00
prematured	0.05	0.01	5.26	0.00
lowbirthw	4.03	11.67	0.35	0.73
Observations:	**2799**		**Adj. R2:**	**0.42**