



GLOBAL JOURNAL OF MEDICAL RESEARCH: K
INTERDISCIPLINARY
Volume 22 Issue 2 Version 1.0 Year 2022
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 2249-4618 & Print ISSN: 0975-5888

Medical Best Practices and the Politics of Science Denial during the COVID-19 Pandemic

By Don Albrecht

Abstract- An analysis of data from over 3,000 U.S. counties revealed that during the second year of the COVID-19 pandemic (March 1, 2021 – March 1, 2022) when vaccines were available to adults, the number of deaths per 100,000 residents was 3 times greater in counties where Trump received more than 75 percent of the vote compared to counties where he received 25 percent or less of the vote. It is clear that widespread misinformation and science denial, often politically motivated, had disastrous consequences. Rebuilding trust in science and medical expertise is vital if we hope to benefit from the important medical break throughs that are occurring.

GJMR-K Classification: DDC Code: 616.2 LCC Code: RC776.S27



Strictly as per the compliance and regulations of:



© 2022. Don Albrecht. This research/review article is distributed under the terms of the Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0). You must give appropriate credit to authors and reference this article if parts of the article are reproduced in any manner. Applicable licensing terms are at <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

Medical Best Practices and the Politics of Science Denial during the COVID-19 Pandemic

Don Albrecht

Abstract- An analysis of data from over 3,000 U.S. counties revealed that during the second year of the COVID-19 pandemic (March 1, 2021 – March 1, 2022) when vaccines were available to adults, the number of deaths per 100,000 residents was 3 times greater in counties where Trump received more than 75 percent of the vote compared to counties where he received 25 percent or less of the vote. It is clear that widespread misinformation and science denial, often politically motivated, had disastrous consequences. Rebuilding trust in science and medical expertise is vital if we hope to benefit from the important medical breakthroughs that are occurring.

I. INTRODUCTION

Longstanding concerns about the possible emergence of a new infectious disease for which humans had little or no natural defense (e.g., Hatchett et al. 2007; Lewis 2021; Morens and Fauci 2007; Quammen 2012; Quick and Fryer 2018; Webster et al. 1997) became reality with the appearance of COVID-19. Between late 2019 and March 2022, the disease spread around the world resulting in the deaths of more than 6 million people. Every person on the planet has been impacted in some way by the pandemic. Critically, however, death rates have varied widely from one location to another, making it apparent that non-medical factors have played a prominent role in disease outcomes (Albrecht 2022a).

By recognizing the significance of non-medical factors to the pandemic, two conclusions can be drawn. First, the response of the medical community to the pandemic was remarkable (Wiersinga et al. 2020). Science and health experts quickly understood the nature of the disease and how it spread. This knowledge allowed experts to recommend best practices to keep people safe. Approaches for the care of the severely ill were refined. Most significantly, safe and effective vaccines were developed in record time, and these vaccines saved many thousands of lives (Harris 2021; Gupta et al. 2021; Le et al. 2020; Zuckerman 2021). Among people who followed best practices and were vaccinated as soon as possible, COVID-19 death rates tended to be relatively low.

A second conclusion is that vast numbers of people failed to follow medical best practices and refused vaccination. Rather than listening to and

following the advice of knowledgeable experts, many people denied science and believed the misinformation available on social media and other sources (Brennan et al. 2020; Bursztyn et al. 2020; Calvillo et al. 2020; Latkin et al. 2021; Lewandosky 2021; Priniski and Holyoak 2022). The results were disastrous and many thousands of lives were unnecessarily cut short.

A primary factor in science denial and the spread of misinformation was politics. Political views strongly influenced people's decisions about the severity of the disease and appropriate actions to take in response (van Holm et al. 2020). Understanding the relationship between political views and the acceptance of misinformation and science denial is vital for the medical community moving forward if societies hope to take full advantage of impressive scientific and medical breakthroughs that are occurring and to more effectively address new problems and concerns that will inevitably emerge. This manuscript seeks to improve our understanding of this critical relationship by exploring the link between political views and COVID-19 outcomes as determined by deaths per 100,000 residents across the more than 3,000 U.S. counties.

a) *Science Denial and Misinformation*

The impact of science on the lives of everyone is immense. Through an improved understanding of disease, developments in antibiotics, and improved sanitation, science has resulted in our lives being healthier and longer (Doig 2022). In the United States, for example, average life expectancy increased from about 49 years in 1900 to 79 years in 2020. Science has made it possible for food production to increase substantially and made it possible for us to have cleaner and safer water (Walker 2019). Because of science, transportation and communication are faster and more extensive (Isaacson 2014). Because of science, our homes are safer and more comfortable. Science is an engine of prosperity and provides an understanding and explanation of the world around us, greatly reducing fear and uncertainty (Pinker 2012).

Despite tremendous and obvious benefits, science has come under increasing attack in recent decades. On a wide range of issues, scientific evidence has been discounted and often ignored (Lewandosky 2021). Among the issues where a clear scientific consensus has been discounted include the health impacts of tobacco (Bell 2011; Bell and Dennis 2013;

Author: e-mail: don.albrecht@usu.edu

Bondurant et al. 2001; Brandt 2007), vaccination safety (Albrecht 2022b; Jolly and Douglas 2014; Loomis 2018), and climate change (Berners-Lee 2021; Carmichael and Brulle 2017; Dunlap and McCright 2008; Giddens 2009; Lahsen 2005; McCright and Dunlap 2003; 2011; Oreskes and Conway 2008; 2011; Rahm 2010; Washington and Cook 2011). The reasons for the attacks on science are numerous and varied and are part of a growing trend in which misinformation and conspiracy theories are believed by significant numbers of the general public (Kavanagh and Rich 2018; Lewandowsky et al. 2012). In some cases, attacks on science are made by industries and individuals who may suffer financially (McCright 2007; McCright and Dunlap 2003; Oreskes and Conway 2008); in other cases, persons are troubled as new information raises questions about cherished beliefs (Garvey 2008); some people may fear that lifestyle changes will be required (Bondurant et al. 2001).

The tactics used in science denial are similar across issues. These techniques have become increasingly effective with the Internet, social media, and the proliferation of websites and news services that lack a commitment to facts and truth (Chou et al. 2018; Lazer et al. 2018; Scheufele and Krause 2019). At the heart of denial campaigns are efforts to create doubt about scientists and the scientific process (Lewandowsky et al. 2017; Oreskes and Conway 2011; Powell 2011). A common approach is to create the illusion that there is disagreement among scientists when in fact disagreements are likely limited to processes and details. Typically, denialist “experts” present flawed evidence that sounds truthful but contradicts the broadly accepted scientific consensus. For example, denialists tend to “cherry-pick” evidence. That is, they will mention exceptions to the rule such as Uncle Henry who was a heavy smoker and lived to be 102 casting doubt on the dangers of tobacco, or that some city in the northeast experienced the coldest January in decades seeming to indicate that climate change can’t be real. Additionally, claims have been made by science deniers that scientists are a cabal seeking to deceive the public for personal gain (Oreskes and Conway 2011). Rush Limbaugh, for example, claimed that science is one of the “pillars of deceit” that seeks to mislead the public.

When scientific evidence becomes overwhelming, science deniers often change tactics and claim that addressing the issue is an attack on individual freedom or that the economic costs of change are too great. Many are concerned that addressing the issue will require an expanded role for government (Oreskes and Conway 2011). The end result is that after decades of science denial and misinformation campaigns, high levels of distrust of science have emerged among certain segments of the population, and this distrust contributes to the spread of misinformation and conspiracy theories (Lewandowsky et al. 2012;

Lewandowsky et al. 2017; Oreskes and Conway 2011). Of relevance to this manuscript, these same approaches have been utilized to spread misinformation during the COVID-19 pandemic (Rutjens et al. 2021; van Der Linden et al. 2020).

b) *Science Denial, Misinformation and Politics with COVID-19*

From the beginning of the COVID-19 pandemic, science denial and misinformation were prominent (Douglas 2021). Examples include claims that false cures such as gargling with lemon juice or salt water or injecting bleach could kill the virus and that wearing a mask would exacerbate spread of the disease (van Der Linden et al. 2020). Especially harmful was misinformation about COVID-19 vaccinations (Jennings et al. 2021; Loomba et al. 2021). Some argued that the vaccines would alter a person’s DNA, would negatively affect fertility or that microchips were being injected into people so their behavior could be monitored and controlled (Romer and Jamieson 2020).

Acceptance of misinformation and science denial were much more prevalent among some segments of the population than others (Roozenbeek et al. 2020). Throughout the pandemic, Democrats were much more likely to take the threat of the virus seriously and to support efforts to control the virus, while Republicans were more likely to accept misinformation (Bruine de Bruin et al. 2020; Hamilton and Safford 2020). This is consistent with other issues where trust in science is greater among Democrats than Republicans (Dunlap and McCright 2008; Oreskes and Conway 2011; Rutjens et al. 2021). Consequently, state and local governments under Republican control were less likely to implement restrictive policies than those under Democrat control (Hsiehchen et al. 2020). Early research found that counties with a higher share of Trump voters tended to have lower perceptions of the dangers of COVID-19, and these perceptions led to riskier behavior (Barrios and Hochberg 2020; Calvillo et al. 2020). States with more Trump voters were more resistant to stay-at-home orders (Hill et al. 2020a). In more religious states, which tend to be heavily Republican, people were found to be more mobile during the pandemic despite recommendations to stay home (Hill et al. 2020b). Perry et al. (2020) found that Christian nationalism, which has strong ties to the Republican Party, was related to many of the far-right responses to COVID-19, including unfounded conspiracy theories. Thus, it is not surprising that persons more able to distinguish scientific facts from misinformation were more likely to be vaccinated (Montagni et al. 2021).

Science denial relative to COVID-19 started at the top. From the beginning, the severity of the pandemic was downplayed by President Trump. Trump talked about how the virus would magically disappear.

He then claimed that the virus would be eliminated by warmer spring weather. For months, he argued that we were turning the corner and that the disease wasn't that bad anyway. He recommended ways of addressing the disease that lacked scientific merit. Trump held political rallies where thousands of people gathered, most not wearing masks. Reacting to shutdown policies intended to slow disease spread, Trump tweeted messages such as "Liberate Michigan" (Paz 2020).

Beyond the president, other political leaders and media outlets sent divergent messages on COVID-19. Again, Republicans and the right-wing media tended to downplay the threat of the disease and express opposition to steps intended to prevent spread (Allcott et al. 2020; Gadarian et al. 2021). With support from Republican leaders and the right-wing media, protests were held throughout the country in opposition to mask mandates, business and school closures and vaccination mandates. Thus, throughout the pandemic, Republicans have been more likely than Democrats to resist medical best practices. Consequently, in this manuscript, it is expected that in counties where the percent voting for Trump in the 2020 presidential election was greater, the number of COVID-19 deaths per 100,000 residents will be more extensive.

This manuscript explores data for the first two years of the pandemic. It could be argued that the pandemic began impacting the lives of most Americans in March 2020. One year later, in March 2021, vaccines were generally available for most American adults. Thus, during the first year of the pandemic (from March 2020 until March 2021), the tools available for people to protect themselves from the virus were limited and included social distancing and wearing masks. For the second year (March 2021 until March 2022), safe and effective vaccines were available. Consequently, it is expected that the strength of the relationship between political views and COVID-19 deaths will be stronger during the second year of the pandemic relative to the first year. This is because persons who accept medical health expertise and best practices had a more effective tool to protect themselves during the second year.

An additional reason that the relationship is expected to be weaker during the first year of the pandemic is that during the early months of the pandemic, the death rates were much higher in major U.S. cities compared to smaller communities and rural areas. This is because metropolitan areas are home to travelers from around the world who may have brought the disease from elsewhere. In cities people live and work in close proximity to one another and are more dependent upon mass transit, all of which makes social distancing more difficult. These circumstances provide prime conditions for the virus to spread. In contrast, in rural areas there are fewer people, and these people are more widely dispersed, making it easier for people to remain apart slowing virus spread (Albrecht 2021;

Rocklov and Sjoden 2020). This is of relevance to this study because residents of large cities are much less likely to vote Republican and thus cast their ballot for Donald Trump in the 2020 election than small town and rural residents (Goetz et al. 2018; Monnat and Brown 2017).

In exploring the relationship between political views and COVID-19 death rates, it is important to control for other independent variables that could impact this relationship. For this manuscript, three control variables will be considered including percent non-Hispanic white, percent of adults 25 years old and older with a college degree, and percent of households in poverty.

II. METHODS

The county is the unit of analysis for this study. Counties are relatively small geographic units where data are available for all of the variables utilized in the study. The analysis is based on 3,112 counties for which data are available on all variables used in the analysis. U.S. counties provide an excellent opportunity to test the relationship between political views and COVID-19 outcomes because there are extensive variations on both variables. The dependent variable is the number of COVID-19 deaths per 100,000 residents for each county. To measure the dependent variables, county-level data were obtained from the New York Times COVID-19 dataset. This dataset provides the number of COVID-19 deaths for each county in the U.S. on a daily basis. The data are obtained from state, regional and county sources on a continual basis. New York Times data are virtually identical to COVID-19 data from other sources since they all obtain their information from the same places. The advantage of the New York Times dataset is that data is available to the public and can be easily downloaded. For this study, the cumulative number of COVID-19 deaths for each county were downloaded on two dates, March 1, 2021 and March 1, 2022. The number of COVID-19 deaths per 100,000 residents for the first year is determined by the number of deaths in each county from pandemic beginnings until March 1, 2021. COVID-19 deaths per 100,000 residents for the second year is based on deaths from March 1, 2021 until March 1, 2022. The variable used in the model is based on total COVID-19 deaths divided by the total population of the county based on the 2014-2018 American Community Survey (ACS) and then multiplied by 100,000.

The primary independent variable is political views, measured by the percent of votes in each county in the 2020 presidential election for Donald Trump. County-level voting data were obtained from the New York Times, and determination was made of the percent of voters in each county that cast their ballot for Donald Trump. Again, New York Times data was chosen

because it is easily downloadable. The three other independent variables are obtained from the 2014-2018 American Community Survey conducted by the U.S. Census Bureau. Race/ethnicity is measured by the percent of residents in each county that are non-Hispanic white. Educational attainment is determined by the percentage of persons aged 25 and older with a college degree in each county. The poverty measure is determined by the percent of households in each county living in poverty.

The analysis begins with a bivariate overview of the relationship between political views and the number of COVID-19 deaths for each of the two years of the pandemic. For this analysis, counties are categorized into five groups based on the percent voting for Trump. The categories are (1) counties where Trump received less than 25 percent of the vote; (2) counties where Trump received from 25 percent to less than 45 percent of the vote; (3) counties where Trump received from 45 to less than 55 percent of the vote; (4) counties where Trump received from 55 percent to less than 75 percent of the vote; and (5) counties where Trump received 75 percent or more of the vote. Following the bivariate analysis, regression models are run with COVID-19 deaths per 100,000 residents for each year as the dependent variable, while the independent variables are the percent voting for Trump, race/ethnicity, educational attainment and poverty levels. The regression models are weighted by the total population in the county.

III. FINDINGS

The data in Table 1 show that during the first year of the pandemic, the relationship between percent voting for Trump and COVID-19 death rates was not especially strong. During the second year, however, the relationship between political views and COVID-19 death rates was very strong. After vaccines were available, the per capita death rate from the disease increased steadily as the percent voting for Trump increased. In counties where Trump received more than 75 percent of the vote, death rates per 100,000 residents was more than 3 times greater (223.4) than in counties where Trump received less than 25 percent of the vote (73.6). Overall, during the first year of the pandemic, more than a half million Americans died (about 153 per 100,000 residents), while during the second year more than 425,000 people died (about 130 per 100,000). In counties where Trump received 55 percent or more of the vote, the death rate during the second year of the pandemic was greater than during the first year. In contrast, in counties where Trump received less than 55 percent of the vote, the death rate during the second year was less than during the first year. In counties where Trump received less than 25 percent of the vote, the death rate during the second year was less than one-half of what it had been during the first year.

Table 1 also presents data on the other independent variables used in the model and their relationship with the percent voting for Trump. It is clear that counties with large shares of Trump voters had high proportions of non-Hispanic white residents, educational attainment levels tended to be low and poverty levels were also relatively low. Thus, counties leaning for Trump in the 2020 presidential election tended to homes of large shares of the white working class.

Table 2 presents the results of regression models for both the first and second years of the pandemic. For the first year, the relationship between the percent voting for Trump and COVID-19 death rates was statistically insignificant. The strongest predictor of death rates during the first year was educational attainment where death rates declined as the percentage of the population with a college degree increased. Also, death rates were lower in counties with large non-Hispanic white populations, and were higher where poverty levels were greater. In total, the independent variables explained about 15 percent of the variation in COVID-19 death rates.

For the second year of the pandemic, results were very different. The best predictor of COVID-19 death rates was the percent voting for Trump. As the proportion of voters for Trump increased, the death rate also increased. Consistent with the first year, as educational attainment increased, death rates declined, and as poverty levels increased, death rates also increased. During the first year of the pandemic, there was an inverse relationship between percent non-Hispanic white and COVID-19 death rates. By the second year of the pandemic, this relationship had switched, with death rates greater in counties with a higher percentage of non-Hispanic white residents. No question, this change can be explained by the fact that counties with large numbers of non-Hispanic white residents tended to vote for Trump, and the death rate increased sharply in these counties. During the second year of the pandemic, the independent variables explained nearly 60 percent of the variation in COVID-19 death rates.

IV. CONCLUSIONS

Widespread misinformation and science denial with respect to the COVID-19 pandemic have had disastrous consequences. Basing their decision on misinformation often driven by politics, millions of people failed to follow the advice of health professionals and refused to get vaccinated. The result was many thousands of unnecessary deaths. The data presented in this manuscript revealed that during the second year of the pandemic (March 1, 2021 – March 1, 2022) when vaccines were available to adults in the U.S., counties where Trump received 75 percent of the vote or more,

had more than 3 times more COVID-19 deaths per 100,000 residents compared to counties where Trump received less than 25 percent of the vote.

The consequences of the results of this study are profound. With respect to the COVID-19 pandemic, the deaths of thousands of people were completely unnecessary. It is estimated that the average person in the U.S. who died from COVID-19 lost over 16 years of life (Dukhovnov and Barbieri 2021). No question there is far more to consider in developing responses to a pandemic than trying to prevent everyone from getting a dangerous disease. School and business closures and extensive social distancing have severe mental health, economic and educational costs that may take years to fully understand and even longer to address. There is plenty of room for political discussion as we seek to find the best balance between safety and other concerns. This political discussion, however, should be based on facts and accurate information rather than misinformation and science denial. Moving forward, there is no question that the world will face other crises. It is vital that we somehow rebuild trust in science and medical health expertise so that in the future more people base their decisions on the best available information and people are better equipped to recognize and reject misinformation and conspiracy theories.

REFERENCES RÉFÉRENCES REFERENCIAS

- Albrecht, Don E. 2021. COVID-19 in Rural America: Impacts of Political Views and Disadvantage." *Rural Sociology*. <https://DOI: 10.1111/ruso.12404>.
- Albrecht, Don E. 2022a. "Politics and the Spread of COVID-19 in the United States." *Medical Research Archives* 10(2).
- Albrecht, Don E. 2022b. "Vaccination, Politics and COVID-19 Impacts." *BMC Public Health* 22: 96.
- Bell, K., 2011. "Legislating Abjection? Secondhand Smoke, Tobacco Control Policy and the Public's Health." *Critical Public Health* 21(1): 49-62.
- Bell, K. and S. Dennis. 2013. "Toward a Critical Anthropology of Smoking: Exploring the Consequences of Tobacco Control." *Contemporary Drug Problems* 40(1): 3-19.
- Berners-Lee, M., 2021. *There Is No Planet B: A Handbook for the Make or Break Years Updated Edition*. Cambridge University Press.
- Bondurant, S., R. Wallace, P. Shetty, and K. Stratton (eds.). 2001. "Clearing the Smoke: Assessing the Science Base for Tobacco Harm Reduction." National Academies Press.
- Brandt, A.M. 2007. *Cigarette Century: The Rise, Fall and Deadly Persistence of the Product that Defined America*. New York: Basic Books.
- Brennen, J.S., Simon, F., Howard, P.N. and Nielsen, R.K. 2020. "Types, Sources, and Claims of COVID-19 Misinformation." *Reuters Institute* 7: 1-13.
- Bursztyjn, L., Rao, A., Roth, C.P. and Yanagizawa-Drott, D.H. 2020. "Misinformation during a Pandemic" (No. w27417). National Bureau of Economic Research.
- Calvillo, D.P., Ross, B.J., Garcia, R.J., Smelter, T.J. and Rutchick, A.M., 2020. "Political Ideology Predicts Perceptions of the Threat of COVID-19 (and Susceptibility to fake news about it)." *Social Psychological and Personality Science* 11(8): 1119-1128.
- Carmichael, J.T. and Brulle, R.J. 2017. Elite cues, media coverage, and public concern: an integrated path analysis of public opinion on climate change, 2001–2013. *Environmental Politics*, 26(2), 232-252.
- Chou, W.Y.S., Oh, A. and Klein, W.M., 2018. "Addressing Health-Related Misinformation on Social Media." *Jama* 320(23): 2417-2418.
- Doig, Andrew. 2022. *The Mortal Coil: A History of Death*. London: Bloomsbury Publishing.
- Douglas, K.M. 2021. "COVID-19 Conspiracy Theories." *Group Processes & Intergroup Relations* 24(2): 270-275.
- Dukhovnov, D. and Barbieri, M. 2021. "County-Level Socio-Economic Disparities in COVID-19 Mortality in the USA." *International Journal of Epidemiology* (Dec.)
- Dunlap, R.E. and A.M. McCright. 2008. "A Widening Gap: Republican and Democratic Views on Climate Change." *Environment* 50: 26-35.
- Gadarian, S.K., Goodman, S.W. and Pepinsky, T.B. 2021. "Partisanship, Health Behavior, and Policy Attitudes in the Early Stages of the COVID-19 Pandemic." *PlosOne* 16(4): e0249596.
- Garvey, K.J., 2008. "Denial of Evolution: An Exploration of Cognition, Culture and Affect." *Journal of social, evolutionary, and cultural psychology* 2(4): 209.
- Giddens, A. 2009. *The Politics of Climate Change*. Malden, MA: Polity Press.
- Goetz, Stephan J., Meri Davlasheridze, Yicheol Han, and David A. Fleming-Muñoz. 2018a. "Explaining the 2016 Vote for President Trump across U.S. Counties." *Applied Economic Perspectives and Policy*. doi:10.1093/aep/ppy026
- Gupta, S., Cantor, J., Simon, K.I., Bento, A.I., Wing, C. and Whaley, C.M. Vaccinations Against COVID-19 May Have Averted Up To 140,000 Deaths in The United States: Study Examines Role of COVID-19 Vaccines and Deaths Averted in the United States. *Health Affairs*, 2021; 40(9): 1465-1472.
- Harris, J.E. "COVID-19 Incidence and Hospitalization Rates are Inversely Related to Vaccination Coverage Among the 112 Most Populous Counties in the United States." *medRxiv*, 2021.
- Hatchett, Richard J., Carter E. Mecher, and Marc Lipsitch. 2007. "Public Health Interventions and

- Epidemic Intensity During the 1918 Influenza Pandemic." *Proceedings of the National Academy of Sciences* 104(18): 7582-7587.
25. Isaacson, Walter, 2014. *The innovators: How a group of inventors, hackers, geniuses and geeks created the digital revolution*. New York: Simon and Schuster.
 26. Jennings, W., Stoker, G., Bunting, H., Valgarðsson, V.O., Gaskell, J., Devine, D., McKay, L. and Mills, M.C. 2021. "Lack of Trust, Conspiracy Beliefs, and Social Media use Predict COVID-19 Vaccine Hesitancy." *Vaccines* 9(6): 593.
 27. Jolley, D. and K.M. Douglas. 2014. "The Effects of Anti-Vaccine Conspiracy Theories on Vaccination Intentions." *PloS one* 9(2): e89177.
 28. Kavanagh, J. and M.D. Rich. 2018. *Truth decay: An initial exploration of the diminishing role of facts and analysis in American public life*. Rand Corporation.
 29. Lahsen, M. 2005. "Technocracy, Democracy, and U.S. Climate Politics." *Science, Technology and Human Values* 30: 137-169.
 30. Latkin, C.A., Dayton, L., Moran, M., Strickland, J.C. and Collins, K. 2021. "Behavioral and Psychosocial Factors Associated with COVID-19 Skepticism in the United States." *Current Psychology*: 1-9.
 31. Lazer, D.M., Baum, M.A., Benkler, Y., Berinsky, A.J., Greenhill, K.M., Menczer, F., Metzger, M.J., Nyhan, B., Pennycook, G., Rothschild, D. and Schudson, M. 2018. "The Science of Fake News." *Science* 359(6380): 1094-1096.
 32. Le, T.T., Andreadakis, Z., Kumar, A., Román, R.G., Tollefsen, S., Saville, M. and Mayhew, S. 2020. "The COVID-19 Vaccine Development Landscape." *Nat Rev Drug Discov* 19(5): 305-306.
 33. Lewandowsky, S. 2021. "Liberty and the Pursuit of Science Denial." *Current Opinion in Behavioral Sciences* 42: 65-69.
 34. Lewandowsky, S., U.K. Ecker, C.M. Seifert, N. Schwarz, and J. Cook. 2012. "Misinformation and its Correction: Continued Influence and Successful Debiasing." *Psychological Science in the Public Interest* 13(3): 106-131.
 35. Lewandowsky, S., U.K. Ecker, and J. Cook. 2017. "Beyond Misinformation: Understanding and Coping with the 'Post-Truth' Era." *Journal of Applied Research in Memory and Cognition* 6(4): 353-369.
 36. Lewis, Michael. 2021. *The Premonition*. New York: W.W. Norton.
 37. Loomba, S., de Figueiredo, A., Piatek, S.J., de Graaf, K. and Larson, H.J. 2021. "Measuring the Impact of COVID-19 Vaccine Misinformation on Vaccination Intent in the UK and USA." *Nature Human Behaviour* 5(3): 337-348.
 38. Loomis, Joshua. 2018. *Epidemics: The Impact of Germs and Their Power over Humanity*. Santa Barbara, CA: Praeger.
 39. McCright, A.M. 2007. "Dealing with Climate Change Contrarians." Pp. 200-212 in S.C. Moser and L. Dilling (eds.), *Creating a Climate for Change: Communicating Climate Change and Facilitating Social Change*. New York: Cambridge University Press.
 40. McCright, A.M. and R.E. Dunlap. 2011. "The Politicization of Climate Change and Polarization in the American Public's Views of Global Warming, 2001-2010." *The Sociological Quarterly* 52: 155-194.
 41. McCright, A.M. and R.E. Dunlap. 2003. "Defeating Kyoto: The Conservative Movement's Impact on U.S. Climate Change Policy." *Social Problems* 50(3): 348-373.
 42. Monnat, Shannon M., and David L. Brown. 2017. "More than a Rural Revolt: Landscapes of Despair and the 2016 Presidential Election." *Journal of Rural Studies* 55: 227-236. doi: 10.1016/j.jrurstud.2017.08.010
 43. Montagni, I., Ouazzani-Touhami, K., Mebarki, A., Texier, N., Schück, S., Tzourio, C. and Confins Group. 2021. "Acceptance of a COVID-19 Vaccine is Associated with Ability to Detect Fake News and Health Literacy." *Journal of Public Health* 43(4): 695-702.
 44. Morens, David M. and Anthony S. Fauci. 2007. "The 1918 Influenza Pandemic: Insights for the 21st Century." *Journal of Infectious Diseases* 195(7): 1018-1028.
 45. Oreskes, N. and E.M. Conway. 2008. "Challenging Knowledge: How Climate Science Became a Victim of the Cold War." Pp. 55-89 in R.N. Proctor and L. Schiebinger (eds.), *Agnology: The Making and Unmaking of Ignorance*. Stanford, CA: Stanford University Press.
 46. Oreskes, N. and E.M. Conway. 2011. *Merchants of doubt: How a handful of scientists obscured the truth on issues from tobacco smoke to global warming*. New York: Bloomsbury Publishing.
 47. Pinker, Steven. 2012. *The better angels of our nature: Why violence has declined*. New York: Penguin Group USA.
 48. Powell, J.L. 2011. *The Inquisition of Climate Science*. New York: Columbia University Press.
 49. Priniski, J.H. and Holyoak, K.J. 2022. "A Darkening Spring: How Preexisting Distrust Shaped COVID-19 Skepticism." *PloS one* 17(1): p.e0263191.
 50. Quammen, David. 2012. *Spillover: Animal Infections and the Next Human Pandemic*. New York: Norton.
 51. Quick, Jonathan D. and Bronwyn Fryer. 2018. *The End of Epidemics*. New York: St. Martins Press.
 52. Rahm, D. 2010. *Climate Change Policy in the United States*. Jefferson, NC: McFarland.
 53. Rocklöv, J. and H. Sjödin. 2020. "High Population Densities Catalyze the Spread of COVID-19." *Journal of Travel Medicine* 27(3): p.taaa038.

54. Romer, D. and Jamieson, K.H. 2020. "Conspiracy Theories as Barriers to Controlling the Spread of COVID-19 in the US." *Social Science & Medicine* 263: 113356.
55. Roozenbeek, J., Schneider, C.R., Dryhurst, S., Kerr, J., Freeman, A.L., Recchia, G., Van Der Bles, A.M. and Van Der Linden, S. 2020. "Susceptibility to Misinformation about COVID-19 around the World." *Royal Society Open Science* 7(10): 201199.
56. Rutjens, B.T., van der Linden, S. and van der Lee, R. 2021. "Science Skepticism in Times of COVID-19." *Group Processes & Intergroup Relations* 24(2): 276-283.
57. Scheufele, D.A. and Krause, N.M. 2019. "Science Audiences, Misinformation, and Fake News." *Proceedings of the National Academy of Sciences* 116(16): 7662-7669.
58. van Der Linden, S., Roozenbeek, J. and Compton, J. 2020. "Inoculating against Fake News about COVID-19." *Frontiers in Psychology* 11: 2928.
59. van Holm, E.J., Monaghan, J., Shahar, D.C., Messina, J.P. and Surprenant, C. 2020. "The impact of Political Ideology on Concern and Behavior during COVID-19". Available at SSRN 3573224.
60. Walker, K.D., 2019. *The Grand Food Bargain: And the Mindless Drive for More*. Island Press.
61. Washington, H. and J. Cook. 2011. *Climate Change Denial*. Washington, DC: Earthscan.
62. Webster, R.G., K.F. Shortridge, and Y. Kawaoka. 1997. "Influenza: Interspecies Transmission and Emergence of New Pandemics." *Immunology and Medical Microbiology* 18(4): 275-279.
63. Wiersinga, W.J., Rhodes, A., Cheng, A.C., Peacock, S.J. and Prescott, H.C. 2020. "Pathophysiology, Transmission, Diagnosis, and Treatment of Coronavirus Disease 2019 (COVID-19): a Review." *Jama* 324(8): 782-793.
64. Zuckerman, Gregory. 2021. *A Shot to Save the World*. New York: Penguin.



Table 1: COVID-19 and Independent Variables by Percent Voting for Trump (N =3,112)

Variable	Percent Voting or Trump						Total (N=3,112)
	Less than 25 Percent (N=54)	25-45 Percent (N=328)	45-55 Percent (N=317)	55-75 Percent (N=1,310)	75 Percent or More (N=1,103)		
March 1, 2021							
Total COVID-19 Deaths	45,514	182,121	97,774	133,636	41,841	500,886	
Deaths Per 100,000	152.8	148.5	146.4	156.6	181.6	152.9	
March 1, 2021 - March 1, 2022							
Total COVID-19 Deaths	21,918	124,453	83,280	144,074	51,453	425,178	
Deaths Per 100,000	73.6	101.6	124.6	168.9	223.4	129.8	
Total Pandemic							
a. Total COVID-19 Deaths	67,432	306,574	181,054	277,710	93,294	926,064	
b. Deaths Per 100,000	226.4	250.1	271.0	325.5	405.0	282.7	
c. Percent Non-Hispanic White	43.5	56.7	68.4	79.6	85.6	77.6	
d. Percent with College Degree	37.3	29.7	25.5	19.7	16.2	20.4	
e. Percent in Poverty	21.5	18.4	17.2	16.1	16.6	16.7	
Total Population	29,778,394	122,572,218	66,801,292	85,319,109	23,036,379	327,507,892	

Table 2: Regression Models Showing Relationship Between Independent Variables and COVID-19 Deaths per 100,000 Residents During Two Years of the Pandemic (N=3,112)

Independent Variables	First Year		Second Year	
	Parameter Estimate	Standard Beta	Parameter Estimate	Standard Beta
Percent Voting for Trump	0.000	0.010	0.001*	0.397
Percent Non-Hispanic White	-0.001*	-0.170	0.000*	0.081
Percent with College Degree	-0.002*	-0.277	-0.002*	-0.327
Percent in Poverty	0.001*	0.104	0.003*	0.233
Intercept	0.002*	-	0.001*	-
F-Value	135*	-	1,098*	-
Model R2	0.148*	-	0.586*	-

