

Understanding Complex Patterns in Social, Geographic, and Economic Inequities in COVID-19 Mortality at the County Level in the US Using Generalized Additive Models

Christian Testa^{1,*}

November 27, 2022

Abstract

I present three types of applications of generalized additive models (GAMs) to COVID-19 mortality rates in the US for the purpose of advancing methods to document inequities with respect to which communities suffered disproportionate COVID-19 mortality rates at specific times during the first three years of the pandemic. First, GAMs can be used to describe the changing relationship between COVID-19 mortality and county-level covariates (sociodemographic, economic, and political metrics) over time. Second, GAMs can be used to perform spatiotemporal smoothing that pools information over time and space to address statistical instability due to small population counts or stochasticity can be summarized by a smooth, dynamic latent surface describing the mortality risk associated with geographic locations over time. Third, estimation of COVID-19 mortality associations with county-level covariates conditional on smooth spatiotemporal variation allows for more rigorous consideration of how socio-environmental contexts and policies may have impacted COVID-19 mortality. Each of these approaches provides a valuable perspective to documenting inequities in COVID-19 mortality by addressing the question of which populations have suffered the worst burden of COVID-19 mortality taking into account the nonlinear spatial, temporal, and social patterning of disease.

Abbreviations used: United States (US), Coronavirus Disease 2019 (COVID-19), Generalized Additive Model (GAM), Centers for Disease Control and Prevention (CDC), Index of Concentration at the Extremes (ICE)

¹ Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

* Correspondence: Christian Testa <catesta@hsph.harvard.edu>

Introduction

As we enter the third winter with the novel coronavirus disease COVID-19 in the United States, evidence documenting the intense disparities in COVID-19 mortality rates comparing socially advantaged and disadvantaged populations continues to mount. Eliminating inequities in health outcomes has been stated as a major policy goal of the Biden administration (The White House, 2021, 2022), representing a revitalized commitment to health equity and underlining the importance of adequate data reporting systems that report timely estimates of prevalent health inequities. To this end, I use generalized additive models (GAMs) as a flexible regression framework to illustrate the evolving roles and relationships sociodemographic, geographic, and economic conditions have with respect to trends in COVID-19 mortality. The code, data, and documentation necessary to reproduce the analyses contained in this paper are online and free to access at <https://github.com/catesta01/covid.gradient.estimation>.

Background

Having passed over 1 million COVID-19 deaths in the United States earlier this year (Donovan, 2022), and facing uncertain prospects for the third COVID-19 winter looming even as new iterations on the COVID-19

vaccines become available, it remains critical that inequities in COVID-19 outcomes are documented and analyzed to reckon with the unjust and unfair burden of preventable illness. Even though the first vaccines were granted emergency use authorization by the U.S. Food and Drug Administration in 2020 (Mayo Clinic, 2022), with the first shots going in arms in December 2020, COVID-19 is still continuing to cause hundreds of deaths a day in the US in the fall of 2022 (“United States COVID - Coronavirus Statistics - Worldometer,” 2022). The new bivalent vaccines released at the end of August 2022 contain mRNA sequences from both the original strain as well as the recently emergent BA.4 and BA.5 lineages in an effort to make the nation’s immunity more up-to-date and robust against the myriad of phylogenetic directions the COVID-19 virus is evolving to explore (Office of the Commissioner, 2022). Despite the updated bivalent boosters representing a significant step forward in prevention strategy, less than 4% of eligible Americans had taken the booster in the first month after it became available (Bendix, 2022; Lambert, 2022). As such, and with an enduring history of inequities in health care access in the US (Bailey et al., 2021; Blendon et al., 2002; Carpenter, 2021; Chrisler et al., 2016; Feldman et al., 2021; Okonkwo et al., 2021; Ortega & Roby, 2021; Rapp et al., 2022; Whitehead et al., 2016), it is clear that without further intervention not all communities will be equally able to benefit from the updated vaccines and inequities in COVID-19 illness and mortality may persist despite the technological innovations in vaccine technology.

The Role of Geography in COVID-19

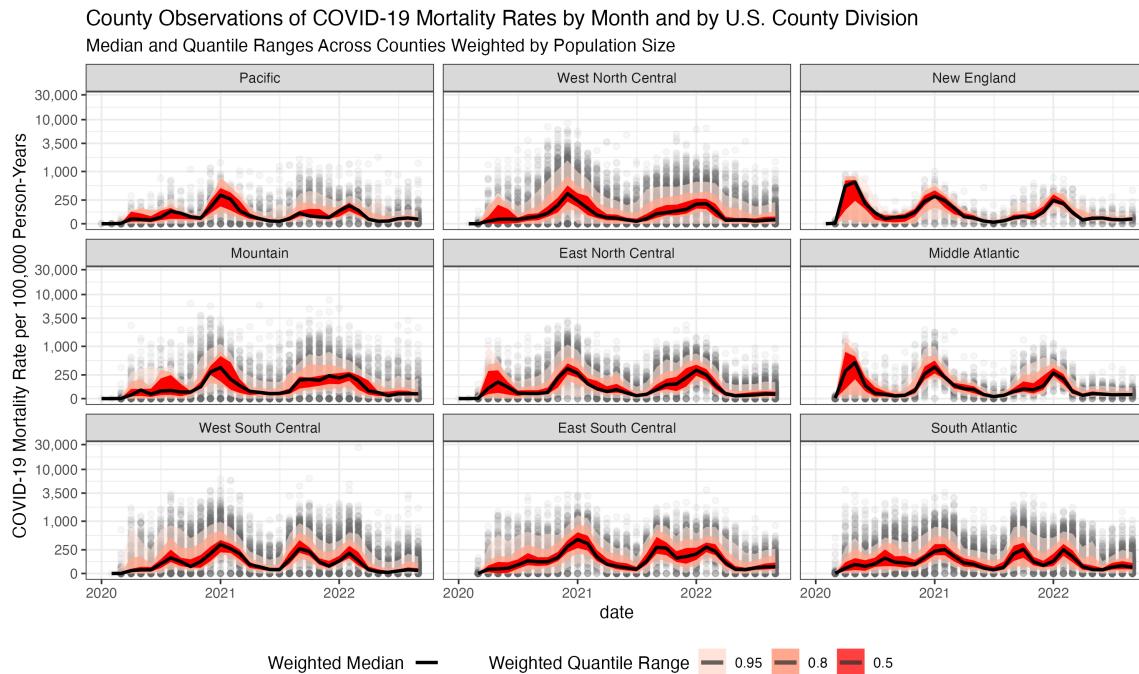


Figure 1: Estimates of monthly COVID-19 mortality rates per 100,000 person-years by county organized by Census Division. For each division, the median trendline and quantile ranges are shown weighted by county population size.

Prior literature has demonstrated that the spread and impact of COVID-19 has varied geography over time reflecting dynamics in the timing of introduction and transmission events. Methods employed to highlight the geographic patterning in COVID-19 outcomes have included quantile regression (Sigler et al., 2021), Besag-York-Mollie mixed models (Whittle & Diaz-Artiles, 2020), spatial cluster analysis (Sugg et al., 2021), geographically weighted regression (Mollalo et al., 2020; Park et al., 2021), and others.

Figure 1 shows the monthly COVID-19 mortality rates for the counties grouped within each of the nine U.S. Census Divisions (U.S. Department of Commerce Economics and Statistics Administration & U.S. Census Bureau, 2000). The figure summarizes each division’s median mortality rates weighted by county population

size. Quantile ranges are included to illustrate the range of mortality rates observed, again weighted by county population size. Notably, the mortality associated with the early surge of cases starting in NYC and spreading through New York, New Jersey, and Massachusetts is visible in the Middle Atlantic and New England division figures. The figure also illustrates how the first peak in the mortality time-series for states in the Midwest (West North Central, East North Central) occurred later, in late 2020 and going into early 2021.

In the US context, one of the key aspects to the geographic story of COVID-19's spread and diffusion was the early surge of cases and epicenter in New York City during March 2020 (Thompson, 2020) followed by subsequent waves of cases in the South and Midwest (Glenza, 2020; Scott, 2020; Shumaker & Wu, 2020). As Park et al. stated summarized trends in the US from March 2020 to May 2021, "hot spots have shifted from densely populated cities and the states with a high percentage of socially vulnerable individuals to the states with relatively relaxed social distancing requirements, and then to the states with low vaccination rates" (2021).

When considering the drivers of the COVID-19 pandemic, it's necessary to note that geography and social conditions are inextricably linked. In July 2021, the CDC reported that "the COVID-19 cumulative death rate in non-metropolitan areas has exceeded that of metropolitan areas since December 2020," noting that of the approximately 1/5th of Americans who live in rural areas, many "are considered highly vulnerable according to CDC's Social Vulnerability Index (SVI), which includes factors such as housing, transportation, socioeconomic status, race, and ethnicity" (CDC, 2021). Moreover, rural communities often have lower health insurance rates, higher disability rates, older populations, and limited access to health care. One of CDC's Morbidity and Mortality Weekly Reports found that vaccination against COVID-19 was lower in rural communities than in urban communities between December 2020 and April 2021 (Murthy, 2021).

The Social Determinants of COVID-19 Mortality

Even since the beginning of the COVID-19 outbreak in the US, data reflected sharp inequities in mortality rates. During January 22nd to May 5th 2020, county COVID-19 mortality rates were 4.94 (95% CI 4.78, 5.09) times higher in counties in the highest quintile of percent People of Color (61%-100%) compared to counties in the lowest quintile of percent People of Color (0%-17.2%) (Chen & Krieger, 2021). This was not wholly unanticipated: as COVID-19 was beginning to take off in the US, some were already calling attention to the fact that COVID-19 threatened to exacerbate existing disparities (Kim et al., 2020). Kim, Marrast, and Conigliaro noted three structural barriers in COVID-19 prevention and care: 1) originally requiring New York residents to have a doctor's prescription for a COVID-19 test reduced the opportunity for healthcare for People of Color as they are less likely to have a primary care provider; 2) drive-through testing made testing disadvantaged those who rely on public transportation; 3) quarantining at home while waiting the 7-10 days originally required for COVID-19 test results to come back posed an economic and social challenge that many in already financially difficult situations may not have been able to take on (2020). Others noted yet more reasons why COVID-19 threatened to worsen an already inequitable healthcare landscape in the US: those who reside in prisons and jails, immigrants and undocumented people, people with disabilities, and people experiencing homelessness all face additional challenges in seeking and getting the healthcare they deserve (Okonkwo et al., 2021). Despite stay-at-home orders that were prevalent in many states (Moreland et al., 2020), workers functioning in capacities essential to the functioning of critical infrastructure operations (later termed "essential workers") were exposed to heightened risk of COVID-19 transmission (Hanage et al., 2020; National Bureau of Economic Research, 2021; National Conference of State Legislatures, 2021; The Lancet, 2020; Wei et al., 2022). It's not just a hypothetical that those with more structurally enfranchised privileges have been more able to mitigate their risk of negative health outcomes associated with COVID-19 — during February 1 to April 1, 2020, New York City residents who lived in more affluent neighborhoods were more likely to have left the city, while New York City residents from more Black and Hispanic neighborhoods were more likely to continue working (Coven & Gupta, 2020).

Contrary to the oft used phrase that the 'virus does not discriminate', the data presented here suggest that this virus, as many other infectious diseases, has the greatest implications for the most vulnerable people. The intersections between health and human rights are clear—the health of a society and vulnerability to a pandemic are directly related to its human rights track record for those who are marginalised. (Okonkwo et al., 2021)

When vaccines became available, vaccine appointments were often only available to be scheduled through online web-portals contributing to the inequities between those who had internet access and technological literacy and those who didn't (Press et al., 2021). Vaccination sites have not been equally distributed and areas determined to be vaccine deserts have been found to have disproportionately more Black and Hispanic residents (Rader et al., 2021). In fact, healthcare facilities in counties with higher Black composition had 32% (95% CI 14%-47%) lower odds of serving as vaccine sites (Hernandez et al., 2022).

What vaccination has been administered hasn't suddenly erased the unequal burden of COVID-19 either; in August 2022 the New York Times was reporting "Black death rates at this winter's peak were greater than those of white people by 34 percent in rural areas, 40 percent in small or medium cities and 57 percent in big cities and their suburbs" (Goldstein, 2022). As COVID-19 case and mortality rates have waxed and waned, the inequities have widen and shrunken, often with racial/ethnic inequities growing during times when COVID-19 rates have surged (Hill & Artiga, 2022). During 2022, the age-standardized COVID-19 mortality rates for white people have, at times, been slightly higher than those of Black and Hispanic people, predominantly because the mortality rate among white people has increased (Johnson & Keating, 2022). It's important to note that white COVID-19 mortality rates overtaking the Black mortality rates does not imply that equity has been established: neither does this undo the cumulative impact of mortality (which has been twice as high for Black people compared to white people (Hill & Artiga, 2022)), nor does it imply the underlying systemic barriers to equity have been overturned (Del Rios et al., 2022). As Del Rios, Chomilo, and Lewis note, instead, COVID-19 leaves in its wake more years of life expectancy lost, wages lost, and degradation of mental health in Communities of Color.

Methods

Data Sources

The following variables were retrieved at the county level:

- Counts of COVID-19 deaths (The New York Times, 2021).
- Population size estimates for 2020 from the U.S. Census (US Census Bureau, 2021).
- Median age, median household income, racial/ethnic composition, population density, percent below the federal poverty line, and number of households with high (\$100k+)/low (<\$25k) household income by racial/ethnic group from the 2014-2019 5-year American Community Survey (US Census Bureau, 2020) through the `tidyverse` R package (Walker & Herman, 2022).
- Votes cast in the 2020 presidential election (MIT Election Data and Science Lab, 2022)

Generalized Additive Models

Generalized additive models (GAMs) improve upon generalized linear models by allowing for the fitting of smooth functions that transform the x variables. This is a convenient means to include nonlinear relationships between the outcome and predictor variables. Whereas a generalized linear model may look like

$$g(\mu_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} \dots$$

a generalized additive model could look like

$$g(\mu_i) = \mathbf{A}_i \boldsymbol{\theta} + f_1(x_{i1}) + f_2(x_{i2}) + f_3(x_{i3}, x_{i4}) + \dots$$

where $\mu_i \equiv \mathbb{E}(Y_i)$, \mathbf{A}_i is a row of the model matrix for any strictly non-parametric model components, $\boldsymbol{\theta}$ is the corresponding parameter vector, and the f_j are smooth functions of the covariates x_k (S. N. Wood, 2017).

The smooth functions estimated as part of fitting a GAM are constructed using spline basis functions. These spline basis functions allow for the smooth interpolation of trends in the data allowing for the incorporation of nonlinearity. To avoid overfitting the data, a penalty term is introduced that controls the degree of "wigginess" or smoothness and this penalty term is fit using generalized cross validation. B-splines are one kind of spline basis function that is commonly used and are especially popular because of their property that they are non-negative on only a finite interval.

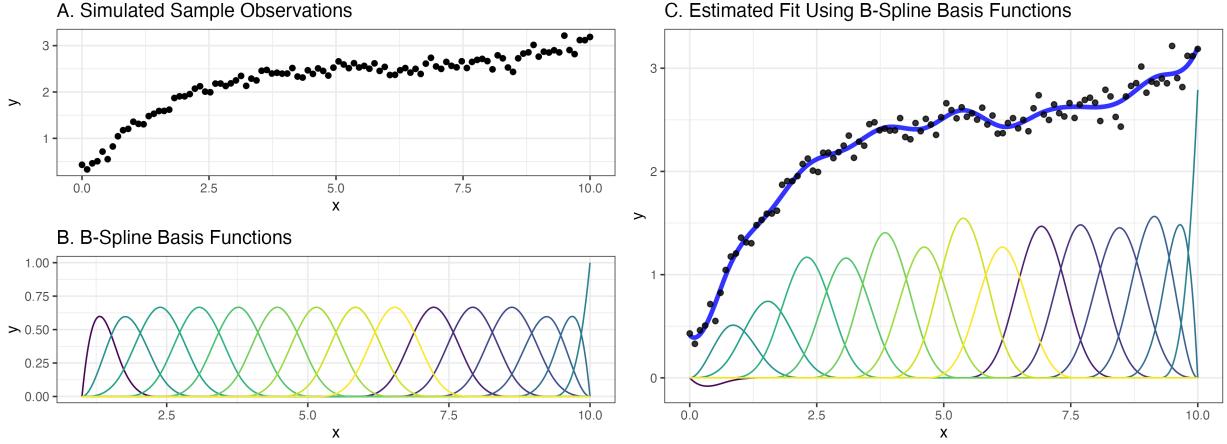


Figure 2: A demonstration of fitting regression models using B-spline basis functions. Part A. shows the simulated dataset. Part B. shows the B-spline basis functions. Part C. shows the weighting of the B-spline basis functions and their weighted sum with an intercept added to create the regression model fit to the data.

While a variety of varying kinds of spline bases exist (cubic splines, B- and P-splines, thin-plate splines, etc.), our particular application setting warrants the use of tensor-product smooths because we require anisotropic penalization. That is to say, when we seek to create spatiotemporally smoothed model estimates, it's inappropriate to assume that the amount of smoothing across space should be the same as the amount of smoothing across time because they're in fundamentally different units (space being measured in Cartesian coordinates and time being measured in years, months, days, etc.). More details about tensor-product smooths are available in Simon Wood's *Generalized Additive Models - An Introduction with R* (2017).

Overdispersion and Event Modeling

Above and beyond using the GAM framework to allow for flexible, nonlinear relationships between our observed county-level variables and COVID-19 mortality, we must have a model specification that agrees with the data generating process. In our case, the data generated are counts of deaths per population, and the class of models most suited to represent counts of events are Poisson, quasi-Poisson, and negative binomial models. Here we've chosen to use the negative binomial model as it accounts for overdispersion and has the intuitive interpretation of a Poisson model with gamma distributed underlying rate parameter (Gelman et al., 2013).

A negative binomial model in the context of modeling count data can be written

$$y_i \sim \text{NegativeBinomial}(u_i\theta_i, \phi),$$

where y_i are the counts observed, u_i is the “exposure”, θ_i are the rates, and ϕ determines the amount of overdispersion. The rates are modeled as $\theta_i = e^{X_i\beta}$ where X_i are the observed covariates and β are the coefficients on the covariates corresponding to log rate ratios. The logarithm of the exposure, $\log(u_i)$ is often called (and later herein referenced as) the offset. In epidemiological contexts, the offset is often representative of the amount of person-time during which observations were recorded. Whereas the Poisson model holds that $\text{var}(y) = \mu$ where μ is the average rate, the negative binomial model instead assumes that $\text{var}(y) = \mu + \mu^2/\phi$. The Poisson model is a special case of the negative binomial model when $\phi \rightarrow \infty$.

An alternative and equivalent formulation of the negative binomial that is commonly used makes the connection to the Poisson model even more clear: instead of θ_i and ϕ , using α and β ,

$$y \sim \text{NegativeBinomial}(\alpha, \beta), \text{ and}$$

$$\text{NegativeBinomial}(y|\alpha, \beta) = \int \text{Poisson}(y|\theta) \text{Gamma}(\theta|\alpha, \beta) d\theta.$$

Introductions to and additional exposition on the negative binomial model, especially in the context of modeling counts of events outcome data, are available in *Bayesian Data Analysis* and *Regression and Other Stories* (Gelman et al., 2020, 2013).

Variables of Interest

Besides age, which is a strong determinant of COVID-19 mortality risk, we have included the following variables as covariates of interest:

- Population Density per Square Mile
- Median Household Income
- Proportion in Poverty
- the Index of Concentration at the Extremes for Racialized Economic Segregation
- Political Lean in the 2020 Election (1 = 100% Republican votes, -1 = 100% Democratic Votes)

Index of Concentration at the Extremes for Racialized Economic Segregation The Index of Concentration at the Extremes (ICE) is a measure which describes how concentrated a given area's population is in terms of the extreme ends of privilege and marginalization (Krieger et al., 2016). In general, the ICE measure is formulated as

$$\text{ICE} = \frac{\text{Number of People in Most Privileged Category} - \text{Number of People in Least Privileged Category}}{\text{Total Population}}$$

Applying the ICE approach to a specific context involves defining the axes of privilege of interest. In this case, data on racialized economic segregation are used from the US Census American Community Survey on White households earning more than \$100,000 a year (the most privileged group) or households of People of Color earning less than \$25,000 a year (the least privileged group). This variable is referred to throughout as the ICE for racialized economic segregation, or `ICEraceinc` in the code.

Compared with the Gini coefficient which is one of the most popular methods for summarizing area-level rates of inequities, the ICE the major advantage that it is more suitable for describing inequities at smaller area levels (Krieger et al., 2016). While the Gini coefficient measures within-area dissimilarity (as in, for example, how unequal wealth is distributed within a county), the ICE measure establishes where on a spectrum a given county's population falls allowing for comparison across counties. The Gini coefficient suffers from the fact that areas which are made up of relatively homogeneous populations will appear as having low within-area inequality (and therefore low Gini coefficient). Instead, the ICE measures how much of the population is either privileged or not. The Gini coefficient remains useful for reporting on the degree of inequity in larger areal units (like countries, states, and regions), but at smaller areal units (like counties, ZIP codes, census tracts) can be more difficult to interpret and compare. Maps of ICE measure can elucidate what spatial social segregation and polarization exist, and the ICE for racialized economic segregation has been repeatedly and significantly associated with COVID-19 outcomes (Brown et al., 2021; Chen & Krieger, 2021; Eichenbaum & Tate, 2022; Hanage et al., 2020; Krieger et al., 2022; Saha & Feldman, 2020; Sonderlund et al., 2022).

Political Lean Political lean has been associated with COVID-19 mortality in numerous studies, with plausible mechanisms explaining the association including differences in non-pharmaceutical intervention uptake (mask usage, social distancing, quarantining), differences in rates of vaccination, differences in political leadership's messaging, resource allocation, and the adoption of policy interventions (Gonzalez et al., 2021; Grossman et al., 2020; Kaashoek et al., 2021; Krieger et al., 2022; Leonhardt, 2021).

Results

Application 1: Non-Spatial Covariate Effects Over Time

The GAM models fit and shown in Figure 3 with the following structure using the `gam` function from the `mgcv` package (S. Wood, 2022):

```
gam(  
  formula = deaths ~ s(median_age) + te(covariate, date, d=c(1,1)), # regression formula  
  offset = log(popsiz/1e5/12), # our offset represents the person-time  
  data = df,      # our data-set of county-level observations  
  family = nb(link='log') # indicates negative binomial family and a log-link function  
)
```

The formula used puts a one-dimensional smoothing spline to represent a nonlinear age-effect and a two-dimensional tensor-product smooth on the interaction between the given covariate and the date. The `d=c(1,1)` argument provides the instruction necessary to consider covariate and date as being on separate scales and therefore to fit the tensor-product smooth with anisotropy — that is, to allow for independent amounts of scaling in the dimensions of the covariate and time. The offset used structures the regression to estimate rates in units of person-time per 100,000 person-years. Since the death counts are aggregated to the monthly level, the person-time in units of 100,000 person-years are calculated by taking each county's population size, dividing by 100,000, and dividing by 12 (for the 12 months in a year).

The above structure is used to estimate models for our different `covariate` variables of interest: median income, percent in poverty, the ICE for racialized economic segregation, political lean. Whereas the other models treat median age as a variable to adjust for, the model presenting the effect of median age over time treats median age as the main covariate of interest including it as the `te(covariate, date, d=c(1,1))` and dropping the `s(median_age)` term which is redundant. Results of these models are summarized in Figure 3 where the additional COVID-19 mortality associated with each covariate is visualized.

Likelihood ratio tests confirmed that models with covariates interacted with time had significantly lower residual deviance ($p \leq 2.2e^{-16}$ for all models) compared to models only including a spline term on median age and the given covariate not interacted with time. The model interacting median age and time was compared to a model with a spline for median age alone. Akaike Information Criteria values were also lower for all models compared to models that did not interact the covariates with time.

Another non-spatial application of GAMs to describe the distribution of COVID-19 mortality in the US over time is to consider the associations of mortality with three-way interactions of time and two covariates taken together. In the following example, the formula used is `deaths ~ te(date, ICEraceinc, median_age, d=c(1,1,1))`. Again, the `d` argument specifying the marginal basis dimensions is used indicate that each of the `date`, `ICEraceinc`, and `median_age` measures are in different units and should not be smoothed assuming that a one unit difference in one variable is comparable to a one unit difference in another variable. This approach is represented in Figure 4.

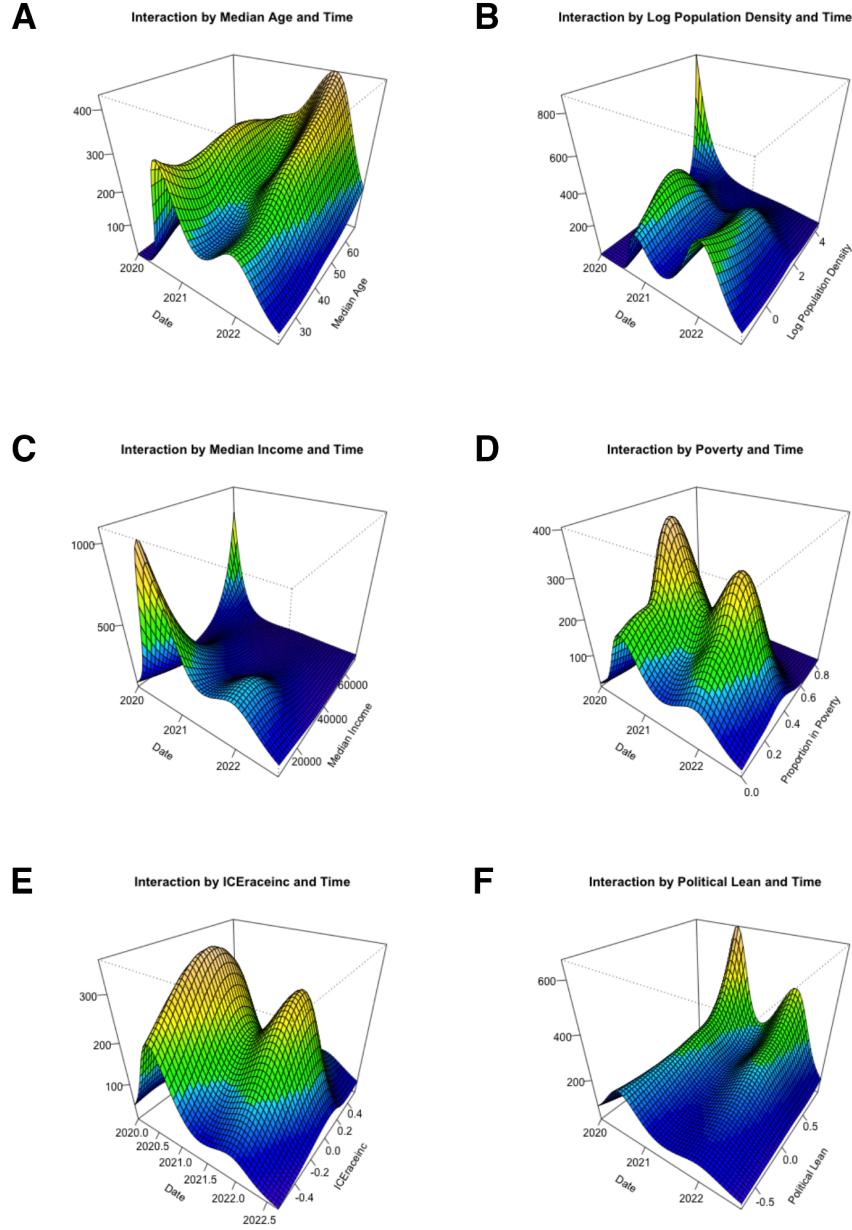


Figure 3: Additional COVID-19 mortality associated with covariates over time. A) age and time, B) log (base 10) population density and time, C) median income and time, D) proportion in poverty and time, E) ICEraceinc and time, F) political lean and time. In panels B-F the effect of age is marginalized out using the median age in the US, 38.8 (US Census Bureau, 2022).

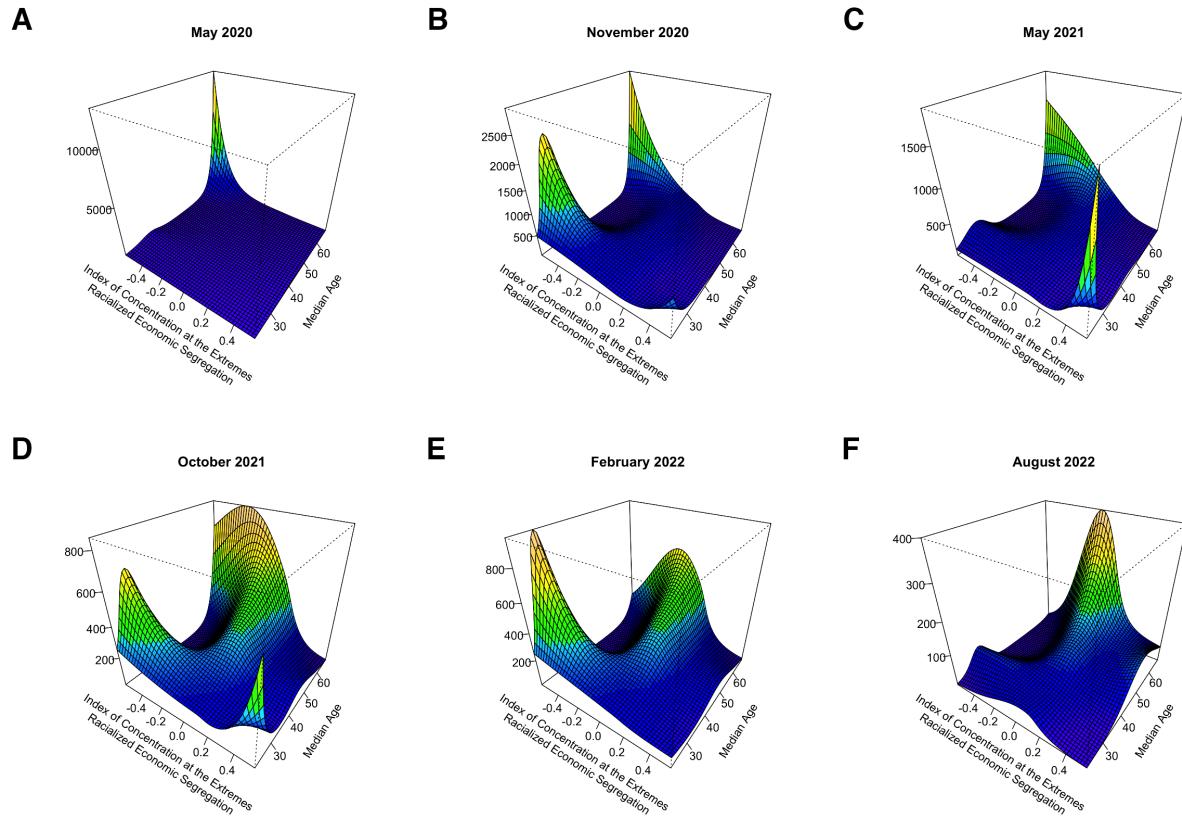


Figure 4: The changing interacted effect of the ICE for racialized economic segregation and age over time. A) May 2020, B) November 2020, C) May 2021, D) October 2021, E) February 2022, F) August 2022. An animated version is available online at https://github.com/ctesta01/covid.gradient.estimation/blob/main/analysis/05_two_variables_at_a_time/animation_ICEraceinc_age/readme.md

Application 2: Spatiotemporal Smoothing

By fitting GAMs with a tensor-product smoothing term on latitude, longitude, and time we can estimate a spatiotemporally smoothed trend in COVID-19 mortality. To do this, the GAM is constructed similarly as in Application 1 but with the smoothing term specified as `te(latitude, longitude, time, d=c(2,1))` where `d=c(2,1)` indicates that `latitude` and `longitude` share the same dimensions (i.e., both are spatial and in units of degrees) while the `time` data are in separate units. Note that results presented in Application 2 and 3 are based on county-level data from the contiguous US excluding Alaska and Hawaii.

Using GAMs to present spatiotemporally smoothed estimates of COVID-19 mortality allows for the synthesis of trends over time. Whereas the raw rates of COVID-19 mortality are noisy due to 72% of the land area in the US being classified as rural and low population density (Health Resources & Services Administration, 2022), the spatiotemporally smoothed GAM estimates use population weighting via the offset specified to estimate a latent surface that represents localized mortality rate averages in spatial coordinates and in time.

Figure 5 shows the difference between crude mortality rates and spatially smoothed mortality rates in January 2022 to illustrate the level of noise present in raw rates and how spatially smoothing synthesizes local geographic patterns into interpretable trends that can be meaningfully interpreted as local area mortality risk levels pooling information across nearby county rates.

Figure 6 shows the results from a spatiotemporally smoothed model in select months to highlight how spatiotemporal smoothing can yield results that intuitively synthesize trends in space and time.

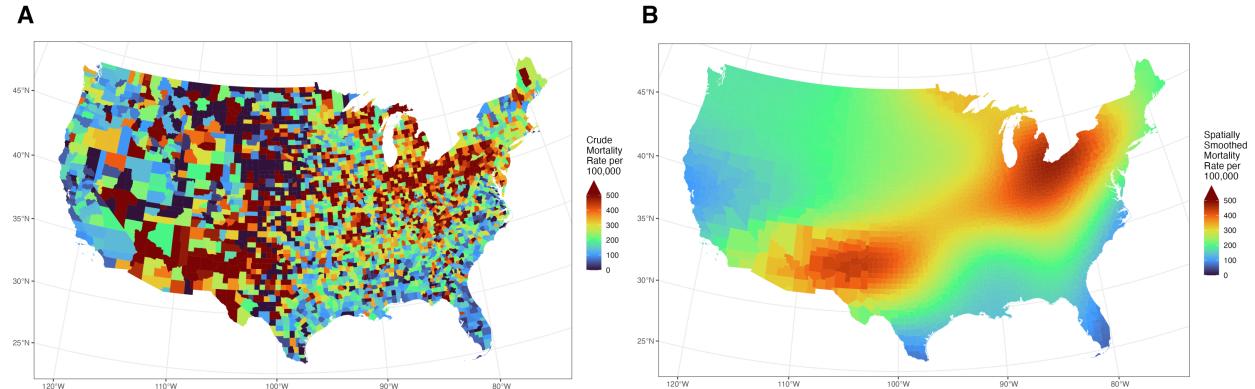


Figure 5: Comparison of crude vs. smoothed mortality rates. A) Crude mortality rates per 100,000 person-years in January 2022. B) Smoothed mortality rates from a GAM applied to mortality rates from January 2022.

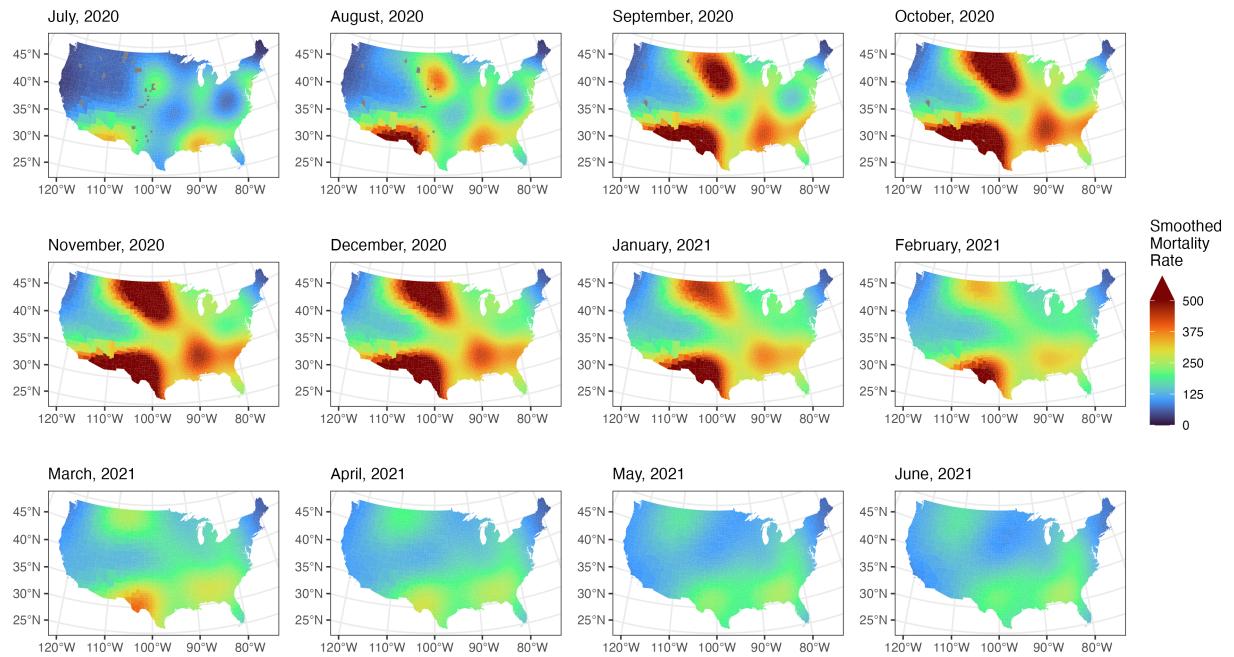


Figure 6: Spatiotemporally smoothed COVID-19 mortality estimates from a GAM fit to data from March 2020-August 2022. Panels show months selected to highlight the changing spatial patterns of COVID-19 mortality risk over time. An animated version is available online at https://github.com/ctesta01/covid.gradient.estimation/blob/main/analysis/09_spatiotemporal_models/animation/readme.md

Application 3: Estimating Covariate Effects Adjusted for Spatiotemporal Auto-correlation

The final application of GAMs presented here is to estimate the effects of covariates after adjusting for a spatiotemporally smoothed term as shown in Application 2. This has the interpretation of asking what are the changes to COVID-19 mortality rates associated with each covariate after taking into account local geographic patterns over time. In particular, this is relevant for understanding what county-level measures are associated with elevated COVID-19 mortality even after adjusting for where COVID-19 rates were locally elevated or depressed due to variation in the timing of local introduction, transmission, and diffusion.

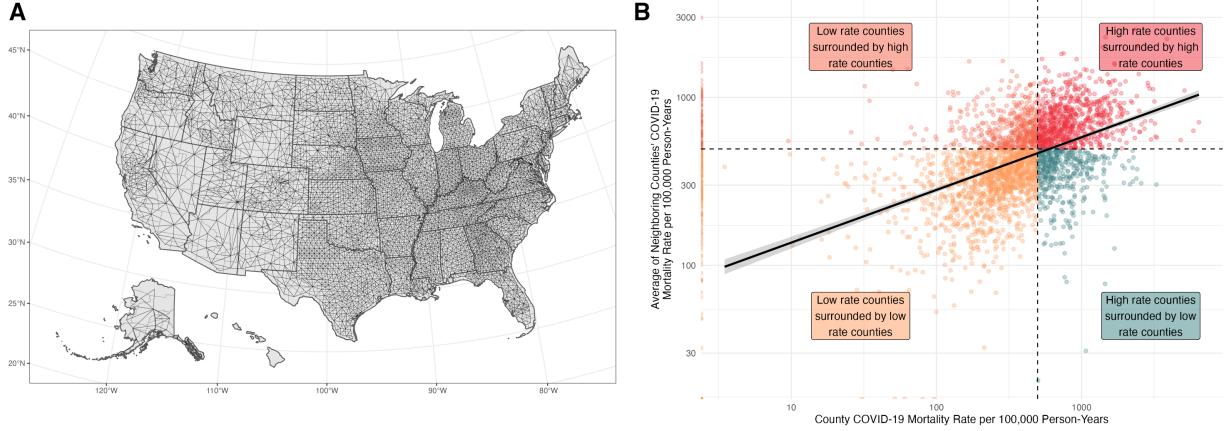


Figure 7: The spatial autocorrelation of COVID-19 rates in January 2022. Panel A shows the graph of which US counties are connected by neighboring relations. Panel B shows a scatterplot depicting each US counties' COVID-19 rate (x-axis) compared to the average of its neighbors' COVID-19 mortality rates (y-axis). A regression line shows the association between counties' COVID-19 rates and their neighboring counties' COVID-19 rates. Dotted lines indicated the average for US county-level crude COVID-19 mortality rates (vertical) and for the average of each counties' neighboring counties' COVID-19 rates (horizontal).

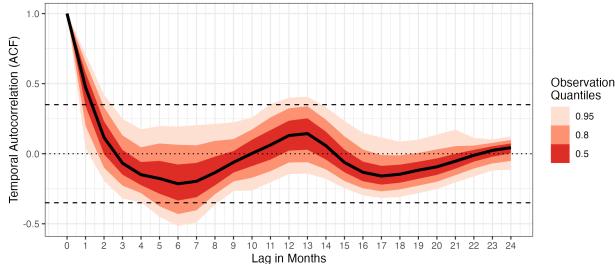


Figure 8: The median (black) and quantiles (shaded bands) of temporal autocorrelation of counties' COVID-19 mortality rates over time starting from April 2020.

To motivate the need for and application of spatiotemporal smoothing in assessing the associated changes in COVID-19 mortality with county-level covariates, Figure 7 presents the Moran's I diagnostic plot for January 2022 which summarizes the amount of autocorrelation between counties' COVID-19 mortality rates and a population-weighted average of each counties' neighboring counties' COVID-19 mortality rates. The observed autocorrelation indicates that there is an association between counties' COVID-19 rates and their neighboring counties' COVID-19 rates, implying that without taking this patterning into account, regression models that do not explicitly model the effect of spatial autocorrelation may be biased due to inappropriately assuming that county-level data are independent of one another. Second, while the Moran's I plot demonstrates the spatial-correlation present in the data at a single time-point, the following Figure 8 shows the tendency of county COVID-19 observations to be autocorrelated between subsequent months and moreover there appears

to be an oscillating trend at the 6-month and 12-month marks suggestive of effects due to the dynamics associated with temporary infection induced immunity and seasonality.

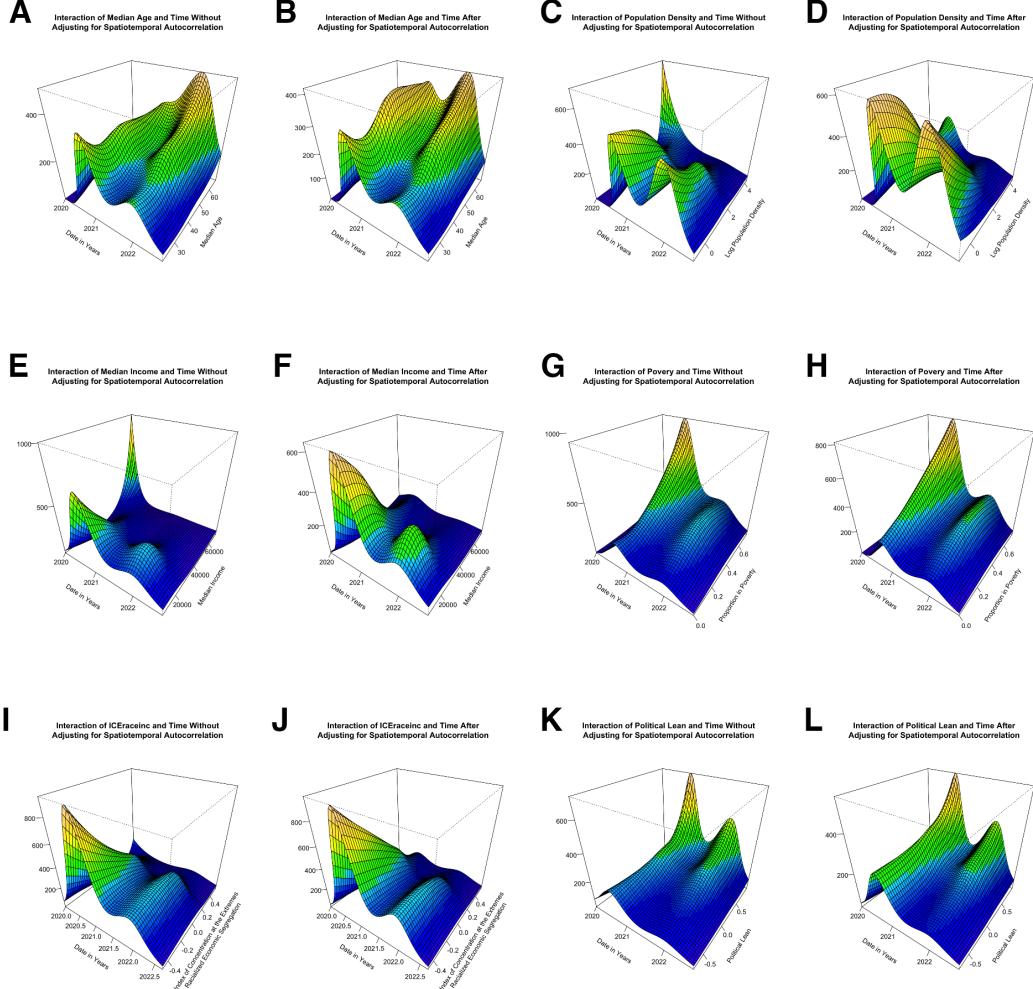


Figure 9: Estimates of increases in COVID-19 mortality associated with county-level covariates without (first) and with (second) adjustment for spatiotemporal autocorrelation. Panels A and B show COVID-19 mortality increases associated with varying levels of median age over time; C and D show associations with log population density; E and F median income; G and H for proportion in poverty; I and J the ICE for racialized economic segregation; K and L political lean.

Figure 9 shows the effects associated with each covariate over time with and without adjustment for spatiotemporal trends. The models for population density and median income show particularly marked changes with the spike at high population density and high median incomes disappearing after adjusting for a spatiotemporally smoothed term. This likely reflects the early emergence and surge of COVID-19 in the greater New York City area as being predominantly a feature of the combined effect of human geography and infectious disease dynamics where the earliest introductions of COVID-19 were made to dense social networks in the US. Other effects remain qualitatively changed very little, suggesting that the trends in COVID-19 mortality associated with these county-level measures remains durable when taking into account spatiotemporal autocorrelation.

Discussion

This paper presents three applications of GAMs to county-level COVID-19 mortality data from the US during March 2020 to August 2022. This paper addresses an important need, which is to assess what measures of the socioeconomic and geopolitical landscape are associated with increases in COVID-19 mortality in a way that takes into account how infectious disease dynamics are locally correlated in space and time. However, the approaches outlined in this paper are not without several limitations which include (at least) the following: the potential for cross-level confounding, lack of individual level data, an inability to include all possible metrics, further improvements to the methods used may be warranted, and we are unable to make claims about the causal relationships between the variables investigated.

In analyses that use area-level aggregated data, the ecologic fallacy refers to the possibility that associations between area-level measures and outcomes may not reflect the associations that would be observed if analyzing individual level data on the same measures and outcomes as a result of cross-level confounding (Greenland, 2001). It's important to note that some of the variables are included to contextualize the places in which people live, reside, and work and area-based social metrics should be included in individual-level analyses so as to accurately capture the effects of both individual-level risk factors and risk factors that stem from the contexts in which people exist (Testa et al., 2022).

One particular improvement that could be made in future work is to address age adjustment by using direct or indirect age standardization (Anderson et al., 1998) or to create age-group stratified models. In the applications presented here, county-level median age is adjusted for in order to control for age effects.

Additional variables like vaccination rates, mobility data, further variables that relate to risk factors for COVID-19, and other COVID-19 related outcomes like case trends and hospitalizations may be worthwhile to investigate under a similar framework. The emphasis on trends in COVID-19 mortality in the applications in this paper was done to prioritize presenting data that are less subject to the reporting inconsistencies in COVID-19 cases and hospitalizations (Galaitsi et al., 2021).

Further improvements to the methods employed here could include use of soap film smoothing splines which are more appropriate in settings where non-convex geographic boundaries are common (as in with peninsulas and bays) (S. N. Wood et al., 2008). Taking a critical eye to the assumptions employed reveals yet another area of potential improvement, which is the nature of how the complexity of the smoothing splines employed are penalized in the GAM framework. It is conceivable that geographic changes in COVID-19 mortality rates are not equally smooth across all regions of the US, potentially warranting rapid changes in some areas and smooth changes in other areas. The Bayesian wombling literature provides the means to identify areas of rapid change in latent surface models and may pose a fruitful direction of exploration for future efforts to understand trends in COVID-19 mortality rates in the US (Gelfand & Banerjee, 2015).

Conclusions

This work introduces generalized additive models (GAMs) applied to COVID-19 mortality data to document the disparities and inequities in which US counties at what times suffered the worst mortality outcomes. The effort to document inequities and explain the driving mechanisms behind them is crucial in building up the evidence necessary to enact policy changes that can mitigate unjust and preventable harm in the future. To this end, it is critical that efforts to model infectious disease dynamics take into account how disease transmission and outcomes are spatiotemporally patterned, violating any misplaced assumptions that area-level disease rates can be treated as independent observations. By presenting novel applications of GAMs to trends in COVID-19 mortality, this paper illustrates new ways of understanding and visualizing the disproportionate burden some communities have suffered incorporating complex patterns of interaction across socioeconomic and geopolitical variables and spatiotemporal trends.

References

- Anderson, R. N., Rosenberg, H. M., & National Center for Health Statistics. (1998). Age standardization of death rates; implementation of the year 2000 standard. *National Vital Statistics Report*. <https://stacks.cdc.gov/view/cdc/13357>
- Bailey, Z. D., Feldman, J. M., & Bassett, M. T. (2021). How Structural Racism Works — Racist Policies as a Root Cause of U.S. Racial Health Inequities. *New England Journal of Medicine*, 384(8), 768–773. <https://doi.org/10.1056/NEJMms2025396>
- Bendix, A. (2022). Less than 4% of eligible people have gotten updated Covid booster shots, one month into the rollout. In *NBC News*. <https://www.nbcnews.com/health/health-news/updated-covid-booster-shots-doses-administered-cdc-rcna48960>
- Blendon, R. J., Schoen, C., DesRoches, C. M., Osborn, R., Scoles, K. L., & Zapert, K. (2002). Inequities In Health Care: A Five-Country Survey. *Health Affairs*, 21(3), 182–191. <https://doi.org/10.1377/hlthaff.21.3.182>
- Brown, K. M., Lewis, J. Y., & Davis, S. K. (2021). An ecological study of the association between neighborhood racial and economic residential segregation with COVID-19 vulnerability in the United States' capital city. *Annals of Epidemiology*, 59, 33–36. <https://doi.org/10.1016/j.annepidem.2021.04.003>
- Carpenter, E. (2021). "The Health System Just Wasn't Built for Us": Queer Cisgender Women and Gender Expansive Individuals' Strategies for Navigating Reproductive Health Care. *Women's Health Issues*, 31(5), 478–484. <https://doi.org/10.1016/j.whi.2021.06.004>
- CDC. (2021). Location, location, location – COVID Data Tracker Weekly Review. In *Centers for Disease Control and Prevention*. <https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/past-reports/07162021.html>
- Chen, J. T., & Krieger, N. (2021). Revealing the Unequal Burden of COVID-19 by Income, Race/Ethnicity, and Household Crowding: US County Versus Zip Code Analyses. *Journal of Public Health Management and Practice*, 27(1), S43–S56. <https://doi.org/10.1097/PHH.0000000000001263>
- Chrisler, J. C., Barney, A., & Palatino, B. (2016). Ageism can be Hazardous to Women's Health: Ageism, Sexism, and Stereotypes of Older Women in the Healthcare System. *Journal of Social Issues*, 72(1), 86–104. <https://doi.org/10.1111/josi.12157>
- Coven, J., & Gupta, A. (2020). *Disparities in Mobility Responses to COVID-19*. <https://arpitgupta.info/s/DemographicCovid.pdf>
- Del Rios, M., Chomilo, N. T., & Lewis, N. A. (2022). Covid-19 is an inverse equity story, not a racial equity success story. In *STAT*. <https://www.statnews.com/2022/10/25/covid-19-inverse-equity-story-not-racial-equity-success-story/>
- Donovan, D. (2022). U.S. Officially Surpasses 1 Million COVID-19 Deaths. In *Johns Hopkins Coronavirus Resource Center*. <https://coronavirus.jhu.edu/from-our-experts/u-s-officially-surpasses-1-million-covid-19-deaths>
- Eichenbaum, A., & Tate, A. D. (2022). Health Inequity in Georgia During the COVID-19 Pandemic: An Ecological Analysis Assessing the Relationship Between County-Level Racial/Ethnic and Economic Polarization Using the ICE and SARS-CoV-2 Cases, Hospitalizations, and Deaths in Georgia as of October 2020. *Health Equity*, 6(1), 230–239. <https://doi.org/10.1089/heq.2021.0118>
- Feldman, J. L., Luhur, W. E., Herman, J. L., Poteat, T., & Meyer, I. H. (2021). Health and health care access in the US transgender population health (TransPop) survey. *Andrology*, 9(6), 1707–1718. <https://doi.org/10.1111/andr.13052>
- Galaitsi, S. E., Cegan, J. C., Volk, K., Joyner, M., Trump, B. D., & Linkov, I. (2021). The challenges of data usage for the United States' COVID-19 response. *International Journal of Information Management*, 59, 102352. <https://doi.org/10.1016/j.ijinfomgt.2021.102352>
- Gelfand, A. E., & Banerjee, S. (2015). Bayesian wombling: Finding rapid change in spatial maps. *WIREs Computational Statistics*, 7(5), 307–315. <https://doi.org/10.1002/wics.1360>
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian Data Analysis. In *Routledge & CRC Press*. <https://www.routledge.com/Bayesian-Data-Analysis/Gelman-Carlin-Stern-Dunson-Vehtari-Rubin/p/book/9781439840955>
- Gelman, A., Hill, J., & Vehtari, A. (2020). *Regression and Other Stories* (1st ed.). Cambridge University Press. <https://doi.org/10.1017/9781139161879>
- Glenza, J. (2020). Covid cases increase across US as upper midwest sees rapid rise. *The Guardian*.

- <https://www.theguardian.com/world/2020/oct/22/covid-cases-coronavirus-us-midwest>
- Goldstein, J. (2022). During the Omicron surge, Black New Yorkers were hospitalized at a rate more than twice that of white residents. *The New York Times*. <https://www.nytimes.com/2022/03/03/nyregion/omicron-hospitalizations-new-york-city.html>
- Gonzalez, K. E., James, R., Bjorklund, E. T., & Hill, T. D. (2021). Conservatism and infrequent mask usage: A study of US counties during the novel coronavirus (COVID-19) pandemic. *Social Science Quarterly*, 102(5), 2368–2382. <https://doi.org/10.1111/ssqu.13025>
- Greenland, S. (2001). Ecologic versus individual-level sources of bias in ecologic estimates of contextual health effects. *International Journal of Epidemiology*, 30(6), 1343–1350. <https://doi.org/10.1093/ije/30.6.1343>
- Grossman, G., Kim, S., Rexer, J. M., & Thirumurthy, H. (2020). Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States. *Proceedings of the National Academy of Sciences*, 117(39), 24144–24153. <https://doi.org/10.1073/pnas.2007835117>
- Hanage, W. P., Testa, C., Chen, J. T., Davis, L., Pechter, E., Seminario, P., Santillana, M., & Krieger, N. (2020). COVID-19: US federal accountability for entry, spread, and inequities—lessons for the future. *European Journal of Epidemiology*, 35(11), 995–1006. <https://doi.org/10.1007/s10654-020-00689-2>
- Health Resources & Services Administration. (2022). *Defining Rural Population*. <https://www.hrsa.gov/rural-health/about-us/what-is-rural>
- Hernandez, I., Dickson, S., Tang, S., Gabriel, N., Berenbrok, L. A., & Guo, J. (2022). Disparities in distribution of COVID-19 vaccines across US counties: A geographic information system-based cross-sectional study. *PLOS Medicine*, 19(7), e1004069. <https://doi.org/10.1371/journal.pmed.1004069>
- Hill, L., & Artiga, S. (2022). COVID-19 Cases and Deaths by Race/Ethnicity: Current Data and Changes Over Time. In KFF. <https://www.kff.org/coronavirus-covid-19/issue-brief/covid-19-cases-and-deaths-by-race-ethnicity-current-data-and-changes-over-time/>
- Johnson, A., & Keating, D. (2022). Whites now more likely to die from covid than Blacks: Why the pandemic shifted. In Washington Post. <https://www.washingtonpost.com/health/2022/10/19/covid-deaths-us-race/>
- Kaashoek, J., Testa, C., Chen, J., Stolerman, L., Krieger, N., Hanage, W. P., & Santillana, M. (2021). *The Evolving Roles of US Political Partisanship and Social Vulnerability in the COVID-19 Pandemic from February 2020 - February 2021* [{SSRN} {Scholarly} {Paper}]. <https://doi.org/10.2139/ssrn.3933453>
- Kim, E. J., Marrast, L., & Conigliaro, J. (2020). COVID-19: Magnifying the Effect of Health Disparities. *Journal of General Internal Medicine*, 35(8), 2441–2442. <https://doi.org/10.1007/s11606-020-05881-4>
- Krieger, N., Testa, C., Chen, J. T., Hanage, W. P., & McGregor, A. J. (2022). Relationship of political ideology of US federal and state elected officials and key COVID pandemic outcomes following vaccine rollout to adults: April 2021–March 2022. *The Lancet Regional Health – Americas*, 16. <https://doi.org/10.1016/j.lana.2022.100384>
- Krieger, N., Waterman, P. D., Spasojevic, J., Li, W., Maduro, G., & Van Wye, G. (2016). Public Health Monitoring of Privilege and Deprivation With the Index of Concentration at the Extremes. *American Journal of Public Health*, 106(2), 256–263. <https://doi.org/10.2105/AJPH.2015.302955>
- Lambert, J. (2022). Most Americans Don't Know About the Omicron Covid Boosters. In Grid News. <https://www.grid.news/story/science/2022/10/04/most-americans-dont-know-about-the-omicron-covid-boosters-that-spells-trouble-for-the-coming-winter/>
- Leonhardt, D. (2021). Red Covid. *The New York Times*. <https://www.nytimes.com/2021/09/27/briefing/covid-red-states-vaccinations.html>
- Mayo Clinic. (2022). History of COVID-19: Outbreaks and Vaccine Timeline. In MayoClinic.org. <https://www.mayoclinic.org/coronavirus-covid-19/history-disease-outbreaks-vaccine-timeline/covid-19>
- MIT Election Data and Science Lab. (2022). *County Presidential Election Returns 2000-2020*. Harvard Dataverse. <https://doi.org/10.7910/DVN/VOQCHQ>
- Mollalo, A., Vahedi, B., & Rivera, K. M. (2020). GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. *Science of The Total Environment*, 728, 138884. <https://doi.org/10.1016/j.scitotenv.2020.138884>
- Moreland, A., Herlihy, C., Tynan, M. A., Sunshine, G., McCord, R. F., Hilton, C., Poovey, J., Werner, A. K., Jones, C. D., Fulmer, E. B., Gundlapalli, A. V., Strosnider, H., Potvien, A., García, M. C., Honeycutt, S., Baldwin, G., CDC Public Health Law Program, CDC COVID-19 Response Team, & Mitigation Policy Analysis Unit. (2020). Timing of State and Territorial COVID-19 Stay-at-Home Orders and Changes in Population Movement — United States, March 1–May 31, 2020. *MMWR. Morbidity and Mortality*

- Weekly Report*, 69. <https://doi.org/10.15585/mmwr.mm6935a2>
- Murthy, B. P. (2021). Disparities in COVID-19 Vaccination Coverage Between Urban and Rural Counties — United States, December 14, 2020–April 10, 2021. *MMWR. Morbidity and Mortality Weekly Report*, 70. <https://doi.org/10.15585/mmwr.mm7020e3>
- National Bureau of Economic Research. (2021). Measuring the Virus Risk of Essential Workers and Dependents. In *NBER*. <https://www.nber.org/digest/202103/measuring-virus-risk-essential-workers-and-dependents>
- National Conference of State Legislatures. (2021). COVID-19: Essential Workers in the States. In *COVID-19: Essential Workers in the States*. <https://www.ncsl.org/research/labor-and-employment/covid-19-essential-workers-in-the-states.aspx>
- Office of the Commissioner. (2022). Coronavirus (COVID-19) Update: FDA Authorizes Moderna, Pfizer-BioNTech Bivalent COVID-19 Vaccines for Use as a Booster Dose. In *FDA*. <https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-update-fda-authorizes-moderna-pfizer-biontech-bivalent-covid-19-vaccines-use>
- Okonkwo, N. E., Aguwa, U. T., Jang, M., Barré, I. A., Page, K. R., Sullivan, P. S., Beyrer, C., & Baral, S. (2021). COVID-19 and the US response: Accelerating health inequities. *BMJ Evidence-Based Medicine*, 26(4), 176–179. <https://doi.org/10.1136/bmjebm-2020-111426>
- Ortega, A. N., & Roby, D. H. (2021). Ending Structural Racism in the US Health Care System to Eliminate Health Care Inequities. *JAMA*, 326(7), 613–615. <https://doi.org/10.1001/jama.2021.11160>
- Park, Y. M., Kearney, G. D., Wall, B., Jones, K., Howard, R. J., & Hylock, R. H. (2021). COVID-19 Deaths in the United States: Shifts in Hot Spots over the Three Phases of the Pandemic and the Spatiotemporally Varying Impact of Pandemic Vulnerability. *International Journal of Environmental Research and Public Health*, 18(17), 8987. <https://doi.org/10.3390/ijerph18178987>
- Press, V. G., Huisingsh-Scheetz, M., & Arora, V. M. (2021). Inequities in Technology Contribute to Disparities in COVID-19 Vaccine Distribution. *JAMA Health Forum*, 2(3), e210264. <https://doi.org/10.1001/jamahealthforum.2021.0264>
- Rader, B., Astley, C. M., Sewalk, K., Delamater, P. L., Cordiano, K., Wronski, L., Rivera, J. M., Hallberg, K., Pera, M. F., Cantor, J., Whaley, C. M., Bravata, D. M., & Brownstein, J. S. (2021). *Spatial Accessibility Modeling of Vaccine Deserts as Barriers to Controlling SARS-CoV-2*. medRxiv. <https://doi.org/10.1101/2021.06.09.21252858>
- Rapp, K. S., Volpe, V. V., Hale, T. L., & Quartararo, D. F. (2022). State-Level Sexism and Gender Disparities in Health Care Access and Quality in the United States. *Journal of Health and Social Behavior*, 63(1), 2–18. <https://doi.org/10.1177/00221465211058153>
- Saha, S., & Feldman, J. M. (2020). *Neighborhood-level Racial/Ethnic and Economic Inequities in COVID-19 Burden Within Urban Areas in the US and Canada*. medRxiv. <https://doi.org/10.1101/2020.12.07.20241018>
- Scott, D. (2020). These 4 Midwestern states are seeing worrying Covid-19 spikes. In *Vox*. <https://www.vox.com/2020/9/2/21418812/covid-19-coronavirus-us-cases-midwest-surge>
- Shumaker, L., & Wu, T. (2020). COVID-19 cases surge in U.S. Midwest and Northeast. *Reuters*. <https://www.reuters.com/article/us-health-coronavirus-usa-trends-idUSKBN26Q30B>
- Sigler, T., Mahmuda, S., Kimpton, A., Loginova, J., Wohland, P., Charles-Edwards, E., & Corcoran, J. (2021). The socio-spatial determinants of COVID-19 diffusion: The impact of globalisation, settlement characteristics and population. *Globalization and Health*, 17(1), 56. <https://doi.org/10.1186/s12992-021-00707-2>
- Sonderlund, A. L., Charifson, M., Schoenthaler, A., Carson, T., & Williams, N. J. (2022). Racialized economic segregation and health outcomes: A systematic review of studies that use the Index of Concentration at the Extremes for race, income, and their interaction. *PLOS ONE*, 17(1), e0262962. <https://doi.org/10.1371/journal.pone.0262962>
- Sugg, M. M., Spaulding, T. J., Lane, S. J., Runkle, J. D., Harden, S. R., Hege, A., & Iyer, L. S. (2021). Mapping community-level determinants of COVID-19 transmission in nursing homes: A multi-scale approach. *Science of The Total Environment*, 752, 141946. <https://doi.org/10.1016/j.scitotenv.2020.141946>
- Testa, C., Chen, J., Hall, E., Javadi, D., Morgan, J., Rushovich, T., Saha, S., Waterman, P., & Krieger, N. (2022). *Public Health Disparities Geocoding Project 2.0 Training Manual*. <https://phdgp.github.io/PHDGP2.0/index.html>

- The Lancet. (2020). The plight of essential workers during the COVID-19 pandemic. *The Lancet*, 395(10237), 1587. [https://doi.org/10.1016/S0140-6736\(20\)31200-9](https://doi.org/10.1016/S0140-6736(20)31200-9)
- The New York Times. (2021). *Coronavirus (Covid-19) Data in the United States*. The New York Times. <https://github.com/nytimes/covid-19-data>
- The White House. (2021). Executive Order On Advancing Racial Equity and Support for Underserved Communities Through the Federal Government. In *The White House*. <https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/executive-order-advancing-racial-equity-and-support-for-underserved-communities-through-the-federal-government/>
- The White House. (2022). Advancing Equity and Racial Justice Through the Federal Government. In *The White House*. <https://www.whitehouse.gov/equity/>
- Thompson, C. N. (2020). COVID-19 Outbreak — New York City, February 29–June 1, 2020. *MMWR. Morbidity and Mortality Weekly Report*, 69. <https://doi.org/10.15585/mmwr.mm6946a2>
- United States COVID - Coronavirus Statistics - Worldometer. (2022). In *Worldometers*. <https://www.worldometers.info/coronavirus/country/us/>
- U.S. Department of Commerce Economics and Statistics Administration, & U.S. Census Bureau. (2000). *Census Regions and Divisions of the United States*. https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf
- US Census Bureau. (2022). Nation Continues to Age as It Becomes More Diverse. In *Census.gov*. <https://www.census.gov/newsroom/press-releases/2022/population-estimates-characteristics.html>
- US Census Bureau. (2021). 2020 Census: Redistricting File (Public Law 94-171) Dataset. In *Census.gov*. <https://www.census.gov/data/datasets/2020/dec/2020-census-redistricting-summary-file-dataset.html>
- US Census Bureau. (2020). American Community Survey 2015-2019 5-Year Data Release. In *Census.gov*. <https://www.census.gov/newsroom/press-kits/2020/acs-5-year.html>
- Walker, K., & Herman, M. (2022). *Tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames*.
- Wei, C.-F., Lan, F.-Y., Hsu, Y.-T., Lowery, N., Dibona, L., Akkeh, R., Kales, S. N., & Yang, J. (2022). Risk of SARS-CoV-2 Infection Among Essential Workers in a Community-Based Cohort in the United States. *Frontiers in Public Health*, 10. <https://www.frontiersin.org/articles/10.3389/fpubh.2022.878208>
- Whitehead, J., Shaver, J., & Stephenson, R. (2016). Outness, Stigma, and Primary Health Care Utilization among Rural LGBT Populations. *PLOS ONE*, 11(1), e0146139. <https://doi.org/10.1371/journal.pone.0146139>
- Whittle, R. S., & Diaz-Artilles, A. (2020). An ecological study of socioeconomic predictors in detection of COVID-19 cases across neighborhoods in New York City. *BMC Medicine*, 18(1), 271. <https://doi.org/10.1186/s12916-020-01731-6>
- Wood, S. (2022). *Mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation*. <https://CRAN.R-project.org/package=mgcv>
- Wood, S. N. (2017). *Generalized Additive Models: An Introduction with R* (2nd ed.). Chapman & Hall/CRC Texts in Statistical Science. <https://www.routledge.com/Generalized-Additive-Models-An-Introduction-with-R-Second-Edition/Wood/p/book/9781498728331>
- Wood, S. N., Bravington, M. V., & Hedley, S. L. (2008). Soap film smoothing. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 70(5), 931–955. <https://doi.org/10.1111/j.1467-9868.2008.00665.x>