The Interplay of Policy, Behavior, and Socioeconomic Conditions in Early COVID-19 Epidemiology in Georgia

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ABSTRACT

Background: As COVID-19 began to spread worldwide, local socioeconomic and health factors and nonpharmaceutical interventions may have affected epidemiological outcomes. To investigate the associations between public health orders, behavior, and population factors, and early epidemic dynamics, we investigated variation among counties in the U.S. state of Georgia. There, a large early outbreak occurred in March 2020 with varying levels of local nonpharmaceutical interventions prior to statewide orders, in addition to considerable socioeconomic disparities.

Methods: We conducted regressions to identify predictors of (1) local public health orders, (2) mobility as a proxy for behavioral responses to public health orders, and (3) epidemiological outcomes (i.e., cases and deaths). We used an event study to determine whether social distancing and shelter-in-place orders caused a behavioral change by using mobility as a proxy for social contacts.

Results: Counties at greater risk for early outbreaks (i.e., larger populations and earlier first reported cases) with a greater share of Democratic voters were more likely to introduce local public health orders. Social distancing orders gradually reduced mobility by 19% ten days after their introduction, and lower mobility was associated with fewer cases and deaths. Air pollution and population size were significant predictors of cases and deaths, while larger elderly or Black population were predictors of lower mobility and greater cases, suggesting self-protective behavior in vulnerable populations.

Conclusions: Early epidemiological outcomes reflected both responses to policy orders and existing health and socioeconomic disparities related to ability to socially distance and vulnerability to disease. Teasing apart the impact of behavior changes and population factors is difficult because the epidemic is embedded in a complex social system with multiple potential feedbacks: socioeconomic factors could affect both the implementation of policy

orders and epidemic dynamics directly; policy orders may both respond to existing epidemic conditions and alter future epidemic trajectories.

Keywords: COVID-19, policy, mobility, socioeconomic, shelter-in-place, social distancing

INTRODUCTION

In the early stages of an emerging epidemic without existing population immunity or effective vaccines or therapeutics, nonpharmaceutical interventions like non-essential business closures and bans on social gatherings are some of the only effective measures to control disease transmission (World Health Organization 2019; Centers for Disease Control and Prevention 2020). These interventions have been successfully implemented historically and were introduced in many locations at the beginning of the COVID-19 pandemic (Hatchett et al. 2007; Pan et al. 2020). Slowing transmission in the early stages of the COVID-19 pandemic has been critical for minimizing deaths and for keeping new hospitalizations below health systems capacity, allowing public health departments to build testing capacity for targeted intervention strategies (i.e., contact tracing), and giving researchers time to develop more effective treatments and vaccines (Tuite et al. 2020; Davies et al. 2020). However, the ability to socially distance is often limited for people with low incomes, including many people of color, due to housing and occupational disparities (e.g., being more likely to live in multigenerational households and to be designated essential workers who have to work in person without adequate protections) exacerbating the disproportionate impact of this virus on marginalized groups (Yancy 2020; Cubrich 2020; Schulz et al. 2020; Porter et al. 2021; Baltrus et al. 2021; Benfer et al. 2021; Centers for Disease Control and Prevention 2021). These populations also tend to have higher rates of relevant comorbidities as a result of health inequities and systemic racism (e.g., heightened exposure to air pollution that may worsen outcomes for COVID-19 patients) (Gray et al. 2020; Williams and Cooper 2020; Maroko et al. 2020; Wu et al. 2020).

The first confirmed case of COVID-19 in the United States was reported in late January, 2020 (Johns Hopkins University Center for Systems Science and Engineering 2020). In the following months, the virus began to spread nationally, often with delayed detection and substantial underdiagnosis, particularly in marginalized communities with less access to testing sites and other medical resources (Perkins et al. 2020; Krantz and Rao 2020; Rader et al. 2020; Baltrus et al. 2021; Childs et al. 2021). State level responses varied tremendously, due in part to spatial heterogeneity in virus spread early in the epidemic, as well as differences in perspectives on the virus that increasingly fell along partisan lines (Christensen et al. 2020; Grossman et al. 2020; Allcott et al. 2020; Adolph et al. 2021). For example, on March 19th, 2020, California Governor Newsom introduced the country's first statewide shelter-in-place order (Courtemanche et al. 2020). Most other states followed, and by April 7th, 2020 all but eight states enacted shelter-in-place orders (Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Oklahoma, Utah, and Wyoming; states that had notably explosive outbreaks months later, in the fall of 2020) (Courtemanche et al. 2020). In some cases, when states delayed nonpharmaceutical interventions despite local transmission, county and municipal governments introduced stricter public health orders than those established at the state level.

Georgia presents a case study to understand the local effects of policy at the beginning of the pandemic due to the combination of a relatively early hotspot, delayed statewide action, and a patchwork of earlier local orders (Lau et al. 2020; Muniz-Rodriguez et al. 2021). In a national analysis, multiple Georgia counties were identified as particularly vulnerable to COVID-19 due to intersecting socioeconomic and health risk factors (Chin et al. 2020). The first COVID-19 case in Georgia was reported on March 3rd, 2020 and by

March 27th Albany, Georgia had the third highest per capita death rate of any metro area in the world, following a February superspreading event that was not detected until several weeks later (Cohn et al. 2020; Johns Hopkins University Center for Systems Science and Engineering 2020). On March 20th, Athens-Clarke County became the first local government in Georgia to issue a shelter-in-place order, while Governor Kemp banned gatherings of more than ten people on March 24th and issued a statewide shelter-in-place on April 3rd (Girtz 2020; Kemp 2020a, b). Twenty-three of 159 counties introduced measures to promote social distancing prior to the Governor's large gathering ban, while twenty counties had shelter-in-place orders prior to the Governor's statewide order (Fig. 1) (Kemp 2020a; Evans et al. 2020). Local interventions tended to be clustered in metro-Atlanta counties, but there was some geographic heterogeneity in county-level measures (Fig. 1).

Understanding the efficacy of county-level ordinances and identifying predictors of worse early outbreaks and reduced ability to follow nonpharmaceutical interventions could guide future efforts to prevent large outbreaks of emerging infectious diseases and inform ongoing COVID-19 response strategies and resource allocation (Dyke 2020; van Holm et al. 2020; Jay et al. 2020; Porter et al. 2021). For example, counties with low median household income and educational attainment and high unemployment and poverty rates are predicted to have larger working class populations who were assigned essential worker status, while high housing density and air pollution may also indicate more urbanized areas with more rapid early spread (van Holm et al. 2020; Cubrich 2020; Jay et al. 2020; Benfer et al. 2021). These analyses are complicated by the presence of several interrelated covariates that may have bidirectional relationships (e.g., nonpharmaceutical interventions may reduce transmission, but counties may enact these policies because they already have high transmission rates) (Dyke 2020; Adolph et al. 2021).

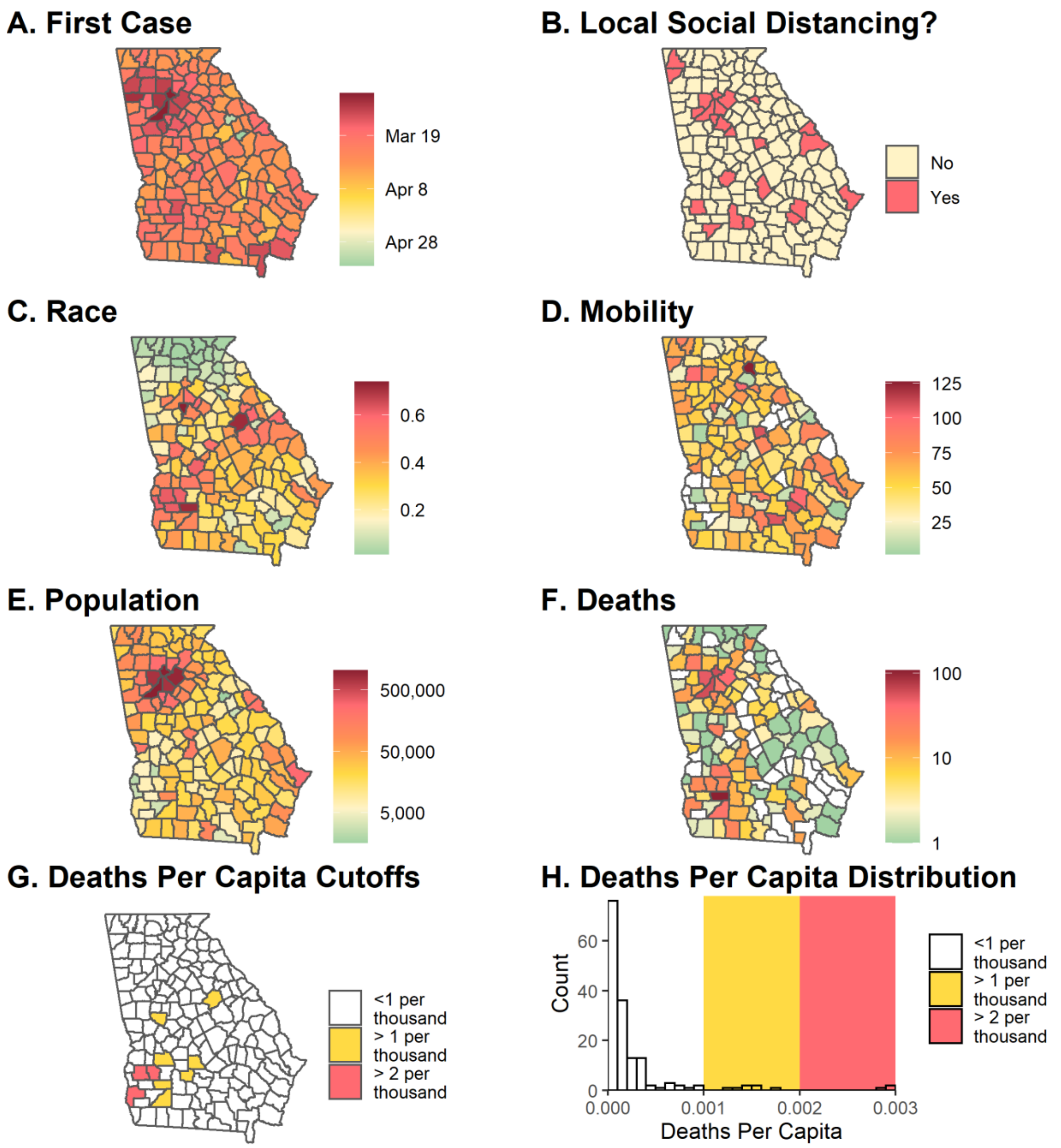

Figure 1: Variation among Georgia counties in date of first case detection, social distancing orders, race, mobility, population size, and COVID-19 deaths. Counties are shaded according to their values for the given covariate used in regressions: (A) the date the first case was reported, (B) whether a local social distancing order was passed prior to the statewide order, (C) the proportion of the county that is Black, (D) mobility normalized to a pre-pandemic baseline (m50_index), averaged across the final week of the statewide shelter-in-place order, (E) natural log of population size, (F) natural log of cumulative COVID-19 deaths reported in the six weeks following a county's first case report, and (G) whether per capita COVID-19 deaths exceeded one per thousand (yellow) or two per thousand (pink); these counties were excluded from regressions in sensitivity analyses. (H) is a histogram that shows the distribution of COVID-19 deaths per capita across Georgia counties, shaded according to the thresholds for per capita deaths (as in G).

In this study, we examined the interplay between health and socioeconomic factors, public health orders, mobility as a proxy for behavior, and early COVID-19 epidemic outcomes, some of which may be bidirectional or cyclical, in Georgia at the county level (Fig. 2). Specifically, we asked: (1) Which county-level demographic and epidemiological characteristics predict the introduction of local public health orders? (2) Did public health orders decrease mobility? (3) Which socioeconomic factors predict lower mobility during the shelter-in-place period, a proxy for behavior? (4) Which socioeconomic, health, and behavioral factors best predict COVID-19 cases and deaths during the early epidemic period (i.e., the first month of detected cases)? To answer questions one, three, and four, we conducted regressions and used model selection to identify the top predictors of each response variable. To answer the second question, we conducted an event study to quantify the causal impact of public health orders on mobility.

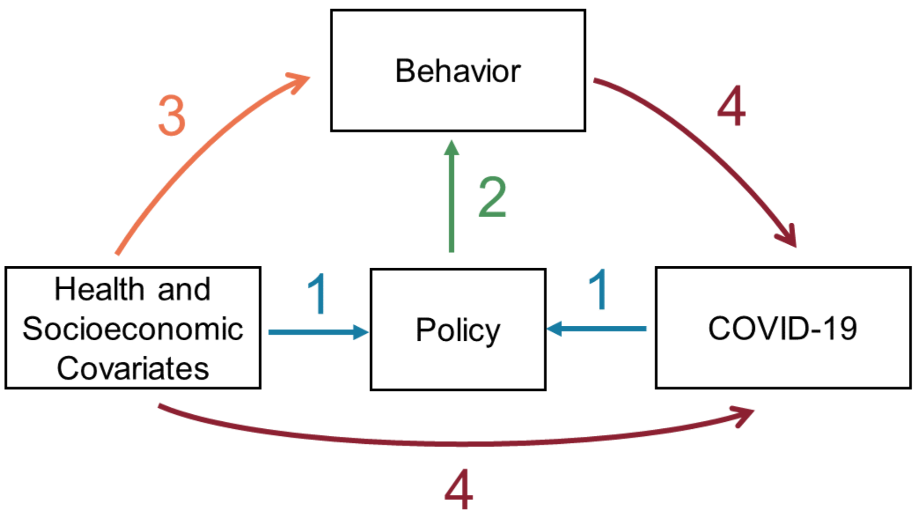

Figure 2: Drivers of COVID-19 epidemiological outcomes—behavior, policy, health, and socioeconomic covariates—are interconnected. Colored arrows correspond with the four-part analyses described here: (1) blue: health and socioeconomic predictors of county-level social distancing or shelter-in-place orders preceding the statewide order (logistic regression), (2) green: effect of social distancing and shelter-in-place policies on mobility as a proxy for behavior (event study), (3) orange: health and socioeconomic predictors of mobility in the final week of April as a proxy for behavior (Gaussian linear regression), (4) red: socioeconomic, health, and mobility predictors of early COVID-19 cases and deaths (negative binomial regression). The color scheme assigned to arrows 1-4 is maintained in the plots pertaining to each of the four components of this study (Figs. 3-6).

METHODS

Epidemiological Data

We used publicly available and de-identified data for this study, which was therefore exempt from Institutional Review Board review. We used daily county-level COVID-19 cumulative cases and deaths reported by the Georgia Department of Public Health and aggregated in the COVID-19 Data Repository (Johns Hopkins University Center for Systems Science and Engineering 2020; Dong et al. 2020). We included cases and deaths reported within four and six weeks, respectively, of each county's first reported case because we were interested in studying early epidemic outcomes. The additional two weeks for deaths accounts for the lag between case detection and mortality (Gaythorpe et al. 2020). We also computed cumulative deaths per capita as of May 21st, reflecting transmission prior to the end of the statewide shelter-in-place order.

Legislative Data

We used daily public health orders implemented at the county level based on State Executive Orders, Departments of Education, and other news sources and aggregated in the Center for the Ecology of Infectious Disease at the University of Georgia's COVID-19-DATA repository (Evans et al. 2020). We defined public health orders that encourage social distancing in the general population as bans on gatherings at non-essential businesses, restrictions on gathering sizes, closures of public use areas, and ordinances that otherwise encouraged social distancing. School closures were not included under this definition of social distancing orders as only nine counties implemented local school closures, all within one week of the March 16th statewide school closures, precluding meaningful comparisons. For each county, we defined the beginning of social distancing and shelter-in-place based on the date of the statewide orders if they were enacted prior to any county-level legislation.

Socioeconomic Data

Population size and the proportion of the county that is Black or African American, Hispanic or Latinx, Asian, and American Indian and Alaska Native were based on the U.S. Census Bureau's county-level estimates for 2018 (U.S. Census Bureau, Population Division 2020a). The White proportion of the population was excluded from the analysis, as it was highly negatively correlated with the Black proportion of the population (File S1). Population size was log-transformed for all regressions. We also incorporated educational attainment (i.e., proportion of the population with a high school diploma), unemployment, percentage of people below the poverty line, median household income, and housing units per square mile compiled previously from U.S. Census Bureau reports as indicators of socioeconomic status and urbanization (Chin et al. 2020). We calculated county-wide predicted age-weighted infection fatality rate based on age-specific infection fatality rates and the U.S. Census Bureau's 2018 estimates of the proportion of each county in corresponding age bins (Verity et al. 2020; U.S. Census Bureau, Population Division 2020b). We computed the proportion of each county's population that works in another county based on the 2011-2015 American Community Survey Commuting Flows (U.S. Census Bureau 2015).

Partisanship Data

The partisanship of each county was defined as the difference in percentage points between the vote shares of the Republican and Democratic candidates for Governor of Georgia in 2018 (i.e., vote margin), with more positive values indicating counties with more Republican voters (Crittenden 2018).

Comorbidity and Health Data

Data on pollution (Particulate Matter PM2.5) and relevant health comorbidities (obesity, coronary heart disease, and diabetes) were compiled previously from the Centers for Disease Control and Prevention, and the Environmental Protection Agency (Chin et al. 2020).

We collected additional data on asthma from the Georgia Department of Public Health (Cheng et al. 2012).

Mobility Data

To measure temporal and spatial variation in mobility, our metric of behavioral changes related to the pandemic, we used daily county-level statistics based on mobile phone data from Descartes Lab (Warren and Skillman 2020). The maximum distance traveled from the initial point on each day was recorded for every device and the daily median across devices (*m50*) in a county was calculated. Normalized daily mobility (*m50*_index) was defined as the proportional change in mobility from the baseline prior to widespread mobility changes in the US (Warren and Skillman 2020). For regressions, we defined mobility as the mean *m50*_index in the final week of April, corresponding to the end of the shelter in place period. Ten counties were excluded from the analyses because they had no available mobility data (Baker, Calhoun, Clay, Glascock, Hancock, Quitman, Stewart, Taliaferro, Warren, Webster, and Wheeler) (Fig. 1).

Part 1: Predictors of local public health orders

We conducted logistic regression to identify predictors of a county's having a local social distancing or shelter-in-place order prior to the statewide orders. Covariates were normalized by subtracting the mean and dividing by standard deviation to allow direct comparisons of effect sizes. Forward and backward model selection were conducted to minimize Akaike's Information Criterion (AIC), balancing goodness-of-fit against overfitting.

We tested whether the inclusion of counties with extreme values for COVID-19 deaths per capita skewed our results by performing sensitivity analyses excluding the three counties involved in an early superspreading event, where per capita death rates exceeded two per thousand (Randolph, Terrell, and Early) or the ten counties where per capita death rates exceeded one per thousand (Randolph, Terrell, Early, Hancock, Turner, Dougherty, Wilcox, Mitchell, Sumter, and Upson) (Fig. 1). We computed Nagelkerke's pseudo-R^2 for all models (Magee 1990; Dabao 2020). All analyses were conducted in R statistical software version 4.0.0.

Part 2: Effect of public health orders on mobility

We used an event study framework to understand the effect of public health orders (social distancing or shelter-in-place) on mobility at the county level. This approach seeks to identify changes in time series data following a pre-specified event. For event study analyses, we included the ten days prior to and following the legislation's introduction in each county, spanning the time difference between the statewide social distancing and shelter-in-place orders to isolate the effects of the two orders. The covariate *NPI_day* was defined as follows:

$$NPI_{day(t,t_0)} = \begin{cases} 0, & t < t_0 \\ t - t_0 + 1, & t \geq t_0 \end{cases} \tag{1}$$

where *t* is the time in days and t_0 is the date that a particular order was introduced.

We used a fixed effect model to adjust for variation due to county and date and to quantify both the binary effects of nonpharmaceutical interventions and the effect of days since a nonpharmaceutical interventions was introduced. The model formulation was:

$$mobility_{i,t} = \alpha + \beta_i county + \beta_t date + \beta_p NPI_{day} + \epsilon_{i,t} \tag{2}$$

where α is an intercept, β's are coefficients for corresponding covariates, and ϵ is an error term for each county *i* and date *t*. In addition to the ten counties excluded from regression due to no mobility data, five more counties were excluded from the both event studies due to incomplete mobility data for the study period (Chattahoochee, Marion, Randolph, Schley, and Twiggs) and Montgomery county was excluded only from the event study for shelter-in-place orders.

Part 3: Predictors of mobility

We examined the relationship between socioeconomic variables and average mobility (m50_index) in the last week of April using a Gaussian linear regression to identify predictors of mobility, a proxy for nonpharmaceutical intervention compliance. Model selection was conducted as described in part one.

Part 4: Predictors of early epidemiological outcomes

We identified the primary socioeconomic, health, and behavioral predictors of early epidemic outcomes by fitting negative binomial regressions to reported COVID-19 cases and deaths within four and six weeks of each county's first reported case, respectively. Both responses were count variables that were overdispersed relative to the expected variance in a Poisson distribution. We performed model selection and computed Nagelkerke's pseudo-R^2 as described in part one (Magee 1990; Dabao 2020).

RESULTS

Part 1: Predictors of local public health orders

In the models that included all counties, the natural logarithm of the odds ratio (log-odds) of introducing a local social distancing order increased by 0.1 with every 4.43 percentage point increase in Democratic vote margin (95% CI: 2.62-12.50) or increase in population size by a factor of 1.24 (95% CI: 1.12-2.89) (Table S1, Fig. 3). In the models that included all counties, the log-odds of introducing a local shelter-in-place order increased by 0.1 with every 0.46 day earlier advance in the date of the county's first reported case (95% CI: 0.27-1.12) or increase in population size by a factor of 1.10 (95% CI: 1.05-1.56). Most of the counties that introduced local public health orders contain large municipalities (e.g., Atlanta, Athens, and Macon). All findings were robust to the inclusion or exclusion of counties with high per capita deaths (greater than one or two deaths per 1000 people). Socioeconomic and demographic variables captured less variation in the passage of local social distancing orders (pseudo-R^2: 0.25-0.31) compared to local shelter-in-place orders

($\text{pseudo-}R^2$: 0.51-0.54), where ranges depended on the subset of outlier counties that were included (Table S1).

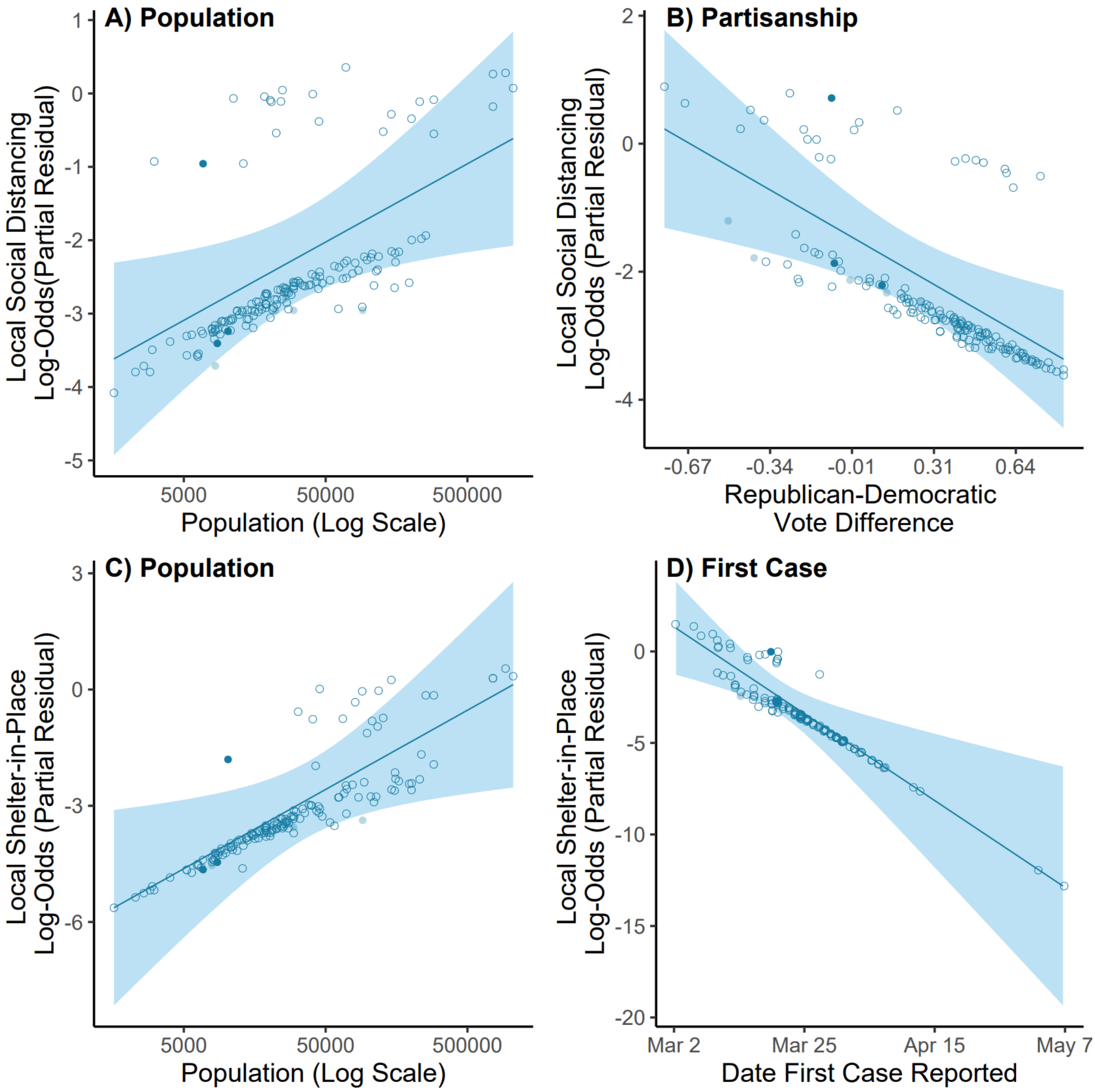

Figure 3: Counties with larger populations were more likely to enact local social distancing and shelter-in-place orders. Partial residual plots with lines giving the estimated relationship between predictors and logit-transformed odds ratio (log-odds) of a local nonpharmaceutical intervention order, with the 95% confidence interval indicated as a shaded band. The points indicate the marginal relationship at the county level between predictors and marginal log-odds of a local public health order, after adjusting for all other predictors selected in the best fit model. The top row shows the two most significant predictors of a local social distancing order: logged population size (Population) and percent point difference of Republican and Democratic vote share in 2018 gubernatorial election, with more negative values indicating a higher proportion of Democratic voters (Partisanship). The bottom row

shows the two most significant predictors of a local shelter-in-place order: logged population size (Population) and date first case in county was reported (First Case). Open circles indicate counties with less than one death per thousand people, while light and dark shaded circles indicate counties with outlying values for per capita deaths (thresholds of one or two deaths per thousand people, respectively).

Part 2: Effect of public health orders on mobility

Mobility decreased by 19 percentage points ($P<0.001$) in the ten days following the introduction of a social distancing order (Table S2). We observed 21 instances (county-days) where mobility exceeded the county- and date-adjusted mean for the event study period by over 35 percentage points—which we designated as mobility extremes—and all occurred prior to the introduction of local social distancing orders (Fig. 4).

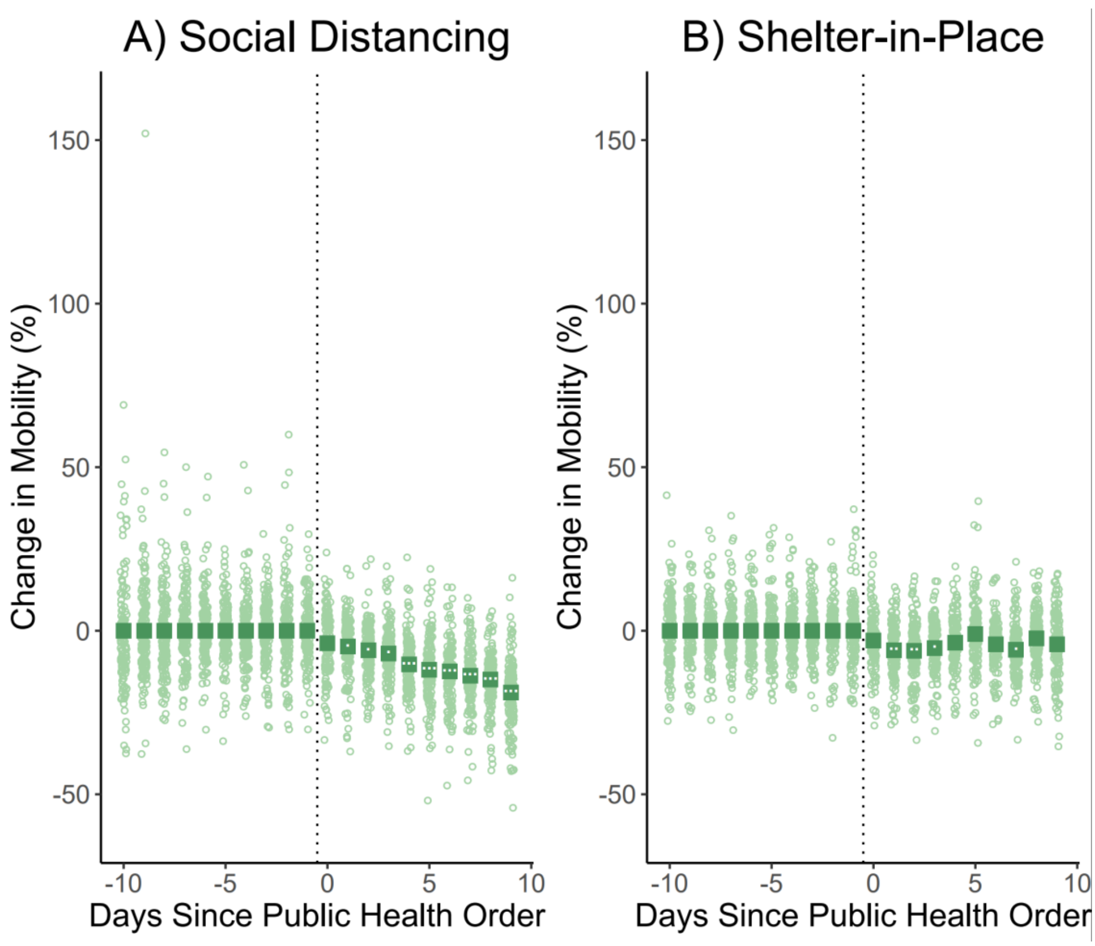

Figure 4: **Social distancing orders gradually reduced mobility by up to 19%, while shelter-in-place orders had only a short-term marginal effect for days 2-4.** The coefficients of the event studies by days since public health order introduction (β_p) for social distancing policies (A) and shelter-in-place orders (B) are given as squares across the ten days preceding and following the introduction of the public health order, with the day the

order was introduced indicated with a vertical dotted line. The significance of the coefficients is indicated by the number of white dots within each square (●: P<0.05; ●●: P <0.01, ●●●: P <0.001). The green circles indicate the marginal effect of the corresponding public health order on mobility by date in each county, after adjusting for county and date fixed effects.

All counties had social distancing orders prior to shelter-in-place orders. Overall, although mobility was significantly reduced two to five days after shelter-in-place orders were passed, we did not detect a sustained marginal effect of shelter-in-place orders on mobility, after accounting for the effects of social distancing orders already in place (Table S2, Fig. 4). County and date fixed effects are reported in Tables S3-S4.

Part 3: Socioeconomic predictors of mobility

Age, income, and the proportion of the population identifying as Black were all significant negative predictors of mobility, a proxy for behavior (Table S5, Fig. 5). Mobility declined by 20 percentage points for every 0.0052 increase in age-weighted infection fatality rate, $5,207 increase in median household income, or 39 percentage point increase in the Black proportion of the population. There was little variation in effect sizes when counties with outlying per capita death rates were excluded. Of the ten counties where per capita deaths exceeded one per thousand, all had median household income below the statewide mean ($44,000), nine had Black population proportions above the statewide average of 0.30 (and six were majority Black), and seven had age-weighted infection fatality rates above the statewide average of 0.011 (Fig. 5). The model only captured 11-13% of observed variation in mobility (Table S5).

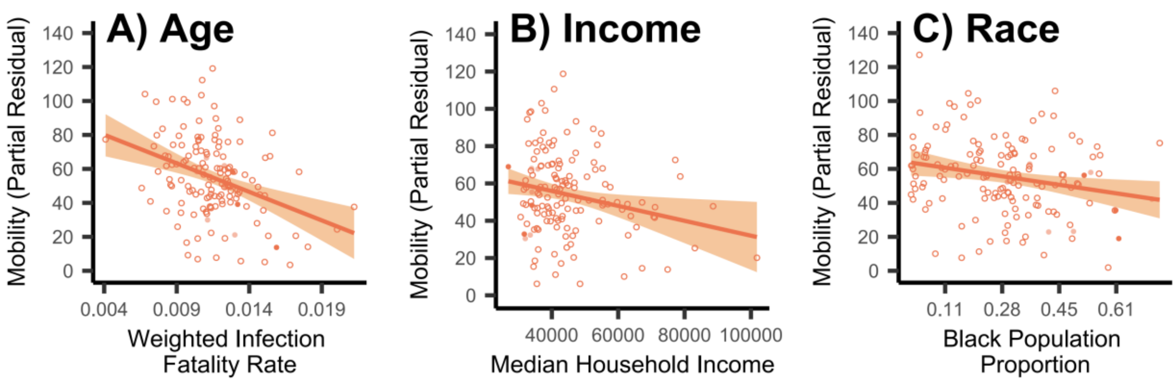

Figure 5: Higher age, median household income, and Black proportion of population all corresponded to lower mobility in the final week of the statewide shelter-in-place order. Partial residual plots with lines indicating the estimated relationship between predictors and mean mobility in the final week of the statewide shelter-in-place order, while the 95% confidence interval is indicated as a shaded band. The points indicate the marginal relationship at the county level between predictors and mobility, after adjusting for all other predictors selected in the best fit model. All predictors selected in the best fit model are displayed: age-weighted infection fatality rates (A. Age), median household income (B. Income), and percent of the population that is Black (C. Race). Open circles indicate counties with less than one death per thousand people, while light and dark shaded circles indicate counties with outlying values for per capita deaths (thresholds of one or two deaths per thousand people, respectively).

Part 4: Socioeconomic, health, and mobility predictors of early epidemiological outcomes

Counties with larger populations and more air pollution had significantly more cases and deaths across all models, while greater mobility was a significant positive predictor of cases and deaths only in the models that excluded the ten counties where per capita deaths exceeded one per thousand (Table S6, Fig. 6). Counties with greater proportions of the population who were elderly or living below the poverty line or with lower rates of coronary heart disease reported more cases, while counties with lower educational attainment and earlier first cases reported more deaths. Additional health and socioeconomic covariates (e.g., diabetes, asthma) were included in some of the models selected by AIC, but their effect sizes were not significantly different from zero unless counties with per capita deaths greater than one per thousand were excluded. All predictors included in the models explained 67-73% of the variation in cases and 49-53% of the variation in deaths.

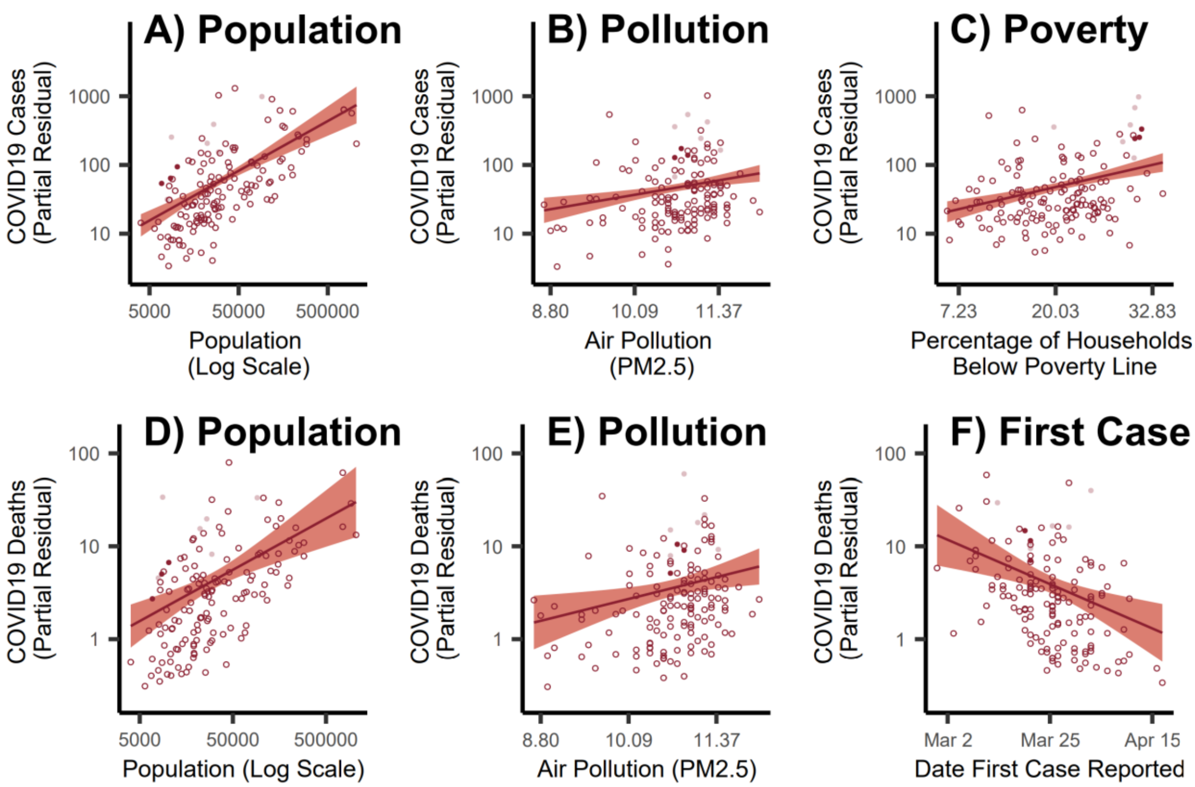

Figure 6: Larger population size, higher pollution, and higher poverty rates were associated with more COVID-19 cases at the county level. Larger population size, more air pollution, and earlier first case reported were associated with more COVID-19 deaths at the county level. Partial residual plots with lines giving the estimated multiplicative relationship between predictors and COVID-19 cases and deaths, with the 95% confidence interval is indicated as a shaded band. The points indicate the marginal multiplicative relationship at the county level between predictors and COVID-19 cases (top) or deaths (bottom), after adjusting for all other predictors selected in the best fit model. The top row shows the three most significant predictors of early COVID-19 cases: logged population size (Population), annual average ambient PM2.5 concentration (Pollution), and percentage of population living below poverty line (Poverty). The bottom row shows the three most significant predictors of early COVID-19 deaths: logged population size (Population), annual average ambient PM2.5 concentration (Pollution), and date first case in county was detected (First Case). Open circles indicate counties with less than one death per thousand people, while light and dark shaded circles indicate counties with outlying values for per capita deaths (thresholds of one or two deaths per thousand people, respectively).

DISCUSSION

Social distancing orders successfully reduced mobility, and lower mobility was associated with fewer COVID-19 deaths and cases in most Georgia counties (Table S5, Fig. 4, Table S6). Mobility gradually declined by 19 percentage points (95% CI: 10% - 27%) over ten days after social distancing orders were introduced, suggesting that, with some lag, these orders contributed to behavioral changes that may be indicative of social distancing (Table S5, Fig. 4). Conversely, we found that undoing this level of mobility change—i.e., a 19 percentage point increase during the final week of shelter-in-place—would be associated with a 17% (95% CI: 1-35%) increase in COVID-19 deaths or 10% (95% CI: 0-20%) increase in cases in the counties where per capita deaths were fewer than one per thousand (Table S6).

We found support for the hypothesis that the relationship between nonpharmaceutical interventions and early epidemiological outcomes was bidirectional, a trend that observed in counties that mandated wearing face coverings later in the epidemic (Dyke 2020; Adolph et al. 2021). Counties with earlier detection of cases and larger populations (predictive of larger outbreaks) tended to pass local orders before the statewide order (Table S1, Fig. 3, Table S6, Fig. 6). At the county level, having a higher proportion of Black or elderly residents was predictive of both lower mobility and more cases, suggesting self-protective behavior in vulnerable groups and a tendency early in the pandemic to detect more severe cases in populations with higher rates of health comorbidities (Table S5, Table S6, Fig. 5, Fig. 6) (Singh et al. 2021; Litwin and Levinsky 2021). The lower mobility in counties with larger Black population shares was surprising, as Black people were disproportionately employed in essential jobs where they were limited in their ability to socially distance, suggesting a need to further assess the relative impact of conflicting influences on compliance with public health orders (Robles et al. 2020; Cubrich 2020; Singh et al. 2021). Causal pathways cannot be inferred from this county-level correlational analysis of predictors at the county level and the findings of this study should be compared to individual-level data where possible to identify mechanisms (Richmond et al. 2020; Wu et al. 2020; Lobelo et al. 2021). Separating the causes and effects of differences in social distancing orders, mobility, and transmission using techniques such as instrumental variables will be important in assessing the efficacy of nonpharmaceutical intervention orders.

Mobility data and the analyses presented here may not fully capture behavioral changes linked to nonpharmaceutical interventions. For example, while mobility did not significantly decrease following shelter-in-place orders when social distancing orders were already in place, Georgians may have reduced social contacts within a small radius of their homes following the shelter-in-place order. On the other hand, the calculated reduction in mobility following social distancing orders may not be directly proportional to the reduction in social contacts and in high-risk transmission settings (including indoor gatherings without face masks). This analysis does not capture the effects of additional public health measures (e.g., mask mandates and school closures) or behavioral changes prior to the public health orders (Lau et al. 2020). This approach to understanding effects of nonpharmaceutical interventions also does not capture spillover effects from geographically and socially connected counties, which could expand or distort the influence of local public health orders (Holtz et al. 2020; Muniz-Rodriguez et al. 2021). However, epidemiological models fit to cases, deaths, and mobility data similar to those used here have demonstrated that time-varying transmission rates can be captured accurately using mobility data (Lau et al. 2020; Kain et al. 2021).

In addition to the association with mobility, epidemiological outcomes were predicted by demographic, socioeconomic, and health factors. As expected, counties with larger populations sustained larger outbreaks because the rate of new infections is directly proportional to the number of susceptible people. Greater air pollution was also associated with more cases and deaths, potentially due to more rapid spread in more urbanized counties and/or to worse outcomes in communities with higher rates of health conditions linked to air pollution exposure (Wu et al. 2020). While the proportion of the population that commutes outside the county was not a significant predictor in these analyses, the data used were from 2011-2015 and may not be fully representative of commuter patterns, especially in the rapidly expanding metro-Atlanta area (U.S. Census Bureau 2015). Contrary to our expectation, we found that the prevalence of comorbidities that are known to worsen individual outcomes for patients with COVID-19 (e.g., obesity and asthma) were not significant predictors of deaths or were negatively associated with early cases and deaths (e.g., coronary heart disease), potentially because they are confounded with factors like income and race (Berman et al. 2021).

Counties with a larger share of residents who were Black or living below the poverty line experienced more cases and/or deaths, a pattern that may reflect disparities and systemic injustices connected to racism in healthcare, housing, and occupation in Georgia and across the United States (van Holm et al. 2020; Azar et al. 2020; Moore et al. 2020; Gray et al. 2020; Williams and Cooper 2020; Schulz et al. 2020; Richmond et al. 2020; Baltrus et al. 2021; Benfer et al. 2021). These covariates may also indicate counties that have larger populations of workers who were deemed essential and unable to work from home under public health orders in addition to lacking sufficient workplace protections (Yancy 2020; Czeisler et al. 2020; Cubrich 2020; Schulz et al. 2020; Christensen et al. 2020). Counties with lower median household income had higher mobility, potentially supporting this hypothesis (Table S5, Fig. 5) (Singh et al. 2021). While the Hispanic or Latinx, Asian, or American Indian and Alaska Native proportions of the population were not significant predictors of cases, deaths, or mobility at the population level, more data and detailed studies are necessary to understand the impacts of discrimination and injustice across different ethnic and racial groups (File S1) (Lobelo et al. 2021). Identifying the mechanisms and relative importance of these potential drivers of disparate outcomes is critical for addressing the disproportionate impact of COVID-19 on marginalized communities. Notably, almost all counties with especially high outlying values for per capita deaths at the beginning of the epidemic had median household incomes below and Black population shares above the statewide averages (Fig. 3).

This analysis could be extended to more locations, and Georgia's heterogeneous response could be compared to states like California, which had an early statewide shelter-in-place order. Focusing this analysis within a single state at the beginning of the pandemic allows us to quantify initial epidemic spread and to assess the efficacy of interventions related to reducing contacts, in addition to understanding risk factors for large outbreaks at a time when treatments and control measures were especially limited. However, testing limitations and lack of early knowledge about the virus may have contributed to substantial underreporting of cases, especially in rural counties lacking public health infrastructure (Rader et al. 2020). Furthermore, the cumulative case and death counts used in this analysis were assigned to dates based on when they were reported online by the Georgia Department of Public Health, which did not initially release time series of daily new cases and deaths and did not note when symptoms or testing occurred (for cases), or when the death occurred, meaning that these counts may not fully capture epidemiological outcomes on their corresponding dates (Johns Hopkins University Center for Systems Science and Engineering 2020; Dong et al. 2020). As statewide orders were lifted across the country, county governments became increasingly responsible for containing local outbreaks, while predictors of more transmission changed over time (Johnson 2020; Lance Bottoms 2020; Porter et al. 2021; Ogwara et al. 2021; Berman et al. 2021; Adolph et al. 2021; California Department of Public Health). Local governments will therefore need to understand the impact of these orders and identify county-level features that may affect outbreak risk and nonpharmaceutical intervention implementation to respond to this ongoing pandemic and other emerging infectious diseases.

CONCLUSION

Here, we showed that while social distancing orders did reduce mobility (Table S2, Fig. 4), and reduced mobility was associated with fewer COVID-19 cases and deaths in most counties (Table S6), the efficacy of these nonpharmaceutical interventions was mediated by the will of municipal and state governments to impose, and ability of community members to observe, public health orders. While changing mobility likely affected COVID-19 transmission, this was one of many factors associated with epidemiological outcomes (Table S6, Fig. 6) (Lau et al. 2020; Singh et al. 2021).

Demographics, health, economic resources, and social and political power—and disparities in these factors—within communities affect both their vulnerability to and responses to disease outbreaks. Because these factors are interconnected through both causal linkages and correlations driven by underlying societal structures and inequities (Fig. 2), it is impossible to completely disentangle the causal effects from observational data. However, this work illustrates the imperative need to consider interconnected policy, behavioral responses, socioeconomic factors, and demographic conditions in evaluating and designing policy to combat emerging epidemics (e.g., expanding public health protections, occupational safety measures, and medical resources in counties at greatest risk of large outbreaks and enhancing outreach and social support, such as housing assistance and paid leave, for populations that are least able to comply with public health orders) (Robles et al. 2020; Moore et al. 2020; Cubrich 2020; Schulz et al. 2020; Porter et al. 2021; Baltrus et al. 2021; Benfer et al. 2021; Lobelo et al. 2021; Adolph et al. 2021).

Data Accessibility

Data and code are available on Github at https://github.com/mjharris95/GA-COVID

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REFERENCES

Adolph C, Amano K, Bang-Jensen B, et al (2021) The Pandemic Policy U-Turn: Partisanship, Public Health, and Race in Decisions to Ease COVID-19 Social Distancing Policies in the United States. Perspectives on Politics 1–23. https://doi.org/10.1017/S1537592721002036

Allcott H, Boxell L, Conway J, et al (2020) Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. Journal of Public Economics 191:104254. https://doi.org/10.1016/j.jpubeco.2020.104254

Azar KMJ, Shen Z, Romanelli RJ, et al (2020) Disparities in outcomes among COVID-19 patients in a large health care system in California. Health Affairs 39:1253–1262. https://doi.org/10.1377/hlthaff.2020.00598

Baltrus PT, Douglas M, Li C, et al (2021) Percentage of Black Population and Primary Care Shortage Areas Associated with Higher COVID-19 Case and Death Rates in Georgia Counties. South Med J 114:57–62. https://doi.org/10.14423/SMJ.0000000000001212

Benfer EA, Vlahov D, Long MY, et al (2021) Eviction, Health Inequity, and the Spread of COVID-19: Housing Policy as a Primary Pandemic Mitigation Strategy. J Urban Health 98:1–12. https://doi.org/10.1007/s11524-020-00502-1

Berman AE, Miller DD, Rahn DW, et al (2021) A County-Level Analysis of Socioeconomic and Clinical Predictors of COVID-19 Incidence and Case-Fatality Rates in Georgia, March–September 2020. Public Health Rep 136:626–635. https://doi.org/10.1177/00333549211023267

California Department of Public Health County Data Monitoring - Step 2. https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/COVID-19/CountyMonitoringDataStep2.aspx. Accessed 10 Jul 2020

Centers for Disease Control and Prevention (2020) Nonpharmaceutical Interventions (NPIs). https://www.cdc.gov/nonpharmaceutical-interventions/index.html. Accessed 7 Oct 2021

Centers for Disease Control and Prevention (2021) Health Equity Considerations & Racial & Ethnic Minority Groups

Cheng V, Clarkson L, Lopez F, Chambers S (2012) Georgia asthma surveillance report

Childs ML, Kain MP, Harris MJ, et al (2021) The impact of long-term non-pharmaceutical interventions on COVID-19 epidemic dynamics and control: the value and limitations of early models. Proc Biol Sci 288:20210811. https://doi.org/10.1098/rspb.2021.0811

Chin T, Kahn R, Li R, et al (2020) US-county level variation in intersecting individual, household and community characteristics relevant to COVID-19 and planning an equitable response: A cross-sectional analysis. BMJ Open 10:e039886. https://doi.org/10.1136/bmjopen-2020-039886

Christensen SR, Pilling EB, Eyring JB, et al (2020) Political and personal reactions to COVID-19 during initial weeks of social distancing in the United States. PLOS ONE 15:e0239693. https://doi.org/10.1371/journal.pone.0239693

Cohn N, Katz J, Sanger-Katz M, Quealy K (2020) Four Ways to Measure Coronavirus Outbreaks in U.S. Metro Areas. The New York Times

Courtemanche C, Garuccio J, Le A, et al (2020) Strong social distancing measures in the United States reduced the COVID-19 growth rate. Health Affairs 1237–1246

Crittenden RA (2018) November 6, 2018 general election Official results.

Cubrich M (2020) On the frontlines: Protecting low-wage workers during COVID-19. Psychol Trauma 12:S186–S187. https://doi.org/10.1037/tra0000721

Czeisler MÉ, Tynan MA, Howard ME, et al (2020) Public Attitudes, Behaviors, and Beliefs Related to COVID-19, Stay-at-Home Orders, Nonessential Business Closures, and Public Health Guidance — United States, New York City, and Los Angeles, May 5–12, 2020. MMWR Morb Mortal Wkly Rep 69:751–758. https://doi.org/10.15585/mmwr.mm6924e1

Dabao Z (2020) rsq: R-Squared and related measures. Version R package version 2.0

Davies NG, Kucharski AJ, Eggo RM, et al (2020) Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. The Lancet Public Health 5:e375–e385. https://doi.org/10.1016/S2468-2667(20)30133-X

Dong E, Du H, Gardner L (2020) An interactive web-based dashboard to track COVID-19 in real time. The Lancet Infectious Diseases 20:533–534. https://doi.org/10.1016/S1473-3099(20)30120-1

Dyke MEV (2020) Trends in county-level COVID-19 incidence in counties with and without a mask mandate — Kansas, June 1–August 23, 2020. MMWR Morb Mortal Wkly Rep 69:1777–1781

Evans M, Richards R, Willoughby A, et al (2020) CEIDatUGA/COVID-19-DATA

Gaythorpe K, Imai N, Cuomo-Dannenburg G, et al (2020) Report 8: Symptom progression of COVID-19. Imperial College London

Girtz K (2020) An Ordinance for the Second Declaration of a Local State of Emergency Related to COVID-19; And for Other Purposes

Gray DM, Anyane-Yeboa A, Balzora S, et al (2020) COVID-19 and the other pandemic: populations made vulnerable by systemic inequity. Nature Reviews Gastroenterology & Hepatology 1–3. https://doi.org/10.1038/s41575-020-0330-8

Grossman G, Kim S, Rexer JM, Thirumurthy H (2020) Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States. PNAS 117:24144–24153. https://doi.org/10.1073/pnas.2007835117

Hatchett RJ, Mecher CE, Lipsitch M (2007) Public health interventions and epidemic intensity during the 1918 influenza pandemic. Proc Natl Acad Sci USA 104:7582. https://doi.org/10.1073/pnas.0610941104

Holtz D, Zhao M, Benzell SG, et al (2020) Interdependence and the cost of uncoordinated responses to COVID-19. Proc Natl Acad Sci USA 117:19837–19843. https://doi.org/10.1073/pnas.2009522117

Jay J, Bor J, Nsoesie EO, et al (2020) Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. Nature Human Behaviour 4:1294–1302. https://doi.org/10.1038/s41562-020-00998-2

Johns Hopkins University Center for Systems Science and Engineering (2020) 2019 novel coronavirus COVID-19 (2019-nCoV) data repository

Johnson V (2020) Emergency Order Requiring That Face Coverings or Masks Be Worn in Public in the City of Savannah During the COVID-19 Public Health Emergency

Kain MP, Childs ML, Becker AD, Mordecai EA (2021) Chopping the tail: How preventing superspreading can help to maintain COVID-19 control. Epidemics 34:100430. https://doi.org/10.1016/j.epidem.2020.100430

Kemp B (2020a) Executive Order 03.23.20.01

Kemp B (2020b) Executive Order 04.02.20.01

Krantz SG, Rao ASRS (2020) Level of underreporting including underdiagnosis before the first peak of COVID-19 in various countries: Preliminary retrospective results based on wavelets and deterministic modeling. Infection Control & Hospital Epidemiology 41:857–859. https://doi.org/10.1017/ice.2020.116

Lance Bottoms K (2020) Executive Order Number 2020-113

Lau MSY, Grenfell B, Thomas M, et al (2020) Characterizing superspreading events and age-specific infectiousness of SARS-CoV-2 transmission in Georgia, USA. PNAS 117:22430–22435. https://doi.org/10.1073/pnas.2011802117

Litwin H, Levinsky M (2021) Network-Exposure Severity and Self-Protective Behaviors: The Case of COVID-19. Innovation in Aging 5:. https://doi.org/10.1093/geroni/igab015

Lobelo F, Bienvenida A, Leung S, et al (2021) Clinical, behavioural and social factors associated with racial disparities in COVID-19 patients from an integrated healthcare system in Georgia: a retrospective cohort study. BMJ Open 11:e044052. https://doi.org/10.1136/bmjopen-2020-044052

Magee L (1990) R^2 measures based on Wald and likelihood ratio joint significance tests. The American Statistician 44:250–253. https://doi.org/10.1080/00031305.1990.10475731

Maroko AR, Nash D, Pavilonis BT (2020) COVID-19 and inequity: A comparative spatial analysis of New York City and Chicago hot spots. Journal of Urban Health 97:461

Moore JX, Langston ME, George V, Coughlin SS (2020) Epidemiology of the 2020 pandemic of COVID-19 in the state of Georgia: Inadequate critical care resources and impact after 7 weeks of community spread. J Am Coll Emerg Physicians Open. https://doi.org/10.1002/emp2.12127

Muniz-Rodriguez K, Chowell G, Schwind JS, et al (2021) Time-varying Reproduction Numbers of COVID-19 in Georgia, USA, March 2, 2020 to November 20, 2020. Perm J 25:20.232: https://doi.org/10.7812/TPP/20.232

Ogwara CA, Mallhi AK, Hua X, et al (2021) Spatially Refined Time-Varying Reproduction Numbers of COVID-19 by Health District in Georgia, USA, March–December 2020. Epidemiologia 2:179–197. https://doi.org/10.3390/epidemiologia2020014

Pan A, Liu L, Wang C, et al (2020) Association of public health interventions with the epidemiology of the COVID-19 outbreak in Wuhan, China. JAMA 323:1915–1923. https://doi.org/10.1001/jama.2020.6130

Perkins TA, Cavany SM, Moore SM, et al (2020) Estimating unobserved SARS-CoV-2 infections in the United States. PNAS 117:22597–22602. https://doi.org/10.1073/pnas.2005476117

Porter G, Desai K, George V, et al (2021) Racial Disparities in the Epidemiology of COVID-19 in Georgia: Trends Since State-Wide Reopening. Health Equity 5:91–99. https://doi.org/10.1089/heq.2020.0089

Rader B, Astley CM, Sy KTL, et al (2020) Geographic access to United States SARS-CoV-2 testing sites highlights healthcare disparities and may bias transmission estimates. Journal of Travel Medicine 27:. https://doi.org/10.1093/jtm/taaa076

Richmond HL, Tome J, Rochani H, et al (2020) The Use of Penalized Regression Analysis to Identify County-Level Demographic and Socioeconomic Variables Predictive of Increased COVID-19 Cumulative Case Rates in the State of Georgia. Int J Environ Res Public Health 17:E8036. https://doi.org/10.3390/ijerph17218036

Robles G, Sauermilch D, Starks TJ (2020) Self-efficacy, social distancing, and essential worker status dynamics among SGM people. Annals of LGBTQ public and population health 1:300. https://doi.org/10.1891/lgbtq-2020-0044

Schulz AJ, Mehdipanah R, Chatters LM, et al (2020) Moving Health Education and Behavior Upstream: Lessons From COVID-19 for Addressing Structural Drivers of Health Inequities. Health Educ Behav 47:519–524. https://doi.org/10.1177/1090198120929985

Singh S, Shaikh M, Hauck K, Miraldo M (2021) Impacts of introducing and lifting nonpharmaceutical interventions on COVID-19 daily growth rate and compliance in the United States. PNAS 118:. https://doi.org/10.1073/pnas.2021359118

Tuite AR, Fisman DN, Greer AL (2020) Mathematical modelling of COVID-19 transmission and mitigation strategies in the population of Ontario, Canada. CMAJ 192:E497–E505. https://doi.org/10.1503/cmaj.200476

U.S. Census Bureau (2015) 2011-2015 5-year ACS commuting flows. https://www.census.gov/data/tables/2015/demo/metro-micro/commuting-flows-2015.html

U.S. Census Bureau, Population Division (2020a) Race: Annual county resident population estimates by age, sex, race, and hispanic origin: April 1, 2010 to July 1, 2018 (CC-EST2018-ALLDATA). https://www2.census.gov/programs-surveys/popest/datasets/2010-2019/counties/totals/

U.S. Census Bureau, Population Division (2020b) Annual county and resident population estimates by selected age groups and sex: April 1, 2010 to July 1, 2018 (CC-EST2018-AGESEX). https://www2.census.gov/programs-surveys/popest/datasets/2010-2018/counties/totals/co-est2018-alldata.csv

van Holm EJ, Wyczalkowski CK, Dantzler PA (2020) Neighborhood conditions and the initial outbreak of COVID-19: the case of Louisiana. Journal of Public Health 1–6. https://doi.org/10.1093/pubmed/fdaa147

Verity R, Okell LC, Dorigatti I, et al (2020) Estimates of the severity of coronavirus disease 2019: a model-based analysis. The Lancet Infectious Diseases 20:669–677. https://doi.org/10.1016/S1473-3099(20)30243-7

Warren M, Skillman S (2020) Mobility changes in response to COVID-19

Williams DR, Cooper LA (2020) COVID-19 and health equity—a new kind of "herd immunity." JAMA 323:2478–2480. https://doi.org/10.1001/jama.2020.8051

World Health Organization (2019) Non-pharmaceutical public health measures for mitigating the risk and impact of epidemic and pandemic influenza (2019)

Wu X, Nethery RC, Sabath MB, et al (2020) Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. Sci Adv 6:eabd4049. https://doi.org/10.1126/sciadv.abd4049

Yancy CW (2020) COVID-19 and African Americans. JAMA 323:1891–1892. https://doi.org/10.1001/jama.2020.6548

The Interplay of Policy, Behavior, and Socioeconomic Conditions in Early COVID-19 Epidemiology in Georgia (Supplementary Materials)

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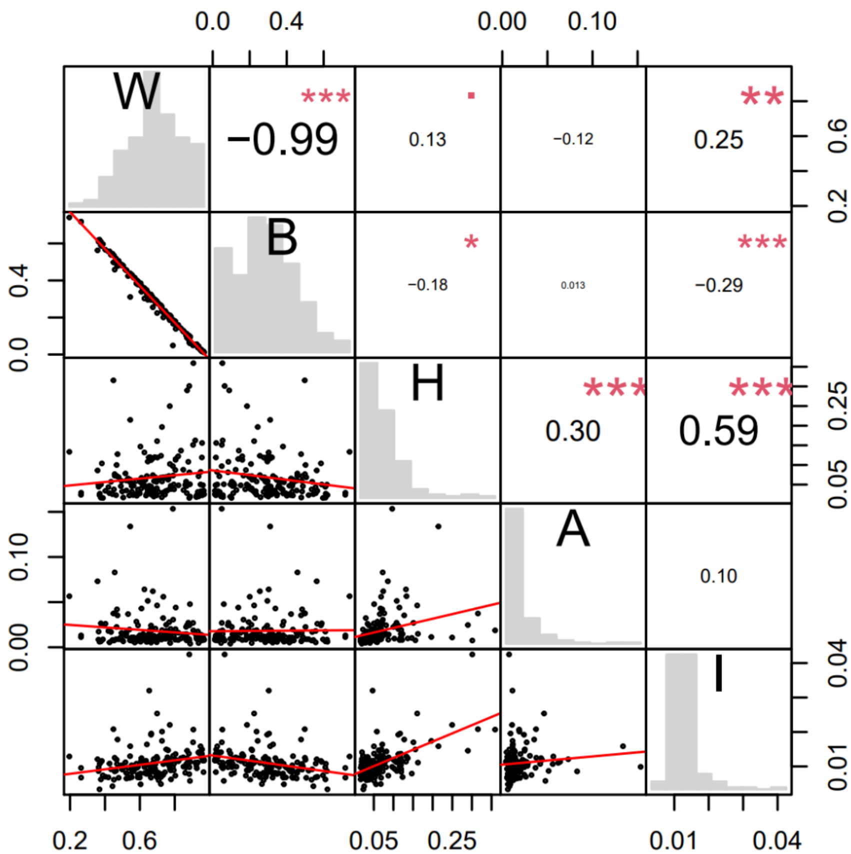
File S1: Evidence of correlations between racial and ethnic covariates to justify covariate selection.

In order to determine which racial and ethnic covariates to include in our models, we first identified highly correlated covariates. The proportions of the population that is White or Black in a given county were strongly correlated (r = -0.99). We choose to focus on the proportion of Black people in the population based on evidence of increased risk for COVID-19 infection and mortality resulting from health and economic disparities connected to racial discrimination (van Holm et al. 2020; Azar et al. 2020; Gray et al. 2020; Williams and Cooper 2020). The remaining three covariates (proportion of the population identifying as Asian, Hispanic or Latinx, or American Indian and Alaska Native) are not included in the best fitting models following model selection, meaning that they were not significant predictors of cases, deaths, or mobility at the county-level.



Supplemental Figure 1: Matrix of correlations between population proportions of census-reported race and ethnicity categories at the county level. Along the diagonal, histograms give the distribution of population proportions for the labeled racial and ethnic categories (W=White; B=Black or African American; H=Hispanic or Latinx; A=Asian; I=American Indian or Alaska Native). Below the diagonal, scatterplots are given of pairs of these variables across counties, with the red line indicating the relationship determined by linear regression. Reflected over the diagonal, correlation coefficients are displayed with font size proportional to magnitude. Statistical significance is denoted using asterisks (.: *P* <0.10; *: *P* <0.05; **: *P* <0.01; ***: *P* <0.001).

Table S1: Coefficients for demographic and epidemiological predictors of local nonpharmaceutical intervention public health orders.

The best fit model for each response variable is given across a row, and the effect size for each predictor is given with a 95% confidence interval in parentheses. Statistical significance is denoted using asterisks (*: P <0.05; **: P <0.01; ***: P <0.001) and progressively darker shading corresponding to the same thresholds. Nagelkerke Pseudo-R^2 values for each model are given in the second column. Predictors (from left to right) are: natural logarithm of population size (Population); median household income (Income); percent point difference of Republican and Democratic vote share in 2018 gubernatorial election (Partisanship); and date first case in county was reported (First Case).

		Demographic	**Socioeconomic**		**COVID-19**
	Pseudo-R^2	**Population**	**Income**	**Partisanship**	**First Case**
Social Distancing (all)	0.31	0.56 (0.11, 1.06)*		-0.74 (-1.24, -0.26)**	
Social Distancing (per capita deaths <2 per thousand)	0.26	0.64 (0.17, 1.17)*		-0.68 (-1.20, -0.19)**	
Social Distancing (per capita deaths <1 per thousand)	0.25	1.01 (0.29, 1.85)*	-0.62 (-1.53, 0.11)	-0.66 (-1.24, -0.09)*	
Shelter-in-Place (all)	0.54	1.08 (0.23, 2.05)*	-0.55 (-1.29 , 0.07)		-1.90 (-3.19, -0.78)**
Shelter-in-Place (per capita deaths <1 per thousand)	0.53	1.28 (0.36, 2.36)*	-0.46 (-1.18, 0.15)		-1.74 (-3.05, -0.59)**
Shelter-in-Place (per capita deaths <2 per thousand)	0.51	1.29 (0.37, 2.37)*	-0.56 (-1.34, 0.08)		-1.84 (-3.19, -0.67)**

Table S2: Event study results for impact of social distancing and shelter-in-place orders on mobility.

Fixed effects by policy day (β_p) with 95% confidence interval. Significance is denoted using asterisks (*: *P* <0.05; **: *P* <0.01; ***: *P* <0.001) and progressively darker shading corresponding to the same thresholds.

Policy Day	All Counties (Social Distancing)	All Counties (Shelter-in-Place)
1	-3.76 (-8.05, 0.53)	-3.03 (-7.05, 1.00)
2	-4.89 (-9.52, -0.24)*	-5.90 (-10.15, -1.65)**
3	-5.96 (-10.97, -0.94)*	-6.11 (-10.54, -1.68)**
4	-6.92 (-12.20, -1.64)*	-5.27 (-9.99, -0.55)*
5	-10.28 (-15.91, -4.65)***	-3.61 (-8.52, 1.30)
6	-11.86 (-17.88, -5.84)***	-0.97 (-6.06, 4.13)
7	-12.48 (-18.96, -6.00)***	-4.08 (-9.30, 1.14)
8	-13.73 (-20.67, -6.78)***	-5.88 (-11.53, -0.23)*
9	-14.97 (-22.62, -7.33)***	-2.35 (-8.22, 3.53)
10	-18.86 (-27.23, -10.49)***	-4.07 (-10.27, 2.13)

Table S3: Event study estimates of fixed effect of county on mobility.

The names of all counties are given along with their corresponding estimates of fixed effect on mobility. Fixed effects were estimated separately for the model of the effects of social distancing and shelter-in-place and both values are given. Blank spaces indicate counties for which no mobility data were provided.

County	Social distancing	Shelter-in-Place
Appling	NA	NA
Atkinson	10.13	10.9
Bacon	19.2	10.25
Baker	NA	NA
Baldwin	30.08	25.55
Banks	8.93	17.25
Barrow	-16.27	-10.55
Bartow	-13.77	-4.94
Ben Hill	2.93	8.5
Berrien	-7.17	-3.75
Bibb	-8.57	-8.4
Bleckley	-18.87	-17.2
Brantley	-15.52	-18.45
Brooks	-16.57	-12.15
Bryan	-18.72	-19.95
Bulloch	29.88	17.85
Burke	4.35	-3.35
Butts	-8.92	-1.75
Calhoun	NA	NA
Camden	-10.52	-12.3
Candler	-0.62	4.3
Carroll	-15.07	-9.41
Catoosa	-10.87	-6.2
Charlton	-17.52	-14.85
Chatham	-10.18	-19.7
Chattahoochee	NA	NA
Chattooga	-17.22	-6.75
Cherokee	-33.67	-28.11
Clarke	29.23	14.29
Clay	NA	NA
Clayton	-26.01	-34.41
Clinch	-0.62	8.65
Cobb	-30.33	-32.06
Coffee	9.83	13.45
Colquitt	-3.72	2.8
Columbia	-10.92	-9.95
Cook	-5.87	-3.8
Coweta	-16.22	-11.6
Crawford	-3.37	-7.75
Crisp	5.13	3.9
Dade	-10.47	-3.1
Dawson	-14.87	-9.15
Decatur	3.18	8.45
Dekalb	-39.46	-44.82
Dodge	1.58	4.8
Dooly	20.48	27.5
Dougherty	-21.97	-14.85
Douglas	-28.12	-22.48
Early	-19.97	-14.47
Echols	8.58	18.35
Effingham	-11.62	-10.5
Elbert	1.93	8.4
Emanuel	-3.02	-4.2
Evans	1.13	2.75
Fannin	-2.22	-3
Fayette	-25.77	-20.3
Floyd	-2.32	3.18
Forsyth	-28.92	-24.5

Franklin	6.58	11.75
Fulton	-25.4	-36.02
Gilmer	-3.67	1
Glascock	NA	NA
Glynn	-4.37	-4.2
Gordon	-1.37	9.3
Grady	-6.97	-6.25
Greene	-16.07	-7.25
Gwinnett	-31.53	-33.34
Habersham	-0.12	6.41
Hall	-11.42	-6
Hancock	NA	NA
Haralson	6.83	13.4
Harris	5.23	8.75
Hart	-5.87	-0.8
Heard	2.73	6.25
Henry	-20.83	-22.9
Houston	-12.02	-13.3
Irwin	13.68	14.9
Jackson	-14.92	-9
Jasper	-9.77	-5.55
Jeff Davis	4.13	7.1
Jefferson	-4.12	-5.6
Jenkins	1.08	-4.05
Johnson	-5.07	4.6
Jones	-3.67	0.6
Lamar	-16.87	-13.75
Lanier	-11.62	-10
Laurens	2.73	5.65
Lee	6.33	15.45
Liberty	-29.82	-29.3
Lincoln	-11.32	-10.35
Long	16.68	20.2
Lowndes	-6.22	-0.72
Lumpkin	12.23	13.5
Macon	-1.02	-3.9
Madison	-6.67	1.35
Marion	NA	NA
Mcduffie	-1.72	3.4
Mcintosh	0.58	-9.95
Meriwether	-25.77	-18.4
Miller	-9.77	-3.25
Mitchell	-16.32	-14.35
Monroe	-5.02	-1.3
Montgomery	NA	4.8
Morgan	-12.47	-5.35
Murray	-3.67	1.9
Muscogee	-18.32	-19.5
Newton	-21.62	-16.6
Oconee	-2.22	6.1
Oglethorpe	-8.72	-1.15
Paulding	-22.82	-15.3
Peach	-5.97	-5.15
Pickens	-15.72	-10.22
Pierce	4.98	7.25
Pike	5.03	10.4
Polk	-20.12	-11.39
Pulaski	-22.12	-16.4
Putnam	-9.27	-6.85
Quitman	NA	NA
Rabun	-10.22	-9.75
Randolph	NA	NA
Richmond	-15.97	-17.8
Rockdale	-36.17	-31.23
Schley	NA	NA
Screven	-9.42	-11.25

Seminole	-5.52	5.15
Spalding	-9.57	-4.07
Stephens	0.78	5.3
Stewart	NA	NA
Sumter	10.18	10.35
Talbot	-10.87	-11.45
Taliaferro	NA	NA
Tattnall	-20.87	-16.9
Taylor	-10.97	-10.65
Telfair	4.68	5.95
Terrell	-33.07	-26.75
Thomas	-0.97	2.7
Tift	8.33	11.98
Toombs	12.88	16
Towns	0.58	-6.6
Treutlen	-2.22	5
Troup	0.73	4.2
Turner	14.58	12.65
Twiggs	NA	NA
Union	-1.12	0.05
Upson	-4.92	-0.6
Walker	-10.02	-5.05
Walton	-14.32	-8.25
Ware	-0.02	3.4
Warren	NA	NA
Washington	4.78	8.8
Wayne	1.53	2.95
Webster	NA	NA
Wheeler	NA	NA
White	-7.37	-3.25
Whitfield	-0.52	6.25
Wilcox	-0.97	-5.85
Wilkes	-5.12	-7
Wilkinson	12.33	13.85
Worth	-24.77	-20.25

Table S4: Event study estimates of fixed effect of date on mobility.

Fixed effects were estimated separately for the model of the effects of social distancing and shelter-in-place and both values are given. Blank spaces indicate dates that were not included in the given model (i.e., no county was within a ten-day time window of the public health order's introduction).

Date	Social distancing	Shelter-in-Place
3/1/2020		
3/2/2020		
3/3/2020		
3/4/2020		
3/5/2020		
3/6/2020		
3/7/2020	4.21	
3/8/2020	-41.14	-28
3/9/2020	-10.21	-15
3/10/2020	-11.31	-10.66
3/11/2020	-6.81	-4.16
3/12/2020	-6.98	-3.66
3/13/2020	-2.16	0.84
3/14/2020	-36.36	-56.14
3/15/2020	-63.11	-87.48
3/16/2020	-37.2	-62
3/17/2020	-46.89	-73.61
3/18/2020	-51.41	-78.91
3/19/2020	-45.3	-73.71
3/20/2020	-42.01	-66.12
3/21/2020	-72.62	-95.92
3/22/2020	-96.53	-121.89
3/23/2020	-69.11	-100.83
3/24/2020	-68.69	-97.48
3/25/2020	-62.91	-92.65
3/26/2020	-61.57	-92.36
3/27/2020	-53.61	-85.28
3/28/2020	-72.52	-107.31
3/29/2020	-86.83	-123.63
3/30/2020	-61.49	-98.92
3/31/2020	-65.73	-104.18
4/1/2020	-56.07	-96.38
4/2/2020	-45.08	-88.81
4/3/2020		-94.38
4/4/2020		-125.11
4/5/2020		-133.8
4/6/2020		-104.01
4/7/2020		-105.55

Table S5: Coefficients for socioeconomic predictors of mobility.

The best fit model for each response variable is given across a row, and the effect size for each predictor is given with a 95% confidence interval. R^2 values for each model are given in the second column. Significance is denoted using asterisks (*: *P* <0.05; **: *P* <0.01; ***: *P* <0.001) and progressively darker shading corresponding to the same thresholds. Predictors (from left to right) are aged-weighted infection fatality rates (Age); percent of population that is Black (Race); and median household income (Income).

		Demographic		**Socioeconomic**
	R^2	**Age**	**Race**	**Income**
Final Mobility (all counties)	0.11	-0.36 (-0.53, -0.20)***	-0.22 (-0.39, -0.05)*	-0.22 (-0.39, -0.04)*
Final Mobility (per capita deaths <2 per thousand)	0.11	-0.34 (-0.51, -0.17)***	-0.19 (-0.37, -0.02)*	-0.24 (-0.39, -0.03)*
Final Mobility (per capita deaths <1 per thousand)	0.13	-0.34 (-0.51, -0.17)***	-0.17 (-0.36, 0.01)	-0.23 (-0.41, -0.04)*

Table S6: Coefficients for socioeconomic, health, and legislative predictors of early epidemiological outcomes.

The best fit model for each response variable is given across a row, and the effect size for each predictor is given with a 95% confidence interval. Significance is denoted using asterisks (*: P <0.05; **: P <0.01; ***: P <0.001) and progressively darker shading corresponding to the same thresholds. Nagelkerke Pseudo-R^2 values for each model are given in the second column in bold. Predictors (from left to right) are aged-weighted infection fatality rates (Age); percent of population that is Black (Race); natural logarithm of population size (Pop.); age-adjusted emergency room visit rate for asthma (Asthma); prevalence of diabetes in adults (Diab.); coronary heart disease-related hospitalization rate (C.H.D.); annual average ambient PM2.5 concentration (Poll.); percent of population with a high school degree (Edu.); proportion of population living in poverty (Poverty); unemployment rate (Unemp.); average normalized daily mobility in the final week of April (Mob.); date first case in county was detected (F.C .).

		Demographic			**Health**			**Socioeconomic**				**Behavior**	**COVID-19**
	Pseudo-R^2	**Age**	**Race**	**Pop.**	**Asthma**	**Diab.**	**C.H.D.**	**Poll.**	**Edu.**	**Poverty**	**Unemp.**	**Mob.**	**F.C**
Cases (all counties)	0.73	0.16 (-0.01, 0.33) *		0.81 (0.62, 1.00) ***			-0.23 (-0.35, -0.11) ***	0.24 (0.10, 0.38) ***		0.37 (0.24, 0.50) ***			-0.22 (-0.39, -0.05) **
Cases (per capita deaths <2 per thousand)	0.68	0.16 (-0.01, 0.32) *		1.00 (0.83, 1.18) ***		0.10 (-0.01, 0.22)	-0.20 (-0.32, -0.08) **	0.25 (0.11, 0.38) ***		0.32 (0.20, 0.45) ***			
Cases (per capita deaths <1 per thousand)	0.67	0.23 (0.85, 0.37) **	0.20 (0.04, 0.35) **	0.89 (0.75, 1.04) ***		0.14 (0.03, 0.25) *		0.16 (0.03, 0.30) **			-0.13 (-0.28, 0.03)	0.11 (0.00, 0.22) *	
Deaths (all counties)	0.53			0.62 (0.34, 0.91) ***	0.17 (-0.05, 0.40)		-0.25 (-0.42, -0.07) *	0.27 (0.06, 0.48) **	-0.23 (-0.50, 0.03)	0.32 (0.05, 0.60) *			-0.43 (-0.71, -0.18) ***
Deaths (per capita deaths <2 per thousand)	0.48			0.75 (0.45, 1.05) ***			-0.23 (-0.41, -0.05) *	0.30 (0.09, 0.51) **	-0.22 (-0.49, 0.05)	0.40 (0.17, 0.63) ***			-0.34 (-0.63, -0.05) *
Deaths (per capita deaths <1 per thousand)	0.49			0.72 (0.46, 0.99) ***	0.24 (0.04, 0.44) *			0.29 (0.09, 0.49) **	-0.24 (-0.46, -0.03) *		-0.18 (-0.43, 0.06)	0.19 (0.02, 0.37) *	-0.20 (-0.46, 0.06)

Table S7: Data dictionary. Names of all predictors and response variables referenced in the texts, along with detailed descriptions of the variable.

Name	Description
Age	aged-weighted infection fatality rates; predictor
Race	percent of population that is Black; predictor
Population (Pop.)	natural log of population size; predictor
Asthma	age-adjusted emergency room visit rate for asthma per 100,000 people; predictor
Diabetes (Diab.)	prevalence of diabetes in adults; predictor
Coronary Heart Disease (C.H.D.)	Coronary heart disease-related hospitalization rate per 1,000 Medicare beneficiaries over age 65+; predictor
Pollution (Poll.)	annual average ambient PM2.5 concentration; predictor
Education (Edu.)	percent of population with a high school degree; predictor
Income	median household income (thousands of dollars); predictor
Partisanship	percent point difference of Republican and Democratic vote share in 2018 gubernatorial election; predictor
Poverty	Percent of population living in poverty; predictor
Unemployment (Unemp.)	unemployment rate; predictor
First Case (F.C.)	date first case in county was reported; predictor
Social Distancing	binary whether policies were introduced at either the county level prior to the statewide order to encourage social distancing in the general population (e.g., ban on gatherings at non-essential businesses, restrictions on gathering sizes, closure of public use areas); binary response variable for analysis 1
Shelter-in-Place	whether a shelter-in-place order was introduced at the county level prior to the statewide order; binary response variable for analysis 1
Mobility (Mob.)	average daily mobility (defined as the median radius of movement across devices in a county) in the final week of April as a proportion of a pre-pandemic baseline between February 17th and March 17th, 2020; continuous response variable for analysis 3 and predictor for analysis 4
Cases	Cumulative COVID-19 cases reported within four weeks of a county's first reported case; discrete response variable for analysis 4
Deaths	Cumulative COVID-19 deaths reported within six weeks of a county's first reported case; discrete response variable for analysis 4

REFERENCES

Gray DM, Anyane-Yeboa A, Balzora S, Issaka RB, May FP. COVID-19 and the other pandemic: populations made vulnerable by systemic inequity. *Nature Reviews Gastroenterology & Hepatology* 2020: 1–3.

Williams DR, Cooper LA. COVID-19 and health equity—a new kind of "herd immunity". *JAMA* 2020; **323**: 2478–80.

van Holm EJ, Wyczalkowski CK, Dantzler PA. Neighborhood conditions and the initial outbreak of COVID-19: the case of Louisiana. *Journal of Public Health* 2020; : 1–6.

Azar KMJ, Shen Z, Romanelli RJ, *et al.* Disparities in outcomes among COVID-19 patients in a large health care system in California. *Health Affairs* 2020; **39**: 1253–62.