County-Level Sociodemographic Factors Associated with COVID-19 Incidence and Mortality in North and South Carolina

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BACKGROUND There is limited research regarding associations between county-level factors and COVID-19 incidence and mortality. While the Carolinas are geographically connected, they are not homogeneous, with statewide political and intra-state socioeconomic differences leading to heterogeneous spread between and within states.

METHODS Infection and mortality data from Johns Hopkins University during the 7 months since the first reported case in the Carolinas was combined with county-level socioeconomic/demographic factors. Time series imputations were performed whenever county-level reported infections were implausible. Multivariate Poisson regression models were fitted to extract incidence (infection and mortality) rate ratios by county-level factor. State-level differences in filtered trends were also calculated. Geospatial maps and Kaplan-Meier curves were constructed stratifying by median county-level factor. Differences between North and South Carolina were identified.

RESULTS Incidence and mortality rates were lower in North Carolina than South Carolina. Statistically significant higher incidence and mortality rates were associated with counties in both states with higher proportions of Black/African American populations and those without health insurance aged < 65 years. Counties with larger populations aged ≥ 75 years were associated with increased mortality (but decreased incidence) rates.

LIMITATIONS COVID-19 data contained multiple inconsistencies, so imputation was needed, and covariate-based data was not synchronous and potentially insufficient in granularity given the epidemiology of the disease. County-level analyses imply within-county homogeneity, an assumption increasingly breached by larger counties.

CONCLUSION While statewide interventions were initially implemented, inter-county racial/ethnic and socioeconomic variability points to the need for more heterogeneous interventions, including policies, as populations within particular counties may be at higher risk.

North Carolina reported its first COVID-19 infection on March 2, 2020 [1]. The state-level stay-at-home order went into effect on March 30 and was scheduled to last for 30 days [2]. Gatherings were limited to 10 people, and residents were instructed to stay at home and follow social distancing guidelines, such as leaving their residence only for health/provisioning purposes. Exceptions were provided to essential workers in health care, food production, distribution, and sales, as well as utility operations and maintenance.

South Carolina reported its first COVID-19 infection on March 6, 2020 [3]. A statewide executive order was issued on March 31 to close nonessential services where individuals could not remain socially distanced [4]. On April 6, the governor passed the Work or Home Order. Similar to the North Carolina mandate, South Carolina residents were asked to stay in their homes except for essential activities until April 30 [5].

Despite these early mandates, COVID-19 infections and deaths continued to increase throughout the Carolinas [6, 7], as well as nationally and globally [8], notwithstanding US recommendations [9, 10] and lockdowns worldwide [11]. Researchers began investigating factors contributing to the spread and mortality of COVID-19. A small number of county-level (mostly univariate) analyses have been conducted, providing preliminary insight into factors contributing to incidence and mortality.

Population density [12] and size [13–15] have been found to be positively associated with COVID-19 incidence and mortality, though with racial/ethnic differences. Higher rates of infections have been found among residents of counties with higher percentages of Black/African American [13–15] or Hispanic populations [13, 15], though with mixed mortality results [12, 13, 16]. However, the univariate nature of some analyses and differing definitions of minority populations make it difficult to draw generalizable conclusions.

There is limited literature investigating associations between county-level differences in disabled population

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rates with heterogeneous disability definitions and infections/deaths [13, 16]. Studies offer diverging results relating income [13, 15] and poverty [12, 13, 16] with incidence/mortality. However, studies did not account for confounders. Percentage rurality has been associated with significant decreases in infections [14]; though, this was in initial stages of the pandemic before rural infection was widespread. Another study assessed associations between the proportion of the state's population in rural areas and its vulnerability to COVID-19 [17]. Among 9 southeastern states, North Carolina showed the second-highest vulnerability, while South Carolina showed the least vulnerability, with similar percentages living in rural areas in both states.

There is a gap in the literature, or research is scarce, regarding associations of infections and deaths with county-level factors such as: 1) unemployment rates [16]; 2) percent uninsured, which has been found non-significant [12]; 3) those aged > 75 years, as previous studies found higher mortality rates but focused on broader definitions of elderly, namely ≥ 60 [15] and ≥ 65 [12] years; or 4) percent employed as essential workers in areas such as manufacturing, education, and social assistance, which are more exposed during the pandemic, and which have been found non-significantly associated with infection rates [15].

National-level studies may suffer from assumptions of inter-state homogeneity. To our knowledge, no study has been conducted exploring associations of county-level characteristics with COVID-19 outcomes within the geographical scope of the Carolinas. We believe that county-level information, some of which has been neglected or analyzed in univariate or purely descriptive approaches in prior studies, could be used to define county-level policies. This could provide policy makers with an additional angle from which to inform decisions and efforts to reduce the disparate impact of pandemics, with county-specific policies in addition to statewide all-encompassing policies.

In this study, we explored these associations during the first 7 months of the pandemic in an effort to identify North Carolina- and South Carolina-specific county-level characteristics associated with increased county-level risks for COVID-19 infection and death. This approach allows for policy and resource differentiation—including health care prevention and management services—and messaging to be targeted toward and heightened within these communities.

Methods

Data and Imputation

Confirmed infections and deaths, representing study outcomes, for all 100 North Carolina and 46 South Carolina counties were retrieved from the publicly available Johns Hopkins University (JHU) Center for Systems Science and Engineering (CSSE) COVID-19 Data Repository [18, 19]. Outcome data were transformed from cumulative form to daily reported infections. County-level population characteristics for North Carolina and South Carolina, representing covariates of interest, were extracted from the 2018–2019 Area Health Resources File (AHRF) provided by the US Health Resources and Services Administration [20]. County-level factors included population estimate; population density; per capita personal income; unemployment rate; and proportion of the population who were: living in rural areas; Black/African American; Hispanic/Latino; disabled aged 18–64; disabled aged ≥ 65 years; aged ≥ 75 years; without health insurance aged < 65; in poverty; employed in education/health care/social assistance; and employed in manufacturing (the latter 2 representing essential workers). Age ranges were collapsed to more closely approximate ranges used by the CDC to evaluate COVID-19 data [21]. All covariate information was complete for all 146 counties. Two covariates were dropped due to high collinearity: population estimate ($r = 0.89$ with population density) and disabled aged 18–64 ($r = 0.68$ with disabled and ≥ 65 years).

The study period was narrowed to the first 7 months involving cases within the Carolinas, from March 1 to September 30, 2020. However, observations for September 30 were largely and widely inaccurate (representing 90% drops in cases and deaths), so that day was removed.

Imputation was performed when the following were identified: 1) daily drops in cumulative cases or deaths; or 2) daily changes > 3 times larger than the highest daily change in the surrounding 14 days of the sample for a given county (whenever cases were observed within that period). The 14-day symmetric window was selected to account for weekly seasonals, and the window was nonsymmetric on the first and last sample weeks. Additional data errors were identified on 2 days for low-count Buncombe and Carteret counties (North Carolina). Values were imputed using weighted moving averages within the imputeTS package in R [22].

Analysis

Descriptive statistics were calculated for county-level characteristics and COVID-19 infection and mortality rates by state. Kaplan-Meier curves were produced to display differences in estimated survival probabilities over the study period, grouped by cross-county median covariate level. Time series rate trends were extracted upon removing seasonal and noise components using an additive filter [23]. Trends were calculated for visualization purposes only in figures and not as part of statistical analyses. Geospatial maps of daily incidence and mortality rates were explored by state, and further stratified by county-level factor, splitting the data by population-adjusted median.

Multivariate Poisson rate regression analyses, offset by county population size and adjusted by all covariates, were performed to identify county-level factors associated with differences in incidence and mortality rates for both North Carolina and South Carolina at the end of the study period. Incidence rate ratios, corresponding 95% confidence intervals (CIs), and *P*-values were calculated for each covariate. Figures only contain some examples, due to space limitation, that demonstrate disparities in outcomes across certain factors. RStudio v4.0.2 was used for analysis.

Results

Imputation was performed on 254 (0.41%) observations from 62,196 (213 days*146 counties*2 outcomes) times in the sample, with a majority (210; 0.34%) corresponding to drops in reported cumulative cases or deaths. Table 1 summarizes county-level factors, and incidence and mortality rates, across counties by state. By the study period's end, North Carolina and South Carolina had experienced 209,712 and 146,872 confirmed COVID-19 infections and 3478 and 3434 deaths, respectively, corresponding to infection rates of 20.2 and 28.9 per thousand, respectively, and mortality rates of 33.5 and 67.5 per 100,000, respectively (Table 1).

Figure 1 portrays de-seasonalized, de-noised incidence and mortality rate time series and cumulative infection maps. A steep increase in infection rates was observed in South Carolina beginning in mid-May, peaking around the second week of July, followed by a sharp decline until mid-August. North Carolina was proportionately impacted but to a lesser degree. Trends in deaths experienced a sharp rise in late June in South Carolina, peaking in mid-July, followed by general declines toward the end of the study period. The peaks for (trendline) rates of daily infections and deaths in North Carolina occurred at approximately the same times, but were 50% smaller relative to those observed in South Carolina. Infection and mortality maps illustrate rate heterogeneity within and between states.

Figure 2 illustrates daily infection and mortality rates, clustered by above versus below population-adjusted, cross-county-median percentage of Black/African American populations, and sub-grouped by state. Trendlines for North Carolina and South Carolina show that daily infection and mortality rates were consistently higher for counties with larger Black/African American populations. Large interstate differences were observed in infection and mortality rates, where South Carolina experienced not only larger rates when compared to North Carolina, but also larger intrastate differences between the aforementioned clusters.

Kaplan-Meier survival curves (corresponding 95% CIs) for the risk of infection and death across counties in North Carolina and South Carolina, clustered by each state's median percent of the population who are Black/African American, are presented in Figure 3. Cumulative infection probabilities were 1.78% throughout North Carolina counties with below-median Black/African American population rates, and 2.19% for counties with above-median rates. Infection rates were higher for South Carolina, at 2.75% and 3.49%, respectively. Differences were exacerbated for mortality rates.

Adjusted incidence rate ratios, corresponding 95% CIs, *P*-values, and concordance (c-) statistics are presented by state in Table 2, which contains the full list of covariates

TABLE 1.
Observed Incidence and Mortality Rates and Descriptive Statistics of County-Level Characteristics Averaged Across Counties and Presented by State

Outcomes (March 1 to September 29, 2020)	**North Carolina**	**South Carolina**
Incidence rate (per 1,000)	20.2	28.9
Mortality rate (per 100,000)	33.5	67.5
County-level factors (2018-19 AHRF)	**Mean (SD)**	**Mean (SD)**
Estimated population	103,836.2 (167,467.6)	110,524.5 (125,427.7)
Population density (per square mile)	195.5 (260.4)	141.1 (132.5)
Race (% of the population)		
White	71.5 (17.7)	58.9 (15.7)
Black/African American	20.6 (16.6)	36.2 (16.6)
American Indian/Alaska Native	1.6 (4.9)	0.5 (0.7)
Asian	1.0 (1.1)	0.8 (0.6)
Native Hawaiian/Other Pacific Islander	0.0 (0.1)	0.0 (0.1)
Other Race	5.2 (2.7)	3.6 (2.1)
Hispanic/Latino population (%)	6.5 (3.8)	4.2 (4.2)
Disabled population aged 18–64 years (%)	14.4 (3.4)	15.3 (3.8)
Disabled population, ≥ 65 years (%)	39.3 (5.8)	39.5(5.6)
People living in poverty (%)	17.1 (4.7)	19.3 (5.8)
Population aged ≥ 75 years (%)	6.7 (1.8)	6.0 (0.99)
Without health insurance aged < 65 years (%)	10.6 (1.6)	10.4 (1.5)
Employed in education, health care, or social assistance (%)	23.8 (4)	21.7 (3.2)
Employed in manufacturing (%)	14.2 (6.1)	16.9 (6.2)
Rural area (%)	61.2 (28.2)	55.0 (24.1)
Unemployment rate (%)	4.3 (1)	4.0 (1)
Per capita personal income (dollars)	38,618.8 (6,530.8)	36,702.0 (6,397.6)

AHRF: Area Health Resources File; According to the data documentation, these factors were collected from 2010–2018.

used in the multivariate Poisson rate regression model. Significant county-level factors associated with increased infections in North Carolina and South Carolina include (P-values ≤ .0209): population density; living in rural areas; Black/African American populations; Hispanics/Latino populations; those without health insurance aged < 65 years; living in poverty; per capita personal income; and employed in essential work areas of education/health care/social assistance. Taking North Carolina infection results as an example (Table 2), the IRR of 1.0573 (95% CI: 1.0513–1.0634; P < .0001) indicates that a 1% increase in a county's population of persons without health insurance aged < 65 years is significantly associated with a 5.73% increase in reported COVID-19 infections in that county.

Counties' percentages of Black/African American populations (North Carolina: P < .0001, South Carolina: P < .0001), aged ≥ 75 years (North Carolina: P < .0001, South Carolina: P = .0165), and uninsured aged < 65 years (North Carolina: P = .0007, South Carolina: P < .0001) were significantly associated with increased mortality rates within both states. For each percentage increase in a county's population without health insurance aged < 65 years, there were associated 7.87% (95% CI: 1.0325–1.1269) and 18.60% (95% CI: 1.1293–1.2456) increases in mortality rates in North Carolina and South Carolina, respectively. Similarly, for each percentage increase in a county's population aged ≥ 75 years, there were associated 7.83% (95% CI: 1.0490–1.1085) and 8.91% (95% CI: 1.0157–1.1677) increases in mortality rates in North Carolina and South Carolina, respectively. Upon accounting for other county-level factors, poverty was associated with a decreased mortality rate in both states (North Carolina: P = .0025, South Carolina: P = .0005). Differences in factor associations' significance by state were found for 5 covariates (population density, rural, Hispanic/Latino, employed in education/health care/social assistance, and employed in manufacturing), with only 1 case where directionality of the estimate was different. Non-significant associations with mortality within both states were found with disabled aged ≥ 65 years, unemployment rate, and per capita personal income, upon accounting for all other factors.

Discussion

This study's results correspond to data available to policy makers at the end of September 2020, with the natural lag between actual infection occurrence and test result reporting that accompanied the pandemic, the latter of which is

FIGURE 1.
COVID-19 Daily Reported Infection (Top Left) and Mortality (Bottom Left) Rates Across Counties by State, and Maps for Population-Adjusted Reported Cumulative Infections (Top Right) and Deaths (Bottom Right) by State, March 1 to September 29, 2020

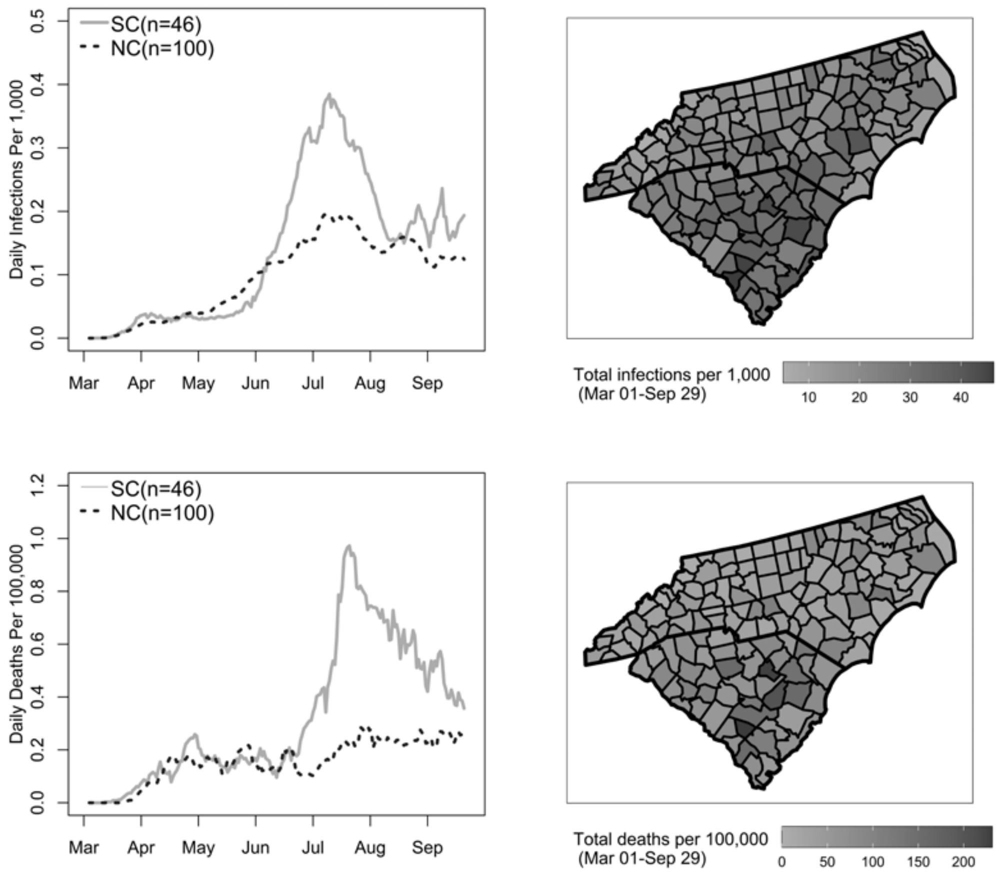
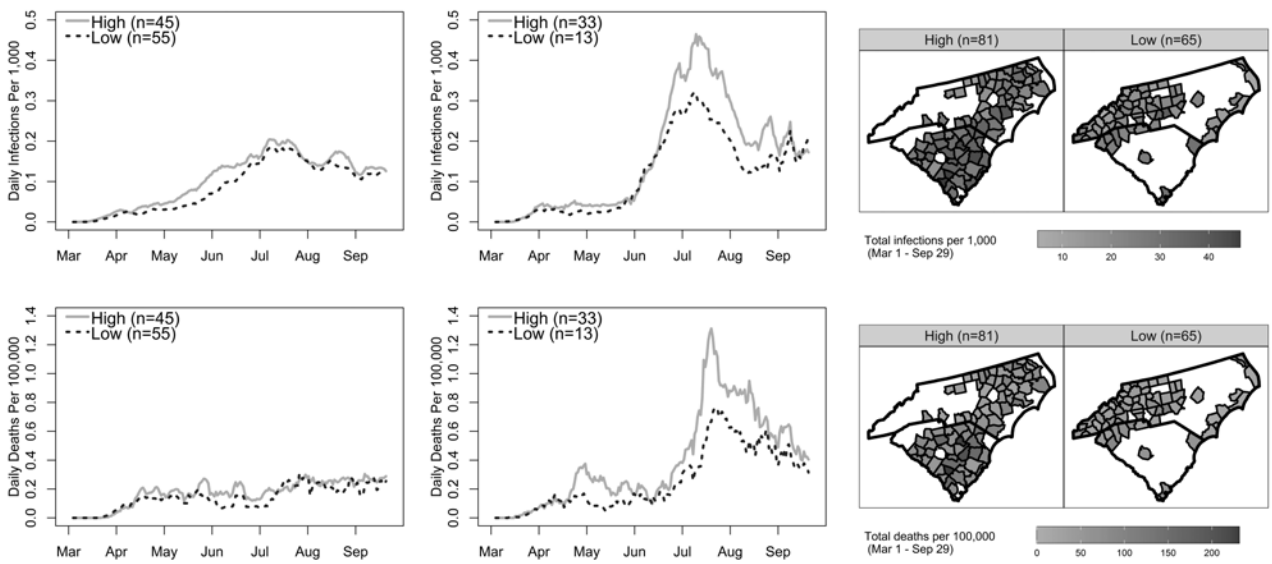


FIGURE 2.
COVID-19 Daily Trendlines of Reported Infection Rates for NC (Top Left) and SC (Top Center), and Mortality Rates for NC (Bottom Left) and SC (Bottom Center), as well as Maps for Reported Cumulative Infections (Top Right) and Deaths (Bottom Right) by State, March 1 to September 29, Clustered by At Least (Labeled as 'High') versus Below (Labeled as 'Low') the Median Percentage of Black/African American Populations Across All Counties within the State



represented in this study. While new information continues to be available, this study's analyses constitute a snapshot of what policy makers knew at the time, including challenges with data accuracy and completeness, and how county-level information could provide timely additional perspectives of the disparate effect of COVID-19 on certain populations.

While some associations between county-level characteristics and COVID-19 incidence and mortality rates are similar between North Carolina and South Carolina, state differences were identified in spread and severity of disease. Trendlines of daily incidence and mortality rates for North Carolina were lower than those of South Carolina during most of the study period, demonstrating that state-level differences were consistently substantial despite the geographical proximity and synchronicity of initial stay-at-home orders. According to AHRF data, South Carolina's Black/African American and poverty populations are 36.2% and 19.3%, compared with North Carolina's 20.6% and 17.1%, respectively. These demographic differences are associated with variations by state. Additionally, wide policy differences were observed throughout the pandemic between the 2 neighboring states, such as differences in mask mandates, which support the findings of inter-state differences despite the geographical proximity.

Our study is the first, to our knowledge, demonstrating significant positive associations in North Carolina and South Carolina between county-level percentages of Black/African American populations and COVID-19 mortality rates, upon accounting for other factors. We found positive associations between county-level Hispanic population percentages and COVID-19 deaths, though only significant for South Carolina. Highly significant increases in incidence and mortality rates were associated with increases in proportions of aged < 65 years without health insurance in both states, which may be due to decreased general preventive care and care maintenance of possible underlying conditions, and a delay in seeking medical care once COVID-19 symptoms presented. We also found significantly positive associations between essential workers and incidence (North Carolina and South Carolina) and mortality (South Carolina). Counties with larger proportions of essential workers, which in highly exposed professions such as nursing or food supply may be disproportionately composed of minority and/or lower-income populations, may also exceedingly suffer versus counties dominated by sectors that allow for more efficient social distancing and/or work from home. Furthermore, employees in highly exposed professions often receive hourly/minimum wages and have part-time jobs in which health insurance is seldom available.

We found a significant positive association in North Carolina (though non-significant in South Carolina) between percentage disabled ≥ 65 years and COVID-19 incidence. No significant evidence was found for mortality. The percentage of the county's population living in rural areas is associated with significant increases in COVID-19 incidence (North Carolina and South Carolina) and mortality (South Carolina only).

Increases in the percentage of those living in poverty are associated, upon accounting for other factors, with significant decreases in mortality. There was considerable multicollinearity between poverty and Black/African American percentages ($r = 0.7$), demonstrating that these variables contain similar information; however, since both of these demographics are central to issues surrounding social justice, we believed it was important to include both. Our analysis also showed that increases in income are associated with significant increases in incidence and non-significant decreases in mortality, upon adjusting for confounders. This is in contrast to other studies [13, 15], though those were univariate and/or used median household income, which does not account for household size and may experience differences by income bracket.

Larger proportions of elderly (defined as ≥ 75) were negatively associated with infection, but positively associated with mortality. This may indicate that these more vulnerable populations were more effective at socially distancing compared to other populations; though, mortality numbers still reflect age-driven differences in prognosis. These better incidence numbers may be due to geospatial differences, with large rural populations and relatively sparse urban settings.

While policies may be designed at the state level and recommendations may be issued for vulnerable populations, county-specific differences reflect the need for county-driven messaging policies and support for higher-risk counties. County-level heterogeneity of infection/mortality rates or underlying anticipated needs may be hidden within statewide metrics. Additionally, statewide numbers do not provide the granularity needed for resource allocations. While some counties may show low infection rates, others may suffer from high rates and overstretched health care facilities. Intra-state allocation of resources based on anticipated demand and supply of health care needs due to county-level differences is essential. This is especially relevant when excess demand of health care resources potentially meets undersupply within impoverished or under-resourced counties. Upon discovering how the pandemic spreads, policies can be implemented to overweigh support for counties most at risk due to prevalence of underlying risk factors.

Strengths and Limitations

A strength of this study is the use of county-level data for COVID-19 infections, deaths, and sociodemographic/

FIGURE 3.
Kaplan-Meier Survival Curves (and Corresponding 95% CIs) for Risk of COVID-19 Infection (Top Panel) and Death (Bottom Panel) Across NC (Left) and SC (Right) Counties, Clustered by Counties 'Below' Versus 'At Least' the Corresponding State's Median Percentage of the Population Who Are Black/African American over the 7-Month Study Period, March 1 to September 29, 2020

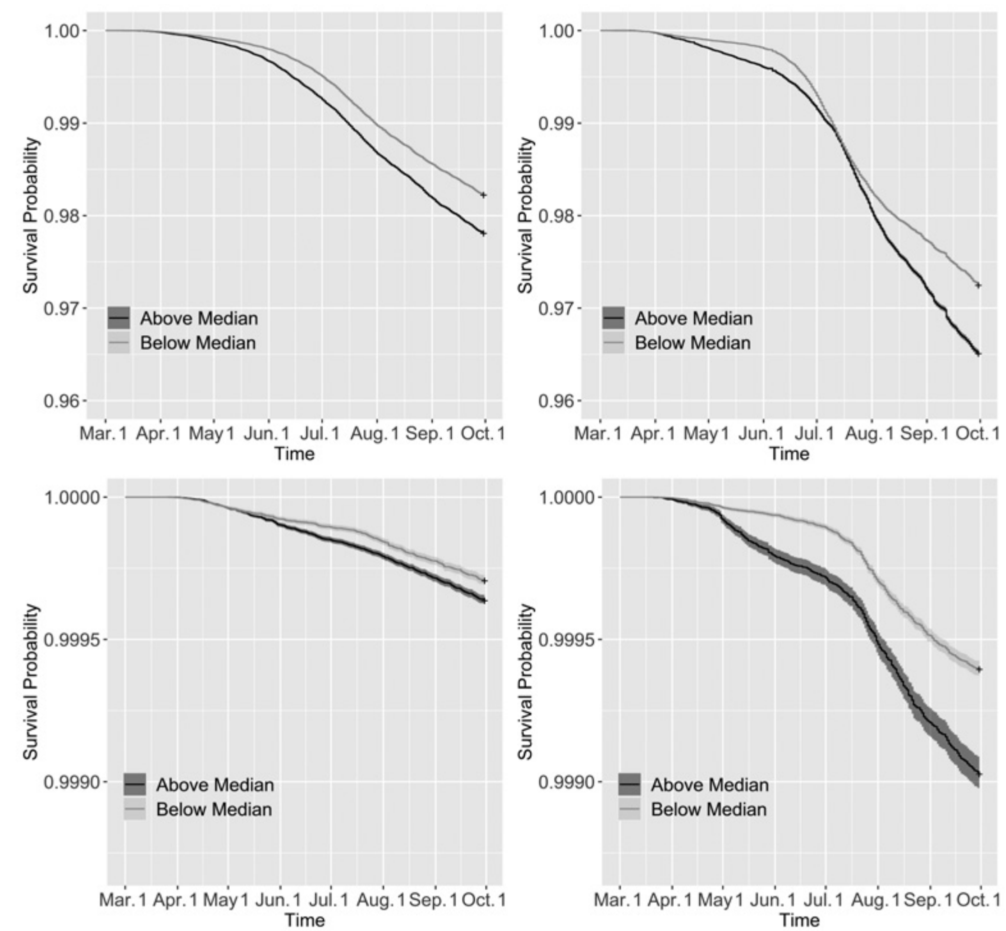


TABLE 2.
Multivariate Poisson Regression Results of COVID-19 Infections (Top) and Deaths (Bottom) Across North Carolina and South Carolina Counties

	North Carolina			South Carolina		
Covariate	**IRR**	**95% CI**	**P-value**	**IRR**	**95% CI**	**P-value**
Infections						
Intercept	0.0025	0.0022 – 0.0029	< .0001	0.0038	0.0032 – 0.0045	< .0001
Population density (per square mile)	1.0002	1.0002 – 1.0002	< .0001	1.0002	1.0002 – 1.0003	< .0001
Living in rural area (%)	1.0013	1.0009 – 1.0016	< .0001	1.0008	1.0001 – 1.0015	.0209
Black/African American (%)	1.0058	1.0051 – 1.0065	< .0001	1.0066	1.0055 – 1.0076	< .0001
Hispanic/Latino (%)	1.0152	1.0131 – 1.0174	< .0001	1.0092	1.0048 – 1.0136	< .0001
Disabled, ≥ 65 years old (%)	1.0083	1.0067 – 1.0100	< .0001	1.0024	0.9995 – 1.0053	.1107
Age ≥ 75 years old (%)	0.9869	0.9831 – 0.9906	< .0001	0.9798	0.9686 – 0.9911	.0005
No health insurance, < 65 years old (%)	1.0573	1.0513 – 1.0634	< .0001	1.0513	1.0435 – 1.0592	< .0001
Poverty (%)	1.0107	1.0082 – 1.0133	< .0001	1.0132	1.0091 – 1.0173	< .0001
Per capita personal income (thousands of dollars)	1.0064	1.0051 – 1.0077	< .0001	1.0113	1.0096 – 1.0130	< .0001
Employed in education/ health care/social assistance (%)	1.0083	1.0067 – 1.0100	< .0001	1.0225	1.0192 – 1.0258	< .0001
Employed in manufacturing (%)	1.0203	1.0191 – 1.0215	< .0001	0.9898	0.9884 – 0.9912	< .0001
Unemployment rate, aged ≥ 16 years	0.9935	0.9828 – 1.0043	.2373	1.0593	1.0409 – 1.0779	< .0001
Concordance (c-statistic)	0.9351	0.9185 – 0.9517		0.9430	0.9156 – 0.9704	
Deaths						
Intercept	0.0000	0.0000 – 0.0001	< .0001	0.0000	0.0000 – 0.0001	< .0001
Population density (per square mile)	1.0000	0.9998 – 1.0002	.8242	1.0007	1.0002 – 1.0012	.0049
Living in rural area (%)	1.0021	0.9995 – 1.0047	.1152	1.0087	1.0046 – 1.0129	< .0001
Black/African American (%)	1.0201	1.0152 – 1.0251	< .0001	1.0245	1.0180 – 1.0310	< .0001
Hispanic/Latino (%)	1.0051	0.9890 – 1.0215	.5365	0.9556	0.9290 – 0.9830	.0016
Disabled, aged ≥ 65 years (%)	1.0044	0.9921 – 1.0169	.4864	1.0004	0.9829 – 1.0181	.9674
Aged ≥ 75 years (%)	1.0783	1.0490 – 1.1085	< .0001	1.0891	1.0157 – 1.1677	.0165
No health insurance, aged < 65 years (%)	1.0787	1.0325 – 1.1269	.0007	1.1860	1.1293 – 1.2456	< .0001
Poverty (%)	0.9718	0.9540 – 0.9900	.0025	0.9585	0.9358 – 0.9818	.0005
Per capita personal income (thousands of dollars)	0.9958	0.9859 – 1.0058	.4105	0.9933	0.9827 – 1.0040	.2210
Employed in education/ health care/social assistance (%)	1.0105	0.9980 – 1.0231	.1006	1.0527	1.0333 – 1.0724	< .0001
Employed in manufacturing (%)	1.0271	1.0181 – 1.0362	<.0001	1.0041	0.9953 – 1.0130	.3571
Unemployment rate, aged ≥ 16 years	1.0310	0.9540 – 1.1142	.4408	0.9570	0.8682 – 1.0549	.3767
Concordance (c-statistic)	0.8584	0.8280 – 0.8888		0.9005	0.8612 – 0.9398	

Note. Incidence rate ratios (IRR) adjusted for all covariates, corresponding 95% confidence intervals, and P-values are reported.

economic characteristics, while providing a regionally focused analysis. To our knowledge, this is the first study to assess associations between the aforementioned factors and COVID-19 outcomes across the Carolinas, as well as the first to include some key covariates such as essential worker employment or uninsured. The approach undertaken in this study is multivariate, leading to more thorough assessments of associations between county-level factors and outcomes. However, while covariate-specific interpretation of results is possible, it must be performed cautiously due to multicollinearity among some covariates (e.g., poverty and Black/ African American populations).

There are limitations to using county-level information. Covariates describing population density, race, ethnicity, age/sex, and rurality were collected from 2010 census data, while the remaining non-COVID-19 data was gathered between 2013 and 2018. The JHU CSSE data, which are live, provisional counts subject to revision rather than fully state-certified numbers, also showed errors that required imputation. This introduces additional uncertainty about the results, though the number of observations imputed was small and mostly concentrated earlier in the study period and among smaller counties. Other errors may have remained undetected. This is a general limitation of data published in real time, and it is not uncommon that data are eventually updated once such inconsistencies are discovered and corrected. However, live analyses, such as those used to address health and medical emergencies, require synchronously available data rather than post-hoc, cleaner/ confirmed data.

County-level COVID-19 testing differences may affect the results, especially in the early stages of the pandemic, when testing rates by county were heterogeneous. Additionally, while county-level aggregate data provide a unique perspective of the impact of COVID-19 by county-level differences, they lack the granularity of individual-specific information, such as information needed for calculation of age-adjusted rates. Finally, county-level analyses naturally miss intra-county heterogeneity, which may be more prevalent among larger counties.

Conclusion

Knowledge of county-level risk can improve allocation models, from initial stages of health care support and information to vaccine deployment, in support of high-risk counties. Success requires that policy makers and health departments partner with community leaders to foster trust and compliance. Long-term measures to improve population health, reduce or eliminate (where possible) identified risk factors, and reduce the incidence and mortality of COVID-19 could include improving government-supported health care coverage for those otherwise uninsured. Both inter-state and inter-county disparities exist within the Carolinas. This study demonstrates the need to complement statewide policies with county-level analyses, recommendations, and support. This work does not intend to provide recommendations for today's policies, but a framework for future county-level research to inform policies when new health emergencies occur. NCMJ

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