ARTICLE

Exploring the socioeconomic drivers of COVID-19 mortality across various spatial regimes

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Abstract
Identifying the socioeconomic drivers of COVID-19 deaths is essential for designing effective policies and health interventions. However, how the significance and impact of these factors varies across different spatial regimes has been scantily explored. In this ecological cross-sectional study, we apply the spatial lag by regimes regression model to examine how the socioeconomic and health determinants of COVID-19 death rate vary across (a) metropolitan vs. non-metropolitan, (b) shelter-in-place vs. no-shelter-in-place order, and (c) Democratic vs. Republican US counties. A total of 20 variables were studied across 3108 counties in the contiguous US for the first year of the pandemic (6 February 2020 to 5 February 2021). The results show that the COVID-19 death rate not only depends on a complex interplay of the population demographic, socioeconomic and health-related characteristics, but also on the spatial regime that the residents live, work and play. Household median income, household size, percentage of African Americans, percentage aged 40–59 and heart disease mortality are significant to metropolitan but not to non-metropolitan counties. We identified lack of insurance access as a significant driver across all regimes except for Democratic. We also showed that the political orientation of the governor might have impacted COVID-19 death rates due to the public response (i.e., shelter-in-place vs. no-shelter-in-place order). The proposed analysis allows for understanding the socioeconomic context in which public health policies can be applied, and importantly, it presents how COVID-19 death related factors vary across different spatial regimes.

KEYWORDS
COVID-19, political divide, shelter-in-place, socio-economics, spatial regression, USA

1 INTRODUCTION

Historically, epidemics and pandemics exert a disproportionate burden on disadvantaged populations that face a greater death risk (Grekousis & Liu, 2021). The COVID-19 pandemic is not an exception. To consider the appropriate public
health response to those more vulnerable, the spatial distribution of health outcomes and socioeconomic characteristics of the underlying population is required (Schrager, 2021). In this way, health inequalities can be traced and reduced through implementing localised interventions.

A growing number of studies show that the uneven spatial distribution of COVID-19 deaths, which is evident worldwide, is related to demographic, socioeconomic, health and environmental disparities across geographical regions (Andersen et al., 2021; Feinhandler et al., 2020; Grekousis et al., 2021, 2022; Maiti et al., 2021; Mollalo et al., 2020). Although these studies have attempted to identify the structural drivers (i.e., environmental, socioeconomic, demographic) and used different spatial regression models (geographically weighted regression [GWR], multiscale geographically weighted regression [MGWR], spatial lag model [SLM] and spatial error model [SEM]) to explain spatially the variability of COVID-19 deaths, they all have two major limitations. First, they do not examine whether the determinants of COVID-19 deaths vary across different spatial regimes (i.e., metropolitan vs. non-metropolitan). Except for GWR models, which allow coefficients to vary from location to location, all other approaches produce fixed coefficients. Even with GWR, there is no control for regimes. In this sense, the potential heterogeneity across specific predefined sub-regions is not examined. Second, all studies focus on the first US pandemic wave. As such, data are restricted from January 2020 to July 2020 at the latest. Although these early studies offer valuable findings in understanding COVID-19 spatial variation, they do not integrate subsequent waves and seasonality, which may affect the distribution of COVID-19 and some of its environmental and socioeconomic determinants. This study fills these gaps and adds to the current literature in multiple ways.

First, we utilised the spatial lag by regimes model to identify the socioeconomic factors and underlying health conditions of COVID-19 death rates across different spatial regimes in the United States. We selected the spatial regimes from three different perspectives:

a. Economic and social interaction: MSA vs. non-MSA. Metropolitan statistical area (MSA) is an extensive area with a core substantial population (over 50,000) and neighbouring communities that interact highly economically and socially (OMB, 2010). On this account, we used MSA and non-MSA regimes to trace whether areas linked at a higher degree (MSA) have different social and health COVID-19 death rate determinants compared with areas that do not exhibit economic and social interactions (non-MSA).

b. Non-pharmaceutical intervention: shelter-in-place vs. no-shelter-in-place order counties. The rationale behind examining shelter-in-place vs. no-shelter-in-place orders is to evaluate whether a different approach in public reaction would infer differences in how social and health factors are related to the COVID-19 death rate.

c. Political orientation: Democratic vs. Republican. An ongoing debate exists regarding the political divide and the attitude towards confronting COVID-19 at the individual and public reaction levels (Desmet & Wacziarg, 2021). Underlying differences in the spatial variability of the disease and its determinants may reflect the different political orientations of the governors and the voters. For these reasons, we studied how the linkage of various health and socioeconomic variables to COVID-19 death rate may differentiate across the party affiliation of each governor during 2020. In this way, we assessed if the political orientation of the governor, and thus the potential higher or lower ranking of COVID-19 pandemic as a major threat and the subsequent acute or relaxed response, could affect COVID-19 death rates.

Second, this study analysed COVID-19 deaths for a reference period of one year (since first registered death). As COVID-19 deaths and case hotspots shift geographically over time from the West coast to the East coast (Zhai et al., 2021) and from urban counties during the first wave to suburban and rural counties in the subsequent waves (Desmet & Wacziarg, 2021), a broader reference period should be considered. Studies that limit their reference period to a few months may miss this critical variation and underestimate or overestimate some factors (i.e., population density).

We used the spatial lag by regimes regression model to measure spatial spillover effects of COVID-19 death rate and account for spatial heterogeneity. Spatial regime models are used to handle discrete spatial heterogeneity (Anselin & Rey, 2014). Different models and thus different coefficients are estimated for each regime based on the hypothesis of different spatial processes across space. Different slope coefficients between regimes suggest that the response of the dependent variable to the explanatory variables is not homogeneous. As such, constructing different models per regime allows for a better understanding of the significance of each variable to COVID-19 mortality. For example, an explanatory variable may be significant in one regime (e.g., strongly linked to COVID-19 death rate) but may not be to the other. Even if a variable is significant to both regimes, the magnitude (coefficient) may differ. In other words, the same variable may exhibit a different impact on COVID-19 death rate in different regimes. This is extremely helpful from the policy perspective as it allows for more targeted interventions based on the specific characteristics of each regime.
Concluding, this is the first study, to the authors’ knowledge, that applied spatial lag by regimes regression model to explore the local association of the socioeconomic and health drivers of COVID-19 death rate for the first year (2020–2021) of the pandemic across three sets of regimes (MSA vs. non-MSA, shelter-in-place vs. no-shelter-in-place, and Republicans vs. democratic counties). The findings of this study can be used to inform national, regional and local strategies regarding those populations that bear a disproportionate burden against COVID-19.

2 | MATERIAL AND METHODS

2.1 | Material

We constructed a county-level dataset for the contiguous United States ($n = 3108$) (see Supporting Information, Section S11). Fifty-nine counties with zero COVID-19 deaths were excluded. The inclusion of isolated polygons in spatial econometric analysis causes complications (Anselin & Rey, 2014). As we are interested in how neighbouring spatial units interact, we considered that, from the spatial analysis perspective, the counties of contiguous United States do not interact with island counties or counties in Alaska. Therefore, we did not include the counties of Alaska and Hawaii, which lie far away from the contiguous United States.

We used three sets of spatial regimes: (a) MSA ($n = 1816$) vs. non-MSA ($n = 1233$) counties, (b) shelter-in-place ($n = 2627$) vs. no-shelter-in-place ($n = 422$) counties, and (c) Democratic ($n = 1318$) vs. Republican ($n = 1731$) counties (Figure 1).

We should highlight that the designation of MSAs and non-MSAs does not define an urban–rural classification (US OMB, 2010). In this respect, non-MSA is not synonymous with rural as according to the American Community Survey, 54.4% of people living in rural areas are within a metro area (USCB, 2021).

We collectively refer to shelter-in-place states as those that issued state-wide shelter-in-place, stay-at-home, closure or shutdown orders in response to the COVID-19 pandemic. Data were obtained from Ballotpedia at the state level (Ballotpedia, 2020). Out of the 48 states in the contiguous United States, 41 issued such orders and seven states did not. We assign all counties within states with stay-at-home, closure or shutdown orders to the shelter-in-place regime ($n = 2627$). Similarly, all counties within states with no stay-at-home, closure or shutdown orders are assigned to the no-shelter-in-place regime ($n = 422$), although some may have experienced local interventions.

The party affiliation of each state’s governor was obtained from Ballotpedia at the state level (Ballotpedia, 2020). Out of the 48 states in the contiguous United States, 25 states had Republican governors ($n = 1731$ counties) and 23 states had Democratic governors ($n = 1318$ counties) in 2020 (Ballotpedia, 2020).

Data on confirmed COVID-19 deaths for each US state at the county level was obtained from USAFacts from 6 February 2020 (the first death in the United States) to 5 February 2021 (USAFacts, 2021). From an initial list of 68 risk factors (demographic, socioeconomic, underlying health condition) linked to COVID-19 deaths (as reported in similar studies; Maiti et al., 2021; Mollalo et al., 2020), we finally retained 20 variables after removing those exhibiting multicollinearity (see Supporting Information, Section S12).

2.2 | Methods

We first utilised the ordinary least square (OLS) regression by regimes (see Supporting Information, Section S13). The model specification takes the cumulative deaths per 100,000 people ($DeathsP100k$) as the dependent variable and the population’s demographic, socioeconomic and health characteristics as the independent/explanatory variables. Then we applied the global Moran’s I statistic and the Lagrange multiplier test statistics to the OLS model’s output to detect spatial dependence and consider the use of a spatial econometric model, either SLM by regime or SEM by regime (Grekousis, 2020). The Lagrange multiplier tests indicated the SLM; therefore, we will not refer to the theoretical part of the spatial error model.

The SLM is a spatial regression method to account for spatial autocorrelation of the dependent variable by including a new variable called the spatially lagged dependent variable (Grekousis, 2020). The SLM is expressed as:

$$y_{ij} = b_{0j} + b_j x_{ij} + \rho W_{ij} y_{ij} + \epsilon_{ij}$$  (1)
where $\rho$ is the spatial autoregressive coefficient, $W_i$ is the spatial weights matrix of county $i$, $W_i y_i$ is the spatial lag variable, $y_i$ is the COVID-19 death rate at county $i$, $x_i$ is the vector of the selected independent variables, $b_0$ is the intercept, $b$ is the coefficient (slope) of each independent variable, $j$ is the spatial regime, and $\varepsilon_i$ is the random error term. We used a first-order Queen spatial weights matrix (counties are neighbours if they share a common boundary or vertex).

The spatial lag variable measures the COVID-19 death rate in the counties defined as surrounding each county in the spatial weights matrix. This variable is an additional explanatory variable to the OLS model to account for potential spatial clustering (detected, for example, with Moran’s I test). The SLM in this study examines how the COVID-19 death rate in a county is influenced by the COVID-19 death rates in the neighbouring counties. Therefore, the spatial lag parameter $\rho$ refers to the estimate of how the average COVID-19 death rate in adjacent counties is associated with the COVID-19 deaths of a focal county. For example, a positive and statistically significant $\rho$ indicates that when the COVID-19 death rate increases in surrounding areas, so does the COVID-19 death rate in the central county. The fact that the lag parameter $\rho$ is statistically significant adds further evidence that SLM is a better model than the OLS regression specification. Details on the interpretation of SLM coefficients and tests used for statistical significance are provided in the Supporting Information (Section SI4). For our statistical analysis (OLS, OLS by regimes and SLM by regimes), we used GeoDaSpace 1.2 open source software (Anselin et al., 2006). Figures were created with ArcGIS 10.2.
3 | RESULTS

3.1 | Summary statistics

The COVID-19 death rate (cumulative COVID-19 deaths per 100,000 population) as of 5 February 2021 ranged from 2.8 to 832.1 per county, with a median of 141.3 (interquartile range 85.6–207.0) (Figure 2; see Supporting Information, Sections SI5 and SI6). For a more detailed presentation on the summary statistics, see Supporting Information (Section SI7). For complicity reasons we also ran global OLS. A complete analysis of OLS results is presented in the Supporting Information (Section SI9).

3.2 | MSA vs. non-MSA regimes

First, we apply OLS by regimes model to decide on the choice of SLM or SEM. The results provide strong evidence of spatial lag autocorrelation (see Supporting Information, Section SI10). For this reason, we ran SLM for both regimes.

The spatial autoregressive coefficient $\rho$ of SLM by regimes is highly significant ($p < 0.001$) (Table 1). There is little evidence of remaining spatial error autocorrelation since the Anselin-Kelejian test is not significant ($p > 0.05$). This suggests that the spatial lag specification is likely sufficient to address the evidence of spatial dependence in the original model.

In both MSA and non-MSA counties, percentage aged 20–39, percentage disabled, percentage with no insurance, and commuting time to work were associated with COVID-19 death rate. However, the coefficient values of these variables

**FIGURE 2** Spatial distribution of the cumulative COVID-19 deaths per 100,000 population as of 5 February 2021
are not the same. For example, each percentage point increase in population lacking insurance in MSA counties is associated with 3.32 more COVID-19 deaths per 100,000 population (1.63 directly, 1.69 via indirect ‘spillover’ driven by the neighbouring counties; \( p < 0.001 \)). However, in non-MSA counties, the same increase in population lacking insurance is associated with 4.33 more COVID-19 deaths per 100,000 population (2.13 directly, 2.20 via indirect ‘spillover’ effect; \( p < 0.001 \)), an increase in the death rate of 30.4% compared with MSA counties. This underscores the importance of including the spatially lagged dependent variable in the model.

In the MSA counties, household size, percentage with no vehicles, heart disease mortality, and percentage who sleep less than seven hours per night were related to the COVID-19 death rate. At the same time, no evidence was found that these factors were related to COVID-19 mortality in non-MSA countries.

### 3.3 Shelter-in-place vs. no-shelter-in-place

The OLS by regimes results (see Supporting Information, Section SI11) of the shelter-in-place \( (n = 2627) \) vs. no-shelter-in-place \( (n = 422) \) reveal spatial lag autocorrelation; we consider the spatial lag by regimes model below as a better choice.

Similar to MSA regimes, the spatial autoregressive coefficient \( \rho \) for SLM by regimes is highly significant \( (p < 0.001) \) (Table 2). The Anselin-Kelejian test is not significant \( (p > 0.05) \). This suggests that there is little evidence of remaining spatial error autocorrelation and that the spatial lag specification is likely sufficient to address the spatial dependence in the original model.

In both no-shelter-in-place and shelter-in-place counties (SLMs), percentage aged 20–39, percentage disabled, percentage of population above high school graduate, and percentage with no insurance were associated with COVID-19 death rate. However, the coefficient values of these variables vary. For instance, each additional percentage point of the population above high school graduate was associated with 8.46 fewer COVID-19 deaths per 100,000 population (4.58 directly, 3.88 via indirect ‘spillover’ driven from the neighbouring counties; \( p < 0.001 \)) in a no-shelter-in-place county, but 3.12 fewer COVID-19 deaths (1.69 directly, 1.43 via indirect ‘spillover’ from the nearby counties; \( p < 0.001 \)) in a shelter-in-place county. This highlights that the effect of a variable (i.e., percentage of population above high school graduate) on the COVID-19 death rate varies across different regions, further emphasising the importance of integrating spatial regimes in regression modelling.

In the shelter-in-place counties, percentage with no vehicles, percentage who work in the social sector, commuting time, and heart disease mortality were related to the COVID-19 death rate, while no evidence can support the idea that these factors were related to COVID-19 mortality in no-shelter-in-place countries. In no-shelter-in-place counties, only population density and percentage male were related to COVID-19 mortality. A Chow test showed that the effect of percentage male, percentage of population above high school graduate, and percentage with no insurance showed a significant difference between two regimes (shelter-in-place vs. no-shelter-in-place).

### 3.4 Democratic vs. Republican

The results of Democratic \( (n = 1318) \) vs. Republican \( (n = 1731) \) are presented in Table 3 (see also Supporting Information, Section SI12), and similar to other regimes, we ran the spatial lag by regime model. The spatial autoregressive coefficient \( \rho \) of the SLM by regimes is highly significant \( (p < 0.001) \). The Anselin-Kelejian test is not significant \( (p > 0.05) \), revealing little evidence of remaining spatial error autocorrelation. This indicates that the spatial lag specification addresses the evidence of spatial dependence in the original model.

In both Democratic and Republican counties (SLMs), percentage aged 20–39, percentage disabled, percentage of population above high school graduate, percentage who work in social sector, and heart disease mortality were associated with the COVID-19 death rate.

In the Democratic regime, percentage with no vehicles was related to COVID-19 death rate, while this factor is not associated with the COVID-19 death rate in the Republican regime. A 1% increase in housing units with no vehicles was associated with 5.61 more COVID-19 deaths per 100,000 population (2.92 directly, 2.69 via indirect ‘spillover’ driven from the neighbouring counties; \( p < 0.001 \)) in a Democratic county. In contrast to Democratic counties, population density, percentage African, household size, percentage with no insurance, and percentage who sleep less than seven hours per night were related to the COVID-19 death rate.
| Variable                  | SLM (GMM) MSA |                     |                     | non-MSA |                     |                     | Chow test | p-value |
|---------------------------|---------------|---------------------|---------------------|---------|---------------------|---------------------|-----------|---------|
|                           | β-direct      | β-indirect          | β-total             | z-statistic | β-direct      | β-indirect          | β-total             | z-statistic | p-value |
| Population density        | 0.00          | 0.00                | −0.01               | −0.95     | 0.21          | 0.22                | 0.43                 | 1.87        | 0.06    |
| % Male                    | −0.65         | −0.67               | −1.33               | −0.60     | 0.21          | 0.22                | 0.43                 | 0.16        | 0.62    |
| % Age 20–39               | −3.75***      | −3.87               | −7.61               | −5.67     | −4.07***      | −4.20               | −8.27                 | −3.38        | 0.81    |
| % Age 40–59               | −2.42*        | −2.50               | −4.91               | −1.97     | −1.29         | −1.34               | −2.63                 | −0.75        | 0.59    |
| % African                 | 0.55*         | 0.56                | 1.11                | 2.57      | 0.18          | 0.19                | 0.37                 | 0.70        | 0.28    |
| % Asian                   | 0.62          | 0.64                | 1.25                | 1.04      | −14.36**      | −14.83              | −29.19               | −2.76        | 0.00    |
| % Other                   | 0.34          | 0.35                | 0.69                | 0.65      | −0.92         | −0.95               | −1.87                 | −1.20        | 0.17    |
| % Disabled                | −2.30**       | −2.37               | −4.67               | −2.91     | −4.41***      | −4.55               | −8.96                 | −4.34        | 0.10    |
| Household size            | −26.97*       | −27.84              | −54.8               | −2.26     | 5.92          | 6.11                | 12.02                | 0.43        | 0.07    |
| % No vehicles             | 3.37***       | 3.48                | 6.85                | 4.33      | 0.22          | 0.22                | 0.44                 | 0.18        | 0.03    |
| % Housing problem         | 0.17          | 0.18                | 0.35                | 0.28      | −1.60         | −1.65               | −3.25                 | −1.60        | 0.13    |
| % >High school graduate   | −2.57***      | −2.65               | −5.22               | −6.97     | −1.09         | −1.13               | −2.22                 | −1.81        | 0.04    |
| % Work social sector      | 1.18*         | 1.21                | 2.39                | 2.32      | 1.37          | 1.41                | 2.78                 | 1.92        | 0.83    |
| Median income             | 0.69**        | 0.71                | 1.40                | 2.95      | −0.73         | −0.75               | −1.48                 | −1.38        | 0.01    |
| % Unemployment            | 0.81          | 0.83                | 1.64                | 0.56      | 2.15          | 2.22                | 4.36                 | 1.42        | 0.52    |
| % No insurance            | 1.63***       | 1.69                | 3.32                | 3.59      | 2.13***       | 2.20                | 4.33                 | 3.26        | 0.52    |
| Commuting time            | −1.02*        | −1.05               | −2.06               | −2.36     | −2.29**       | −2.36               | −4.65                 | −3.28        | 0.12    |
| Heart disease mortality   | 0.12***       | 0.12                | 0.24                | 4.06      | 0.07          | 0.07                | 0.14                 | 1.52        | 0.39    |
| Obesity prevalence        | −0.38         | −0.39               | −0.76               | −0.76     | 1.24          | 1.28                | 2.51                 | 1.29        | 0.13    |
| % Sleep < 7 h             | −1.91***      | −1.97               | −3.88               | −2.97     | −0.87         | −0.90               | −1.77                 | −0.72        | 0.45    |
| Constant                  | 439.77***     | 453.96              | 893.73              | 4.77      | 313.31***     | 323.42              | 636.72               | 2.85        | 0.38    |
| ρ (fixed across regimes)  | 0.51***       | 9.73                | 0.51***             | 9.73      | 0.51***       | 9.73                | 9.73                 | 0.51***      | 0.00    |
| Adjusted R²               | 0.41/0.29     |                     |                     |           |               |                     |                     |             |         |
| Anselin-Kelejian test     | 3.31          |                     |                     |           |               |                     |                     |             |         |

Note: β = coefficient. β-direct can be interpreted as the COVID-19 mortality associated with a given indicator within a given county; β-indirect accounts for the spillover spatial effects on neighbouring counties; and β-total can be interpreted as the COVID-19 mortality associated with an indicator in a given county plus neighbouring counties.

Abbreviations: GMM, General Method of Moments; MSA, metropolitan statistical area; SLM, spatial lag model.

*The coefficient refers to pseudo R² and spatial pseudo R².

bThe coefficient refers to the p-value for the global Chow test.

*p < 0.05; **p < 0.01; ***p < 0.001.
| Variable                  | Shelter-in-place | No-shelter-in-place | Chow test |
|---------------------------|------------------|---------------------|-----------|
|                           | β-direct        | β-indirect         | β-total   | z-statistic | p-value        |
|                           | β-direct        | β-indirect         | β-total   | z-statistic | p-value        |
| Population density        | 0.00            | 0.00               | 0.00      | 0.55        |                 |
|                           | 0.10**          | 0.09               | 0.19      | 2.61        | 0.76           |
| % Male                    | −0.32           | −0.27              | −0.6      | −0.36       |                 |
|                           | 8.36**          | 7.08               | 15.44     | 2.58        | 0.01           |
| % Age 20–39               | −4.15***        | −3.51              | −7.66     | −6.82       |                 |
|                           | −5.28**         | −4.47              | −9.75     | −2.94       | 0.60           |
| % Age 40–59               | −2.18*          | −1.85              | −4.03     | −2.08       |                 |
|                           | 0.75            | 0.63               | 1.38      | 0.22        | 0.32           |
| % African                 | 0.43*           | 0.37               | 0.80      | 2.45        |                 |
|                           | −0.37           | −0.32              | −0.69     | −0.57       | 0.26           |
| % Asian                   | 1.11            | 0.94               | 2.04      | 1.79        |                 |
|                           | −9.62*          | −8.15              | −17.76    | −2.50       | 0.06           |
| % Other                   | −0.08           | −0.07              | −0.15     | −0.18       |                 |
|                           | 1.21            | 1.03               | 2.24      | 0.54        | 0.28           |
| % Disabled                | −2.92***        | −2.47              | −5.39     | −4.07       |                 |
|                           | −5.82**         | −4.93              | −10.75    | −2.74       | 0.28           |
| Household size            | −4.41           | −3.74              | −8.15     | −0.39       |                 |
|                           | −32.84          | −27.81             | −60.65    | −1.34       | 0.17           |
| % No vehicles             | 2.24**          | 1.89               | 4.13      | 2.66        |                 |
|                           | 1.24            | 1.05               | 2.29      | 0.43        | 0.79           |
| % Housing problem         | −0.80           | −0.68              | −1.48     | −1.37       |                 |
|                           | 2.25            | 1.91               | 4.16      | 0.92        | 0.09           |
| % >High school graduate   | −1.69***        | −1.43              | −3.12     | −5.17       |                 |
|                           | −4.58***        | −3.88              | −8.46     | −4.26       | **0.00**       |
| % Work social sector      | 1.52***         | 1.29               | 2.80      | 3.36        |                 |
|                           | 1.24            | 1.05               | 2.29      | 0.87        | 0.89           |
| Median income             | 0.21            | 0.18               | 0.39      | 0.86        |                 |
|                           | −0.58           | −0.49              | −1.07     | −0.56       | 0.42           |
| % Unemployment            | 1.60            | 1.35               | 2.95      | 1.34        |                 |
|                           | 4.69            | 3.97               | 8.65      | 1.57        | 0.16           |
| % No insurance            | 2.29***         | 1.94               | 4.22      | 5.41        |                 |
|                           | −7.75**         | −6.57              | −14.32    | −2.79       | **0.00**       |
| Commuting time            | −1.78***        | −1.51              | −3.29     | −4.25       |                 |
|                           | −1.45           | −1.23              | −2.67     | −0.72       | 0.47           |
| Heart disease mortality   | 0.11***         | 0.09               | 0.20      | 3.72        |                 |
|                           | 0.01            | 0.01               | 0.02      | 0.13        | 0.06           |
| Obesity prevalence        | −0.31           | −0.26              | −0.58     | −0.61       |                 |
|                           | −2.11           | −1.79              | −3.9      | −1.27       | 0.22           |
| % Sleep < 7 h             | −0.13           | −0.11              | −0.24     | −0.23       |                 |
|                           | −0.48           | −0.40              | −0.88     | −0.15       | 0.97           |
| Constant                  | 318.25***       | 269.56             | 587.81    | 4.48        |                 |
|                           | 384.97          | 326.08             | 711.06    | 1.66        | 0.39           |
| ρ (fixed across regimes)  | 0.45***         | 0.45***            | 0.45***   | 0.45***     | 0.45***       |
| Adjusted R²               | 0.41/0.30       | 0.41/0.30          | 0.41/0.30 |          | 0.41/0.30     |

Note: β = coefficient; β-direct can be interpreted as the COVID-19 mortality associated with a given indicator within a given county; β-indirect accounts for the spillover spatial effects on neighbouring counties; and β-total can be interpreted as the COVID-19 mortality associated with an indicator in a given county plus neighbouring counties.

Abbreviations: GMM; MSA, metropolitan statistical area; SLM, spatial lag model.

*The coefficient refers to pseudo R² and spatial pseudo R².

bThe coefficient refers to the p-value for the global Chow test.

*p < 0.05 (bold); **p < 0.01 (bold); ***p < 0.001 (bold).
| Variable                              | SLM(GMM)                                                                 |
|--------------------------------------|--------------------------------------------------------------------------|
|                                      | Democratic                                                                |
|                                      | β-direct | β-indirect | β-total | z-statistic |
| Population density                   | 0.00     | 0.00       | 0.00    | 0.04        |
| %Male                                | 0.33     | 0.30       | 0.63    | 0.26        |
| %Age 20–39                          | −4.74*** | −4.37      | −9.10   | −5.48       |
| %Age 40–59                          | −2.44    | −2.24      | −4.68   | −1.69       |
| %African                             | 0.40     | 0.37       | 0.78    | 1.30        |
| %Asian                               | 1.35     | 1.24       | 2.60    | 2.05        |
| %Other                               | 0.31     | 0.28       | 0.59    | 0.45        |
| %Disabled                            | −4.54*** | −4.18      | −8.72   | −3.82       |
| Household size                       | 15.42    | 14.20      | 29.62   | 0.90        |
| %No vehicles                         | 2.92***  | 2.69       | 5.61    | 2.03        |
| %Housing problem                     | −1.54    | −1.42      | −2.96   | −1.82       |
| %> High school graduate              | −1.88*** | −1.73      | −3.61   | −3.74       |
| %Work social sector                  | 1.70***  | 1.56       | 3.26    | 2.74        |
| Median income                        | −0.04    | −0.04      | −0.08   | −0.11       |
| %Unemployment                        | 2.03     | 1.87       | 3.89    | 0.93        |
| %No insurance                        | 1.33     | 1.22       | 2.55    | 1.39        |
| Commuting time                       | −1.88*** | −1.74      | −3.62   | −2.92       |
| Heart disease mortality              | 0.14***  | 0.13       | 0.28    | 2.58        |
| Obesity prevalence                   | −1.29    | −1.19      | −2.47   | −1.75       |
| %Sleep < 7 h                         | −0.02    | −0.02      | −0.03   | −0.02       |
| CONSTANT                             | 334.93***| 308.50     | 643.42  | 2.98        |
| ρ (fixed across regimes)             | 0.48***  | 8.53       | 0.48*** | 8.53        |

|                                      | Republican                                                                |
|                                      | β-direct | β-indirect | β-total | z-statistic |
| Population density                   | 0.02**   | 0.02       | 0.04    | 2.92        |
| %Male                                | 0.56     | 0.51       | 1.07    | 0.46        |
| %Age 20–39                          | −4.67*** | −4.30      | −8.97   | −5.90       |
| %Age 40–59                          | −1.60    | −1.48      | −3.08   | −1.18       |
| %African                             | 0.41     | 0.37       | 0.78    | 1.99        |
| %Asian                               | −2.11    | −1.95      | −4.06   | −1.44       |
| %Other                               | −0.43    | −0.40      | −0.83   | −0.72       |
| %Disabled                            | −3.04*** | −2.80      | −5.85   | −3.70       |
| Household size                       | −25.17***| −23.18     | −48.35  | −2.32       |
| %No vehicles                         | 1.25     | 1.15       | 2.40    | 1.31        |
| %Housing problem                     | −0.09    | −0.08      | −0.17   | −0.10       |
| %> High school graduate              | −1.71*** | −1.57      | −3.28   | −3.82       |
| %Work social sector                  | 1.28     | 1.18       | 2.46    | 2.14        |
| Median income                        | 0.16     | 0.15       | 0.31    | 0.47        |
| %Unemployment                        | 2.22     | 2.04       | 4.26    | 1.63        |
| %No insurance                        | 3.96     | 3.96       | 5.3     | 3.96        |
| Commuting time                       | −1.71*** | −1.57      | −3.28   | −3.22       |
| Heart disease mortality              | 0.06*    | 0.06       | 0.12    | 2.03        |
| Obesity prevalence                   | 1.37     | 1.26       | 2.64    | 1.89        |
| %Sleep < 7 h                         | −2.23**  | −2.06      | −4.29   | −2.61       |
| CONSTANT                             | 373.06***| 343.63     | 716.69  | 3.94        |
| ρ (fixed across regimes)             | 0.48***  | 8.53       | 0.48*** | 8.53        |

|                                      | Chow test                                                                |
|                                      | p-value                                                                 |
| Population density                   | 0.02                                                                 |
| %Male                                | 0.90                                                                 |
| %Age 20–39                          | 0.95                                                                 |
| %Age 40–59                          | 0.67                                                                 |
| %African                             | 1.00                                                                 |
| %Asian                               | 0.03                                                                 |
| %Other                               | 0.42                                                                 |
| %Disabled                            | 0.30                                                                 |
| Household size                       | 0.05                                                                 |
| %No vehicles                         | 0.05                                                                 |
| %Housing problem                     | 0.33                                                                 |
| %> High school graduate              | 0.79                                                                 |
| %Work social sector                  | 0.62                                                                 |
| Median income                        | 0.69                                                                 |
| %Unemployment                        | 0.47                                                                 |
| %No insurance                        | 0.94                                                                 |
| Commuting time                       | 0.33                                                                 |
| Heart disease mortality              | 0.19                                                                 |
| Obesity prevalence                   | 0.01                                                                 |
| %Sleep < 7 h                         | 0.06                                                                 |
| CONSTANT                             | 0.79                                                                 |
| ρ (fixed across regimes)             | 0.01                                                                 |

Note: β = coefficient; β-direct can be interpreted as the COVID-19 mortality associated with a given indicator within a given county, β-indirect accounts for the spillover spatial effects on neighboring counties, and β-total can be interpreted as the COVID-19 mortality associated with an indicator in a given county plus neighboring counties.

aThe coefficient refers to Pseudo $R^2$ and Spatial Pseudo $R^2$.
bThe coefficient refers to the $p$-value for global Chow test.

*p < 0.05 (bold), **p < 0.01 (bold), ***p < 0.001 (bold).
This work tested several spatial lag models by regimes to assess county-level associations between socioeconomic and underlying health condition factors and COVID-19 death rate. Our findings reveal high variability in the demographic, socioeconomic and underlying health condition determinants of the COVID-19 death rate across the tested spatial regimes. Although the spatial regression models do not achieve high pseudo-$R^2$ or spatial pseudo-$R^2$, they can assess the relationships among the dependent and independent variables. The low fit values reveal that the models cannot fully account for the spatial pattern. Even with this caveat, the residual maps allow us to better comprehend the spatial patterning of the model fit and identify potential hidden drivers (Figure 3).

OLS residuals for the SLMs by regimes model show that the COVID-19 death rate is over/underpredicted, mainly across Great Plains and Texas (Figure 3a–c). In contrast, the Atlantic coast and southeast counties exhibit low residuals indicating a better fit. The pattern of large over/under-predictions appearing mainly in counties in central US states is also observed in other efforts that applied spatial regression (with no regimes) to model COVID-19 (Maiti et al., 2021; Sun et al., 2020). Even with the adoption of regimes in our study, we could not address this model’s inefficiency. We observe a checkerboard-like pattern in COVID-19 death rate residuals across the Great Plains states and Texas, with counties exhibiting severe over-prediction adjacent to counties with under-predictions. This finding reveals spatial heterogeneity and is consistent with other works that report that spatial heterogeneity is common in US counties (Mollalo et al., 2020).

**FIGURE 3** Spatial distribution of the standardised residuals from SLMs for each county. (a) SLM residuals for MSA vs. non-MSA regimes. (b) SLM residuals for shelter-in-place vs. no-shelter-in-place regimes. (c) SLM residuals for Democratic vs. Republican regimes. MSA, metropolitan statistical area; SLM, spatial lag model.
For example, Sun et al. (2020) identified a similar pattern of COVID-19 prevalence residuals (confirmed cases per 100,000 population) in the same states. We cannot fully understand why spatial regression lag models with or without regimes cannot be properly specified to better model the variability of COVID-19 deaths in these areas. We believe that this topic deserves future research.

### 4.1 | Regimes effect

We used spatial regimes because we presume that the relationship of the predictors to the outcome may play out differently across these sub-regions. Our analysis confirmed this research hypothesis.

For example, MSA counties have different demographic, social and health factors linked to COVID-19 death rate than non-MSA counties (Table 4). Household median income, household size, percentage of African American population, percentage of the population aged between 40 and 59, and heart disease mortality are significant only to MSA and not to non-MSA counties. Although MSA counties exhibit higher economic and social interactions compared with non-MSA counties, they have a lower median COVID-19 death rate (131.1) compared with non-MSA counties (162.8) (see Supporting Information, Sections SI5 and SI6). The lower COVID-19 death rate in MSA can be attributed to better residents’ access to healthcare with experienced personnel capable of successfully reacting to an emerging event (Andersen et al., 2021). Moreover, on median values, MSA counties have a slightly lower percentage of people without insurance (14.8%) than non-MSA counties (15.8%). However, we identified that the effect of lack of insurance variable in the COVID-19 death rate is 33% higher (coefficients difference) in non-MSA counties.

This shows that although the same variable is statistically significant in both regimes, the effect on the dependent variable may vary substantially. This highlights the need for spatial regression models, for example, the SLM, which handles
spatial heterogeneity by identifying (a) different factors per regime and (b) a different effect to the dependent variable for common variables across regimes.

In addition, contrary to early findings (Feinhandler et al., 2020; Hamidi et al., 2020), population density is not a driver for higher COVID-19 death rates in MSA or non-MSA counties. This misunderstanding may have been created because large urban areas within MSAs were hit first by the pandemic (Desmet & Wacziarg, 2021). As such, the population density was identified as the COVID-19 driver compared with less densely populated areas that were hit later. Density may have affected the time of the outbreak in each county, with those counties densely populated more likely to experience an early epidemic outbreak but not COVID-19 deaths (McFarlane, 2021). This also emphasises the need to analyse a dynamic phenomenon, as an epidemic, on a broader reference period and avoid jumping to conclusions from early findings (pertaining only to the first waves). To address this weak point, we analysed cumulative data for the first year of the pandemic so that findings are more reliable and can better inform policy-makers and health specialists.

That is why, in this work, we studied two politically related sets of regimes: Democratic vs. Republicans and shelter-in-place vs. no-shelter-in-place counties. For example, this study shows that population density, household size, lack of insurance, and sleeping less than seven hours per night were only significant to Republican counties and not to Democratic. Democratic-leaning states and counties were first hit hard at the pandemic beginning compared with Republican-leaning areas (Desmet & Wacziarg, 2021). This may have led Republican areas to policies and behavioural preferences in favour of more relaxed measures and attitudes. For example, all states that did not place a shelter-in-place order had a governor of Republican affiliation. As these states downplayed the importance of such actions and proceeded to either local orders or just recommendations, a sense of more lax behaviour was observed (Desmet & Wacziarg, 2021). This could also be the result of mixed messages and misinformation often communicated through officials of Trump's administration (including himself) regarding the COVID-19 threat (Yamey & Gonsalves, 2020).

As a consequence, many people did not change their social behaviour. For example, Chen et al. (2020) showed that likely Republican voters reduced movement by 9% compared with a 21% reduction among Democratic voters. Other differences in social distancing behaviour and beliefs among Democrats and Republicans were documented with the latest being, in general, less willing to change their pre-pandemic behaviours (Allcott et al., 2020). However, the initial advantage of the Republican counties was lost in the subsequent pandemic waves. As shown in the analysis, Republican counties have higher COVID-19 death rates (median 160.1) than Democratic counties (median 117.5) (see Supporting Information, Section S16).

Lastly, population density, male population and Asian population were significant in no-shelter-in-place counties and not in the shelter-in-place regime. The fact that all states that did not issue shelter-in-place orders had a Republican governor makes it hard to distinguish if the effect of this non-pharmaceutical intervention was the likely reason that shelter-in-place counties had a lower COVID-19 death rate (137.2) than no-shelter-in-place counties (166.4), or it was the governor’s political affiliation and the subsequent political party effect. It should be mentioned though that counties belonging to states with a Republican governor who also imposed shelter-in-place orders had much higher COVID-19 death rate (median 157.8) than counties in states that also imposed a shelter-in-place order but had a Democratic governor (median 117.4). In other words, controlling for a shelter-in-place order, Republican counties (mainly located in the southern United States, like New Mexico, Texas, Kansas, Mississippi, Alabama and Georgia; Figure 2) were hit harder than Democratic counties. However, this may not be the result of political influence both at the public reaction and people’s behaviour against the severity of the epidemic, but due to the different socioeconomic composition of the underlying population across the two regimes. A more detailed discussion regarding the demographic, socioeconomic and pre-existing health condition effects on COVID-19 per regime can be found in Sections 4.2 and 4.3.

### 4.2 | Demographic effects per regime

Many studies have identified the percentage of African American population as a determinant (positive relationship) of the COVID-19 death rate (Andersen et al., 2021; Feinhandler et al., 2020). Our study confirms this finding for the MSA, shelter-in-place and Republican regimes, but not for the rest (Table 4). Evidence from other researchers pertaining to health disparities in the United States, particularly with respect to African Americans, can potentially explain this relationship (McLaren, 2020). In addition, African Americans are more likely to have a higher prevalence of underlying health conditions, explaining the positive relationship to the COVID-19 death rate (Hamidi et al., 2020). We also found that the percentage of the Asian population is negatively related to the COVID-19 death rate in non-MSA and no-shelter-in-place counties but not related to the other regimes. Recent research regarding COVID-19 deaths in US counties as of
November 2020 also identified a negative association of the Asian population to COVID-19 deaths (Desmet & Wacziarg, 2021). This could be potentially explained by the culture of Asians in confronting epidemics (i.e., wearing face masks without having to be ordered) and by their behavioural attitude (i.e., avoiding handshakes) (Leung et al., 2020). This is probably the reason why this variable is significant only in non-MSA and no-shelter-in-place areas. For example, we speculate that the Asian population would follow protective measures (e.g., wearing masks) even in the counties that did not issue shelter-in-place orders, and as such they had a negative effect on the COVID-19 rate. On the other hand, in regimes where the entire population was ordered to follow specific measures, the effect of the Asian population was not significant because the majority of people would follow the same rules.

The age structure of the population has been shown to be related to COVID-19 transmission and deaths (Dowd et al., 2020). Our research shows that the age group 20–39 is negatively linked to the COVID-19 death rate across all regimes while the age group 40–59 is negatively linked only for MSA and shelter-in-place but for the other regimes it is insignificant. Many scholars have raised concerns about protecting high-risk population groups with close intergenerational ties with other population groups, such as grandparents with children and grandchildren (Dowd et al., 2020). Although the percentage of people between 20 and 30 is negatively related to the COVID-19 death rate, this does not mean that they cannot transmit the virus to older people (for example, their parents). For this reason, mapping age-related spatial clustering could improve critical care forecasts and healthcare system preparedness.

This study found that population density is significant only for no-shelter-in-place and Republican regimes but not for other regimes, which contrasts with early studies. For example, a study referring to data up to 3 August 2020 for US counties concluded that population density is a crucial driver for COVID-19 deaths (Feinhandler et al., 2020). Because urban areas tended to vote Democrat in the 2016 presidential election, they estimated that the death rate (per 100,000) for the Democratic counties was 71.0 and 36.8 for the Republican counties. Due to this association, the urban–rural divide and related population density were suggested as a viable explanation for the large difference in death rates. However, here we show that the death rates are reversed after the first year of the pandemic, with a death rate (median) of 117.5 for Democratic counties and 160.1 for Republican counties (see Supporting Information, Section S5). In another study, Fielding-Miller et al. (2020) reported that population density is significant when analysing all US counties. However, when they stratified the analysis they found that population density is significant for rural counties but not urban counties.

4.3 Socioeconomic and underlying health condition effects per regime

How median household income is linked to COVID-19 is not entirely clear as results from studies are contradictory. For example, income inequality and median household income were significant explanatory variables of a multiscale GWR model used to explain the spatial variability of COVID-19 incidence in the United States from 22 January 2020 to 9 April 2020 (Mollalo et al., 2020). However, another study that used OLS, SLM and SEM to study COVID-19 deaths at the county level for the United States from 22 January 2020 to 26 July 2020, found no evidence for median household income to be linked either with COVID-19 deaths or confirmed cases (Maiti et al., 2021).

In our analysis, the median household income is significant only in the MSA regime and not in other regimes. This indicates that income is not strongly related to the COVID-19 death rate, but it may be a significant driver under specific contexts such as the MSA regime. We found a positive relationship between median income and COVID-19 death rate, which contrasts with the general belief that people with lower income are more prone to COVID-19 death (Drefahl et al., 2020). However, the poorer populations are more likely to lack access to health services (Duminy, 2021), which may lead to higher COVID-19 death rates. In fact, our analysis showed that the population with a lack of insurance access is positively related to the COVID-19 death rate with all regimes except for Democratic. This highlights the importance of health insurance against COVID-19. Those without health insurance are more likely to work in service-oriented industries with a decreased ability to work from home and are most susceptible to COVID-19 (Chin et al., 2020). In addition, the medical cost of COVID-19 treatment is high in the absence of health insurance, with an estimated US$14,366 on median values per single symptomatic patient with SARS-CoV-2 needing hospitalisation (Bartsch et al., 2020). This may create a sense of financial insecurity for the expected cost of medical treatment, even for those with adequate income (but no insurance), thus avoiding visiting a hospital in the case of early symptoms and losing precious time, which may be fatal.

Like others, we found that those having comorbidities are more prone to die from COVID-19 (Drefahl et al., 2020). Our findings support the substantial impact of heart disease mortality on COVID-19 death rate for MSA, shelter-in-place,
Democratic and Republican regimes. The percentage of the population sleeping less than seven hours per night was negatively associated with the COVID-19 death rate, which agrees with multiple findings that associate insufficient sleep with seven of the 15 leading causes of death in the United States (Kochanek, 2014). Based on our study, the percentage of other population, the percentage of households with housing problems, the unemployment rate, and obesity prevalence did not seem to be influential on the COVID-19 death rate.

A limitation of the study is that the count of COVID-19 deaths at any given time is undercounted due to a lag in reporting deaths (Fineberg, 2020). Missed or presumed COVID-19 death diagnosis (i.e., patients dying at home and not tested for COVID-19, or individuals who actually died from other causes) may infer additional bias in the official COVID-19 death counts. Excess mortality could be used to assess the pandemic’s total impact on mortality. However, in the absence of excess deaths data at the county level, and similar to others (Andersen et al., 2021; Maiti et al., 2021; Mollalo et al., 2020), we used the confirmed COVID-19 deaths.

5 | CONCLUSIONS

This study's proposed modelling framework captures geographical, socioeconomic and underlying health factors as important contributors to COVID-19 death rates. It illustrates the strength of local spatial regression modelling to capture spatial heterogeneity, which enhances our understanding of rapidly evolving phenomena. We show that spatial variation of COVID-19 is significantly associated with a wide range of demographic, socioeconomic and underlying health characteristics across spatial regimes. We found a persistent role of the percentage of the population aged between 20 and 39 and percentage of the population with disability. We also identified a lack of insurance access as a significant driver across all regimes except for Democratic. Other factors display changing patterns. For example, the heart disease mortality rate is not significant in non-MSA and no-shelter-in-place counties while it is for all others.

Moreover, the coefficient of a variable may change a lot across the same set of regimes, indicating that spatial regimes are necessary to model spatial heterogeneity. We also showed that the governor’s political orientation might have impacted the COVID-19 death rates due to the public response (i.e., shelter-in-place vs. no-shelter-in-place order). Policy-wise, the take-home message of this study is that the COVID-19 death rate not only depends on a complex interplay of the population demographic, socioeconomic and health-related characteristics but also on the spatial regime where the residents live, work, and play. This provides a foundation for policies that are sensitive to local specificities, as identifying the demographic, socioeconomic and health drivers of COVID-19 deaths, and how they spatially vary across regimes, assist governments to efficiently manage health crises so that all people have equal opportunities of staying healthy.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study were derived from the following resources available in the public domain: US Census Bureau https://data.census.gov/cedsci/ and USAFacts https://usafacts.org/visualizations/coronavirus-covid-19-spread-map

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Additional supporting information may be found in the online version of the article at the publisher’s website.

Supporting text, tables, and figures

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