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Space, mortality, and economic growth

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Abstract

Currently, most academic research involving the mortality modeling of multiple populations mainly focuses on factor-based approaches. Increasingly, these models are enriched with socio-economic determinants. Yet these emerging mortality models come with little attention to interpretable spatial model features. Such features could be highly valuable to demographers and old-age benefit providers in need of a comprehensive understanding of the impact of economic growth on mortality across space. To address this, we propose and investigate a family of models that extend the seminal Li-Lee factor-based stochastic mortality modeling framework to include both economic growth, as measured by the real gross domestic product (GDP), and spatial patterns of the contiguous United States mortality. Model selection performed on the introduced new class of spatial models shows that based on the AIC criteria, the introduced spatial lag of GDP with GDP (SLGG) model had the best fit. The out-of-sample forecast performance of SLGG model is shown to be more accurate than the well-known Li–Lee model. When it comes to model implications, a comparison of annuity pricing across space revealed that the SLGG model admits more regional pricing differences compared to the Li-Lee model.

KEYWORDS

annuity pricing, economic growth, mortality, mortality forecasting, spatial lag model

1 | INTRODUCTION

With life expectancy undergoing substantial improvements over recent decades, institutionally managed financial needs of a rapidly aging population are getting more costly (Blake & Cairns, 2020). The process of aging of a population yields a change in the relative number of retirees compared to the number of active workers, which given political constraints of taxation, can create financial uncertainty for these institutions. That is why the ability to understand human survivorship is essential for actuarial, economic, and demographic practices, especially with regards to mortality modeling (Li & O'Hare, 2019; Renshaw & Haberman, 2003; Seklecka et al., 2017), annuity pricing (D'Amato et al., 2011; Pitacco, 2016), and social security affordability (Soneji & King, 2012).

The relationship between mortality and economic growth is particularly complex when it comes to social security affordability. For example, in the case of the United States (US) if there is a positive correlation of economic growth and longevity, then a program such as the US federal Old-Age and Survivors Insurance (OASI) could be more expensive in the long term, as a result of the economy performing well and vice versa. In the context of the European Union (EU), it is not hard to see how this relationship would be of interest to insurers or reinsurers who conduct business across the entire EU. As the economy may grow faster in one location than others, it may lead to better habits in life and better health care and opposite when an economy declines. For instance, it is well known that smoking is more prevalent in populations with a declining economy (Franks et al., 2007). In fact, the demographic literature recognizes that there exists a long-run relationship between economic developments and mortality changes in various countries and there is a cross-sectional positive dependence between life expectancy and real per capita income (Preston, 1975). Also, significant co-movements between mortality dynamics and the gross domestic product (GDP) per capita have been shown (Hanewald, 2011). A particular complexity is the relationship between neighboring states' GDP, mortality, and mortality of a state under consideration. At present, there is a lacking of a state-level literature that investigates this nexus. However, when it comes to US, the relationship between measures of economic growth and regulatory and economic freedoms of neighboring states has been shown to exist (Hall et al., 2019).

All considered models of mortality and economic growth in the US should ultimately be heterogeneous in their analyses of the different states and allow for the interconnections of mutual influences between space, mortality, and economic growth. Thus, we propose and investigate a new class of models, with one of the defining features being the ability to capture the heterogeneous economic growth impact on human mortality across space. When considering the connection between mortality and GDP in different states, our models' second defining feature is investigating the effect that neighboring states' economic growth has on the mortality of a particular state. With this approach, we focus on the intricacies of the relationship between mortality and economic growth and show that even though these dynamics are by no means trivial, by considering stochastic models of economic and mortality patterns across space and time, this relationship can be much better understood.

Previously, Niu and Melenberg (2014) and Boonen and Li (2017) added economic growth as a risk factor to the Lee–Carter model (Lee & Carter, 1992) and to the Li–Lee model (Li & Lee, 2005), respectively. Also, Seklecka et al. (2019) obtained better mortality forecasts by adding economic growth as a risk factor to O'Hare-Li model (O'Hare & Li, 2012). The recent works of Li and Lu (2017), Doukhan et al. (2017), Ludkovski et al. (2018), and Shi (2020) implemented spatial considerations into the mortality modeling framework by defining spatial relationships based on closeness in age and time; however, we investigate spatial patterns from a geographical perspective, in spirit of Quick et al. (2018). Also, multi-population models have gained significant interest in recent years, with various institutions such as the Dutch and Belgian Actuarial Institute relying on them to provide mortality projections for insurers (Antonio et al., 2017). That is why in this work, we propose a multi-population model with economic growth and extend Boonen and Li (2017) to introduce spatial dependence of mortality dynamics in the short-run. The spatial effect parameters account for the spillover effects among adjacent geographic locations. While such effects can be present in any region comprised of neighboring populations, we will use the United States of America as a motivating example throughout this paper. Intuitively, in the context of the US, it is not difficult to imagine that due to labor mobility or health care systems, an increase in life expectancy or GDP per capita in Massachusetts may have a direct positive impact on the life expectancy in Rhode Island but no direct effect on the life expectancy in Arizona.

Our contributions in this paper are manifold. First, we comprehensively discern the impacts that the structural inequalities in economic growth on mortality across space. Specifically, we disentangle the heterogeneous impact across space of GDP on mortality, the effect of neighboring GDP on mortality of a particular state, the effect of mortality in neighboring states has on mortality of a particular state, the effect that the national GDP has on mortality in individual states, and the effect that the GDP in previous years has on mortality. Second, we compare and validate the best performing models, by performing thorough backtesting and forward testing assessments, as well as residual analysis. Third, we benchmark the model implications by performing an annuity pricing comparison between leading model candidates.

Our work should garner significant interest of academics and practitioners in the actuarial, economic, and demographic communities. To the best of our knowledge, we are the first to model the connection between structural economic inequality and mortality at the comprehensive level for the case of the US, thus bridging the actuarial, economic, and demographic disciplines. For various practitioners and stakeholders, this paper provides a justification for considering interconnected spatial components in mortality models of any given state, while also considering economic characteristics.

The paper is organized as follows. In Section 2, we describe the data that we use in this paper. The mortality models with GDP are introduced and examined in Section 3. In Section 4, we define our forecasting method and validate the forecast performance of mortality models as well as a forecast comparison in an application of annuity pricing. Finally, Section 5 concludes the study.

2 | DATA

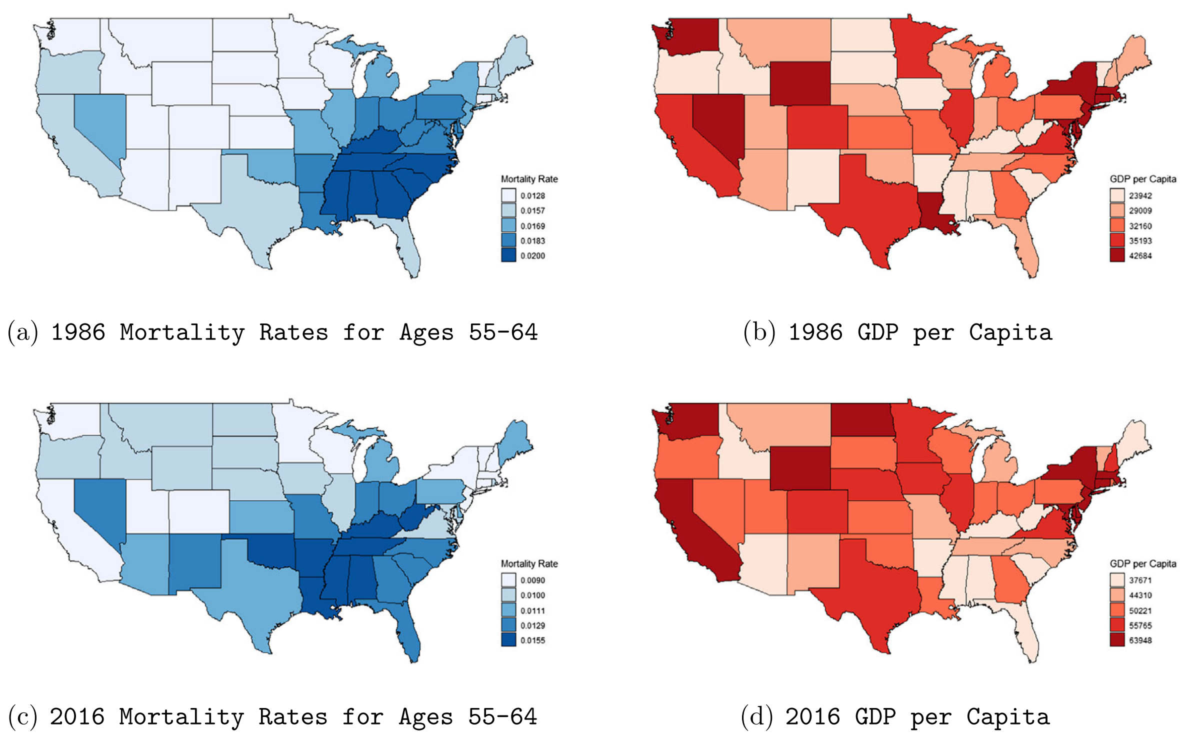
In this paper, we measure economic growth by the GDP per capita. Data of the real GDP per capita per state in the US from 1977 to 2016 are collected from the Bureau of Economic Analysis.[12]

To model human mortality, we focus on the central death rates in every state of the US, and we consider only the male population. For notational convenience, we label the 48 contiguous states with numbers from 1 to 48. The states Hawaii and Alaska are excluded because they do not share a land-border with another state. The central death rate of a population for a given year is the number of deaths occurring among a population during a given year relative to the number of people that are alive at the beginning of that given year. We let $m_{i,x,t}$ denote the central death rate for age group $x \in \{0, 1-4, 5-9, 10-14, 15-19, 20-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85+\}$ at time $t \in \{1977, 1978, ..., 2016\}$ in state $i \in \{1, 2, ..., 48\}$, to be

$$m_{i,x,t} = \frac{\text{Number of deaths in age group } x \text{ at year } t \text{ in state } i}{\text{Number of people alive in age group } x \text{ at time } t \text{ in state } i}.$$

The mortality data that we investigate in this study are obtained from the Centers for Disease Control and Prevention's (CDC) WONDER internet databases.[3] The Compressed Mortality File (CMF), produced by the National Center for Health Statistics, is a national mortality and population database, which spans the years 1968–2016. This dataset specifically features the crude mortality rates for each age bracket among the individual counties of the contiguous US, as identified by their respective Federal Information Processing Standards (FIPS) codes.

As an example, in Figure 1, we display the central death rates for all contiguous states of the age group of 55–64 years, for two different years. To compare the central death rates, we also show in this figure the GDP per state. All plots in Figure 1 display the value of the death rate (in red) and GDP per capita (in blue) relative to the US average. With a darker shade, a relatively higher value of the death rate or GDP is represented. For instance, the states California and New York have a high relative GDP per capita, while having a low death rate. Each of the maps presents a clear spatial pattern of mortality, with states having similar mortality rates clustered together across the entire country. These are the effects that we capture in this paper.



(a) 1986 Mortality Rates for Ages 55-64 (b) 1986 GDP per Capita

(c) 2016 Mortality Rates for Ages 55-64 (d) 2016 GDP per Capita

FIGURE 1 Comparison between the mortality rates of the 55–64 age group and the GDP per capita for the years (a, b) 1986 and (c, d) 2016. A darker shade represents a relatively higher death rate or GDP when compared to the national average.

3 | MODEL EXAMINATION

3.1 | Spatial mortality models with state GDPs

Rather than generating separate models for each individual state, Li and Lee (2005) show the plausibility of improving mortality forecasts for individual populations by taking into account the mortality dynamics in a larger group. The Li–Lee model is a multi-population generalization of the Lee–Carter model, in which a common mortality pattern is incorporated and a coherence assumption is imposed where forecasts of different populations could not diverge in the long run. The Li–Lee model is given by

$$\log(m_{i,x,t}) = \alpha_{i,x} + B_x K_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t},$$

with the following normalization conditions: $\sum_x \beta_{i,x} = 1$ and $\sum_t \kappa_{i,t} = 0$ for all i, and $\sum_x B_x = 1$ and $\sum_t K_t = 0$. The error terms $\varepsilon_{i,x,t}$ are assumed to be i.i.d. Gaussian with mean 0. Here, the parameter $\alpha_{i,x}$ describes the time-average mortality for each state i and age x, the common factor K_t captures the evolution of national mortality rates over time, and the age effect B_x explains this sensitivity to this K_t of the age-specific mortality rates. To ensure coherency, the $\kappa_{i,t}$ time-series processes need to be stationary (Li & Lee, 2005). Li and Lee (2005) propose to estimate the parameters in a two-step procedure, by first estimating the common parameters B_x and K_t from the combined data for all the populations and then, second, estimating the remaining population-specific parameters. In both estimation steps, the parameters are estimated by a singular value decomposition.

Starting from the above, to develop a family of multi-population mortality models that combine coherency, macroeconomic variable GDP, and spatial effects, we begin by recalling the simple extension of the Li–Lee model developed by Boonen and Li (2017).

$$\log(m_{i,x,t}) = \alpha_{i,x} + \gamma_x GDP_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t},$$

where $\alpha_{i,x}, \beta_{i,x}$ and $\kappa_{i,t}$ are the state population-specific parameters and GDP_t is the demeaned GDP per capita of the US at time t, with respective loading γ_x. The following normalization conditions apply: $\sum_x \beta_{i,x} = 1$ and $\sum_t \kappa_{i,t} = 0$. The error terms $\varepsilon_{i,x,t}$ are assumed to be i.i.d. Gaussian with mean 0. In this base model, the parameters are estimated in two steps. First, parameters $\alpha_{i,x}$ and γ_x are estimated by OLS. Second, the remaining parameters $\beta_{i,x}$ and $\kappa_{i,t}$ are estimated by a singular value decomposition. We refer to Boonen and Li (2017) for a further discussion on the estimation.

To extend this model to the spatial domain, we propose incorporating spatially autoregressive and lagged components to generate a class of models of the form

$$\begin{aligned}\log(m_{i,x,t}) = {} & \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) \\ & + \psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t} + \gamma_{i,x} GDP_{i,t} + \beta_{i,x}\kappa_{i,t} \\ & + \varepsilon_{i,x,t}. \qquad (1)\end{aligned}$$

The following normalization conditions apply: $\sum_x \beta_{i,x} = 1$, $\sum_t \kappa_{i,t} = 0$, $\operatorname{cov}(\sum_{k\neq i} W_{i,k}\log(m_{j,x,t}),\ \kappa_{i,t}) = \operatorname{cov}(\sum_{k\neq i} W_{i,k} GDP_{k,t},\ \kappa_{i,t}) = \operatorname{cov}(GDP_{i,t},\ \kappa_{i,t}) = 0$. Here, cov means the sample covariance. These constraints identify the parameters uniquely, which proof follows the same steps as in theorem 3.1 of Boonen and Li (2017) and is thus omitted. The $\alpha_{i,x}, \beta_{i,x}$ and $\kappa_{i,t}$ are the state-specific parameters; $GDP_{i,t}$ is the demeaned GDP per capita of state i at time t, with respective loadings $\gamma_{i,x}$; and W is a fixed matrix that indicates whether states are neighbors. Each state is represented in the matrix W by a row i, and potential neighbors by the columns j, with $j \neq i$. The existence of a spatial relationship between states i and j is defined as $w_{i,j} = 1$, and the elements of W are comprised of the row-standardized weights $W_{i,j} = w_{i,j}/\sum_j w_{i,j}$. Conceptually, $W_{i,j}$ is non-zero if the two states i and j share a common border, such as California and Arizona, and zero if they are not adjacent, such as California and New York. In that context, rather than treat the US as an "island," Canada and Mexico are also included in our spatial models.

Including $\rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t})$ and $\psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t}$ into our model allows for the exploration of spatial lag coefficients. Specifically, $\rho_{i,x}$ provides means for an investigation of the effect that mortality rates from neighboring states have on the mortality of a specific state, while $\psi_{i,x}$ focuses on the relationship between the economic growth of specific states in relation to the mortality rates of their neighbors, which addresses the impact that the economic growth in a state has on the mortality dynamics of states that it shares close proximity with.

The parameters of the proposed model are estimated in two steps where we combine the approaches of Haining and Haining (2003) for spatial models and Niu and Melenberg (2014) for mortality models. First, we estimate the parameters $\alpha_{i,x}$ as

$$\widehat{\alpha}_{i,x} = \frac{\sum_{t=1977}^{2016}\log(m_{i,x,t})}{2016-1977+1},$$

and we estimate the spatial parameters and the parameters $B_{i,x}$ by ordinary least-square (OLS). Second, the parameters $\beta_{i,x}$ and $\kappa_{i,t}$ are estimated using a singular value decomposition. This procedure ensures that the $\kappa_{i,t}$ parameters are estimated orthogonally to the other terms in the model.

3.2 | Model specifications

We will refer to the model given by expression (1) as spatial complete. We also study possible simplifications of this model by setting certain parameters to zero or by focusing on national GDP rather than state-specific GDP. Table 1 contains an overview of all of the models that we investigate in this study. There are a variety of models that will be investigated. For example, the "Time Lagged GDP" model assumes that mortality in an individual state at any point in time is only concerned with an unobservable latent factor and the first time lag of the state's individual GDP per capita. The "Spatial Lag of GDP" model only considers the effects that the GDP of neighboring states have on mortality of an individual state. The "Spatial Autoregressive with National GDP" model considers the effects that the mortality of an individual states' neighbors, in combination with the GDP of the entire country, has on mortality rates in the state, and so on.

3.3 | Model selection

To evaluate the in-sample fit for model selection, the AIC and BIC ratios are compared for the mortality models. The AIC ratio is introduced by Akaike (1973) and is defined as

$$AIC = -2 \cdot \log\left(\widehat{L}\right) + 2 \cdot k,$$

where $\log\left(\widehat{L}\right)$ is the log-likelihood of the model and k is the number of its free parameters to be estimated. Moreover, as defined by Schwarz (1978), the BIC ratio is given by

$$BIC = -2 \cdot \log\left(\widehat{L}\right) + k \cdot \log(n),$$

where n is the number of data points. The number of free parameters, k, is the number of total parameters minus the number of constraints placed in the model. A lower AIC or BIC ratio means that the model has a better in-sample fit. The difference between the AIC and the BIC is that the BIC ratio imposes a higher penalty for the number of free parameters. Multi-population mortality models contain typically many free parameters. A well-cited reference that explains the differences between the AIC and BIC ratios is Yang (2005).

Table 2 displays the number of free parameters, the AIC and BIC ratios and the R^2 for each of the models in the study. After fitting procedure, we find that the BIC ratio of the Li–Lee model is the smallest, indicating the best in-sample fit. For the AIC ratio, we observe that the Spatial Lag of GDP with GDP (SLGG) model has the best in-sample fit. While our hypothesis was that the mortality of a particular state may be affected by the evolution of

TABLE 1 Family of multi-population mortality models that are studied in this paper.

Name	Model specification
Li–Lee	$\log(m_{i,x,t}) = \alpha_{i,x} + B_x K_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Base	$\log(m_{i,x,t}) = \alpha_{i,x} + \gamma_x GDP_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \gamma_{i,x} GDP_{i,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial autoregressive Li–Lee	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + B_x K_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Time lagged GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \phi_{i,x} GDP_{i,t-1} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
GDP with time lagged GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \gamma_{i,x} GDP_{i,t} + \phi_{i,x} GDP_{i,t-1} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial time lagged GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \xi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t-1} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
GDP with spatial time lagged GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \gamma_{i,x} GDP_{i,t} + \xi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t-1} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial autoregressive	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial lag of GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial autoregressive with GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + \gamma_{i,x} GDP_{i,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial lag of GDP with GDP (SLGG)	$\log(m_{i,x,t}) = \alpha_{i,x} + \psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t} + \gamma_{i,x} GDP_{i,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial autoregressive with national GDP	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + \gamma_x GDP_t + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + \psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$
Spatial complete	$\log(m_{i,x,t}) = \alpha_{i,x} + \rho_{i,x}\sum_{j\neq i} W_{i,j}\log(m_{j,x,t}) + \psi_{i,x}\sum_{k\neq i} W_{i,k} GDP_{k,t} + \gamma_{i,x} GDP_{i,t} + \beta_{i,x}\kappa_{i,t} + \varepsilon_{i,x,t}$

TABLE 2 The total number of parameters, AIC and BIC ratios, and the R^2 for each of the multi-population mortality models.

Name	Total number of parameters	AIC	BIC	R^2
Li–Lee	3,221	−30,857.11	**−5,490.77**	0.9323
Base	3,181	−29,868.97	−4,803.26	0.9296
GDP	3,792	−30,671.82	−641.71	0.9347
Spatial autoregressive Li–Lee	3,845	−29,605.71	830.65	0.9323
Time lagged GDP	3,744	−29,962.10	−414.35	0.9386
GDP with time lagged GDP	4,368	−29,619.02	4,982.95	0.9407
Spatial time lagged GDP	3,744	−30,524.76	−977.02	0.9399
GDP with spatial time lagged GDP	4,368	−30,706.31	3,895.66	**0.9431**
Spatial autoregressive	3,792	−26,789.46	3,240.65	0.9245
Spatial lag of GDP	3,792	−31,259.67	−1,229.56	0.9361
Spatial autoregressive with GDP	4,416	−29,420.78	5,679.34	0.9347
Spatial lag of GDP with GDP (SLGG)	4,416	**−31,979.41**	3,120.72	0.9407
Spatial autoregressive with national GDP	3,805	−27,137.65	2,998.09	0.9256
Spatial	4,416	−30,011.46	5,088.67	0.9361
Spatial "complete"	5,040	−30,731.44	9,438.71	0.9407

Note: The models are defined in Table 1, and the best models bold-faced for all three model selection criteria.

mortality of its neighboring states, this has implicitly been rejected in the model selection process as the chosen models do not feature any spatial lag of neighboring mortality rates. However, the main hypotheses that economic inequalities have an impact on mortality still remains to be explored. Based on this, we proceed our investigation by studying the Li–Lee model and the SLGG model.

In addition to the AIC and BIC ratios, heat maps of the residuals for the SLGG model are displayed in Figure 2 for the states of Arizona, California, Florida, and Texas, to further assess the fitting performance of the model. The residuals illustrated in these maps are presented as a function of both age group and calendar year, with the lighter gray areas displaying more negative valued residuals, and similarly, darker regions in black corresponding to more positive residuals. From these plots, we observe no discernible systematic structure in terms of the residuals for the SLGG model in these selected states.

3.4 | Discussion of estimation results

The parameter estimates for $\gamma_{i,x}$ and $\psi_{i,x}$ in the SLGG model allow us study the effect that economic growth has on the mortality rate of each individual state, as well as to understand the influence that the GDP of a particular state's neighbors have on their mortality rate. To visually investigate the impact that the economic growth of a state's neighbors has on its mortality, Figure 3 displays a map of the estimates for the state specific parameter $\psi_{i,x}$ obtained by the SLGG model. The parameter $\psi_{i,x}$ represents the spatial spillover effects that GDP of neighboring states of State i has on the mortality of age-group x in State i. These maps allow us to gain insight into the sensitivity of the mortality with respect to changes in GDP of the neighboring states. The states colored in blue represent a negative relationship, indicating a lower mortality experience associated with the improved economic situation of their neighboring states, and similarly, states colored in red indicate a higher mortality experience associated with the improved economic situation of their neighbors.

From these maps, we observe the strongest associations between mortality rates and neighboring states' economic situations occur for the 65 to 74 age group, as indicated by the darkest shaded in regions, which contain the peak retirement ages for the majority of the US. In the northeastern states of Maine, New Hampshire, New Jersey, and Connecticut, we observe that the improved economic situation of neighbors corresponds with a lower mortality experience. The state of Massachusetts experiences an opposite effect, where the improved economic situation of its neighbors corresponds to higher mortality rates. Further research is needed to investigate whether the higher costs of living in the state of Massachusetts may cause retirees to take advantage of

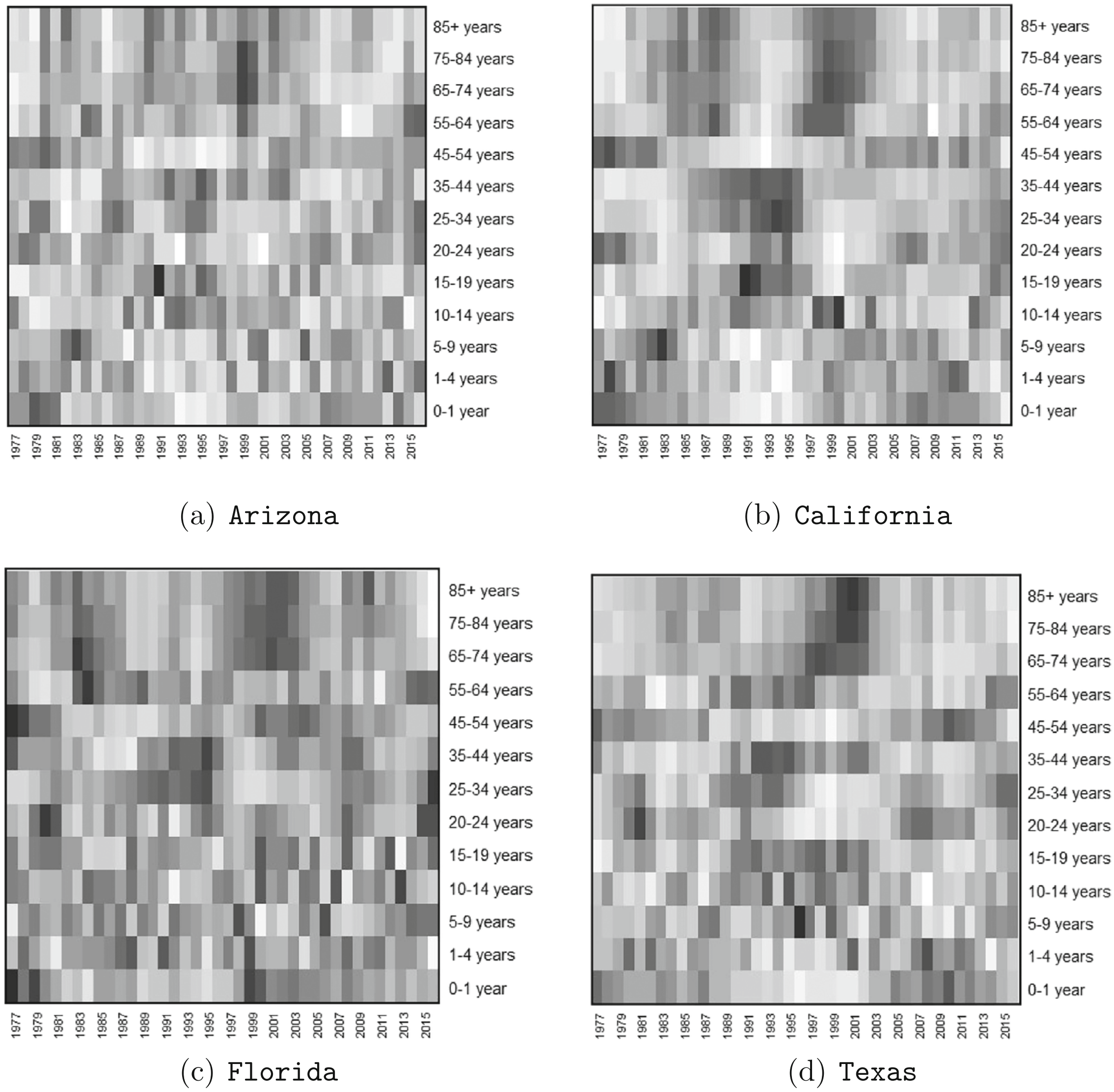
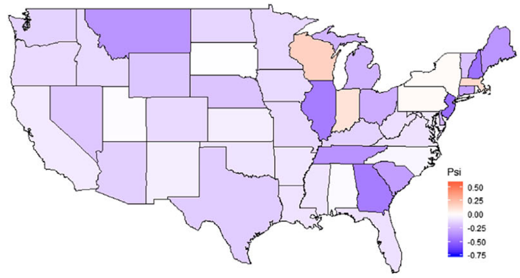


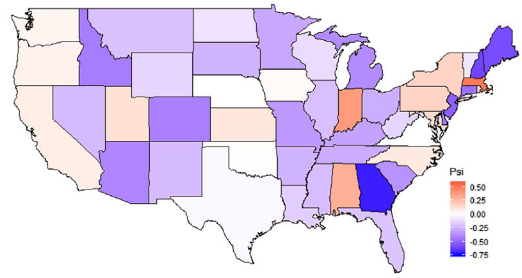
FIGURE 2 Comparison of residual plots of the SLGG model for the studied age groups across the years of 1977 to 2016 for the states of (a) Arizona, (b) California, (c) Florida, and (d) Texas.

better conditions in neighboring states when the economic situation is flourishing and would be valuable for better understanding the mortality experiences of small states that are in very close proximity to each other. It should be noted that affluent states such as California and Texas, which have some of the largest GDPs in the US, are not greatly affected by the economic situation of their neighboring states.

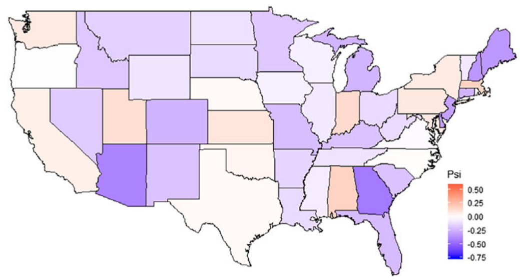
To investigate the impact that a state's GDP has on mortality, the state specific parameter estimates of $\gamma_{i,x}$ are presented in Table 3. From the table, we observe how the relationship between economic growth and mortality differs for each state across the four oldest age groups being studied. We see that in the western states of Washington and Oregon, the estimates are similar in magnitude and direction across the age groups, indicating that the economic growth within each of these states has a similar impact on their respective mortality rates. This contrasts the estimates in the midwestern states of Nebraska and Missouri, in which the estimated parameters indicate that economic growth has a different impact on mortality for each of the age groups. We see that parameter estimates of $\gamma_{i,x}$ in the affluent states of California and Texas are much greater in magnitude than their respective estimates of $\psi_{i,x}$. This demonstrates that the mortality experience within these states is much more impacted by their individual GDPs, than by the economic growth of their neighboring states. For annuity providers, these observed relationships between mortality and GDP in space, which greatly differ across the age groups in study, further demonstrate the need of more nuanced techniques to accurately model pricing.



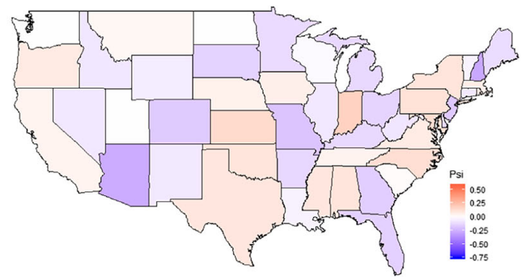
(a) $\psi_{i,x}$, Ages 55-64



(b) $\psi_{i,x}$, Ages 65-74



(c) $\psi_{i,x}$, Ages 75-84



(d) $\psi_{i,x}$, Ages 85+

FIGURE 3 Mapped estimates of the state specific parameter $\psi_{i,x}$ for the four oldest age groups, as obtained from the SLGG model: (a) ages 55–64, (b) ages 65–74, (c) ages 75–84, and (d) ages 85+.

Interestingly, we find that when it comes to big and affluent states such as California and Texas, there is a large direct impact of the GDP on mortality, while the GDP in neighboring states is relatively small (a very negative estimate of $\gamma_{i,x}$ and an estimate of $\psi_{i,x}$ close to zero). On the other hand, for states with big and affluent neighbors such as Arizona, Georgia, or New Mexico, we find the opposite effect (an estimate of $\gamma_{i,x}$ close to zero and a very negative estimate of $\psi_{i,x}$).

4 | FORECASTING AND COMPARISON OF THE BEST PERFORMING MODELS

To compare the best performing models, we begin by formulating an approach to model individual states' GDP. Following that, we perform both backtesting and forward testing assessments.

4.1 | GDP model

To capture the time-dependent variables for the selected models, we propose time series models. In line with Li and Lee (2005), Niu and Melenberg (2014), and Boonen and Li (2017), we fit a random walk with drift to the common latent factor, assuming

$$K_t = K_{t-1} + c + \eta_t,$$

where c is the drift term and the error term η_t is i.i.d. Gaussian with mean 0. The common factors are assumed to be non-stationary with a linear trend. Following Li and Lee (2005), to allow for stationary of the population-specific processes $\kappa_{i,t}$, we fit each with an $AR(1)$ specification:

$$\kappa_{i,t} = c_{i,0} + c_{i,1}\kappa_{i,t-1} + \omega_{i,t},$$

where the error term $\omega_{i,t}$ is i.i.d. follows a Gaussian distribution with mean 0.

Forecasting the GDP of each individual state over time requires attention to the dependencies that each of the states have on one other. Vector autoregressive (VAR) models are used to model vectors of variables that are assumed stationary, allowing for lagged relationships between the variables and for the correlations between the variables. A pth-order vector autoregression, VAR(p), based on p lags of the variables is given by

$$y_t = c + \mathbf{\Phi}_1 y_{t-1} + \mathbf{\Phi}_2 y_{t-2} + \ldots + \mathbf{\Phi}_p y_{t-p} + \epsilon_t,$$

TABLE 3 Estimates of the state specific parameter $\gamma_{i,x}$ for the four oldest age groups, as obtained from the SLGG model.

Parameter $\gamma_{i,x}$ State (i)	Age group (x) 55–64	65–74	75–84	85+
Alabama	−0.0810	−0.4039	−0.2291	−0.0823
Arizona	−0.0033	0.2301	0.2861	0.2380
Arkansas	0.0070	0.1530	0.0720	0.1237
California	−0.1398	−0.2768	−0.2079	−0.1121
Colorado	−0.0675	0.2198	0.1271	0.1357
Connecticut	0.0864	0.2616	0.1025	0.0248
Delaware	0.0443	0.2453	0.1747	0.1034
Florida	−0.0531	0.0379	0.1020	0.1131
Georgia	0.2480	0.5629	0.3568	0.1782
Idaho	−0.0311	0.2614	0.0860	0.0620
Illinois	0.2250	0.0327	−0.0545	0.0241
Indiana	−0.2486	−0.5143	−0.2318	−0.2035
Iowa	−0.0277	−0.1640	−0.0515	−0.0813
Kansas	−0.0648	−0.2148	−0.1757	−0.1567
Kentucky	0.0201	0.1995	0.1268	0.1146
Louisiana	−0.0348	0.0227	0.0313	0.0457
Maine	0.1390	0.4007	0.2349	0.1006
Maryland	−0.1417	−0.3591	−0.2307	−0.1819
Massachusetts	−0.3726	−0.7063	−0.3047	−0.1034
Michigan	0.0800	0.2156	0.1294	0.0912
Minnesota	−0.0760	0.0915	0.0483	0.0843
Mississippi	0.0017	0.1258	0.0038	−0.0915
Missouri	−0.0132	0.1960	0.1255	0.1608
Montana	0.1803	0.0312	0.0388	−0.0563
Nebraska	0.0224	−0.1524	−0.1170	−0.0656
Nevada	0.0206	0.0921	0.0676	0.0503
New Hampshire	0.2189	0.3979	0.2243	0.2511
New Jersey	0.2552	0.3063	0.1524	0.1154
New Mexico	−0.0712	0.0642	0.0900	0.0364
New York	−0.2498	−0.3920	−0.2474	−0.1845
North Carolina	−0.1472	−0.2255	−0.0901	−0.1157
North Dakota	−0.0167	−0.0570	−0.0105	−0.0522
Ohio	0.1109	0.1157	0.0208	0.1154
Oklahoma	0.0418	−0.0868	−0.0857	−0.1031
Oregon	−0.0550	−0.2120	−0.0938	−0.1006
Pennsylvania	−0.2134	−0.3583	−0.2186	−0.1551
Rhode Island	−0.2023	−0.3225	−0.1323	−0.1186
South Carolina	0.1498	0.1946	0.1142	0.0135
South Dakota	−0.1572	0.0854	0.0115	0.1080
Tennessee	0.2474	0.1687	0.0271	−0.0396
Texas	0.0124	−0.1319	−0.1201	−0.1129
Utah	−0.1388	−0.2912	−0.2315	−0.0209

(Continues)

TABLE 3 (Continued)

Parameter $\gamma_{i,x}$ State (i)	Age group (x) 55–64	65–74	75–84	85+
Vermont	−0.0529	−0.1324	−0.0549	0.0077
Virginia	−0.1339	−0.1952	−0.0996	−0.0898
Washington	−0.0467	−0.2128	−0.1892	−0.0361
West Virginia	−0.0204	0.0169	0.0497	0.0831
Wisconsin	−0.3526	−0.0500	−0.0636	−0.0078
Wyoming	0.0519	−0.0232	−0.0257	0.0184

where the GDPs of the individual state being modeled at time t, along with its neighboring states,[4] are denoted by the vector y_t, $\mathbf{c}$ is a vector of constants, $\mathbf{\Phi}_i$ is a matrix of autoregressive coefficients for $i=1,2,\ldots,p$, and ϵ_t is the i.i.d. Gaussian error term with mean 0. The lag order of the VAR, p, is determined by using selection criteria such as Akaike's Information Criteria (AIC), Hannan-Quinn Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FRE) (Akaike, 1973; Hamilton, 1994; Hannan & Quinn, 1979; Schwarz, 1978).[5] For the modeling of the GDP in each of the individual US, these four tests displayed inconclusive results, with the SC consistently indicating a lag order of one, and the AIC, HQ, and FRE varying from one to three depending on the state being evaluated. As this study is focused on forecasting mortality, to keep the model simple, a VAR(1) was determined to be the most suitable model for the GDP in each of the individual contiguous US.

In our setting, specific situations do arise. For example, in order to model the future GDP in California, we also need to consider the economic growth occurring in the neighboring states: Arizona, Nevada, and Oregon, as well as the economic growth in Mexico. The GDP of all these neighbors of California and California itself are jointly forecasted using a VAR(1) model. The same reasoning applies to all states neighboring either Mexico or Canada.

4.2 | Out-of-sample backtesting

To further compare the accuracy of the SLGG model with the Li–Lee model, we evaluate the out-of-sample forecast performance. We fit the two models to data up to a jump-off year $\hat{u}$ and compute the forecasting error for the rest of the sample. A cross-validation is performed by letting $\hat{u}$ range from 2006 to 2015 (1 year before the end of the sample), allowing for a comparison of the forecast accuracy for the two models under a range of forecast horizons. For each model and jump-off year, the forecasting performance is compared using the mean root mean squared forecast error (RMSFE) of the logarithm of mortality rates. We let $\log(\widehat{m}_{i,x,t})$ denote the forecasted logarithm of mortality rate for state i, age group x, and year t. The mean of the RMSFE of mortality rates across the states for jump-off year $\hat{u}$ is given by

$$\text{Mean RMSFE}(\hat{u}) = \frac{1}{48}\sum_i \sqrt{\frac{1}{13\times(2016-\hat{u})}\sum_{u=\hat{u}+1}^{2016}\sum_x \frac{(\log(m_{i,x,u})-\log(\widehat{m}_{i,x,u}))^2}{|\log(m_{i,x,u})|}}.$$

We use the mean RMSFE to measure the relative forecasting errors for all future years in the sample and all ages.

Figure 4 displays the mean RMSFE of for all jump-off years for each of the two models. For each model, the mean RMSFE of all the states is shown. We observe that although the forecasting accuracies of the two models are rather similar, the mean RMSFEs of the Li–Lee model are routinely higher than those from the SLGG model. This demonstrates that while both methods capture mortality improvements well, the forecasts from the SLGG model are generally more accurate.

4.3 | Comparison of model implications: Annuity pricing

Our proposed approach to the spatial modeling of mortality with GDP lends itself to many applications. Mortality forecasts and their differences have crucial impact on pricing of mortality linked insurance products, most notable of which are annuities. That is why the annuity pricing is of key concern to insurance providers and retirement planners who are tasked with managing the financial risks associated with human longevity.

In this section, we compare the impact of the LL and SLGG models on annuity pricing. To proceed, we use the following well-known definition of a T-year fixed term annuity of a y-year old individual

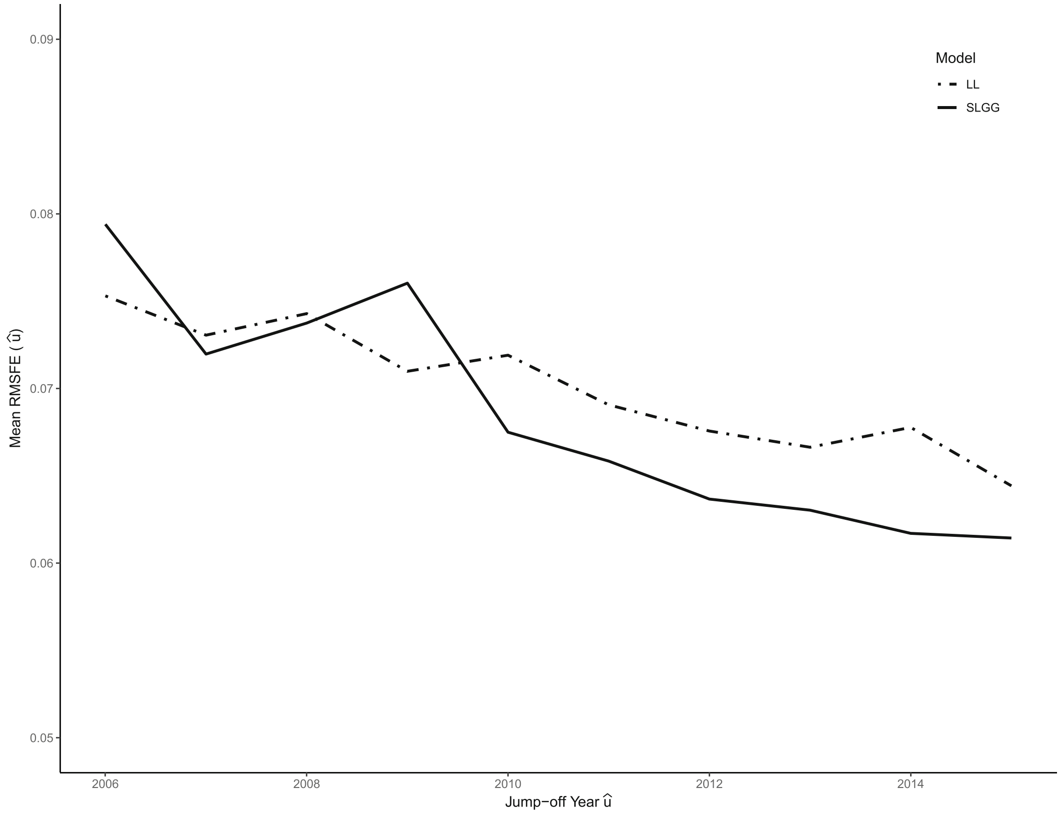


FIGURE 4 Comparison of the relative RMSFE for the logarithm of mortality rates obtained from the Li–Lee and SLGG models.

$$\ddot{a}_{i,y} = \sum_{t=0}^{T} {}_tp_{i,y}/(1+r)^t, \quad (2)$$

where r is the yearly discount rate and ${}_tp_{i,y}$ is the probability that a (male) life age y from state i survives for t years, that is,

$${}_tp_{i,y} = \prod_{k=0}^{t-1} \left(1 - q_{i,y+k,2016+k}\right)$$

where, starting with year 2016, $q_{i,y+k,2016+y}$ is the time-0 death probability determined from forecasts of $m_{i,y+k,2016+k}$. We calculate the present value of a 45-year fixed term annuity of 1 unit per year commencing at age 65 for a male individual in each of the US. Similarly as in Su and Sherris (2012), to obtain $q_{i,y+k,2016+k}$ for each individual age y, we assume a uniform distribution of death (UDD) among our 10-year age-group central death rate forecasts (Bowers et al., 1997). Forecasts of mortality rates from the LL and SLGG models were used to calculate ${}_tp_{i,y}$. Table 4 displays values of $\ddot{a}_{i,65}$ as priced with fixed rates r of 1%, 3%, and 5%.

From the results in Table 4, we observe that for both models, the values of $\ddot{a}_{i,y}$ appear to be greatest in states with higher GDP when compared with the states with lower GDP (cf. Figure 1). From the table, we see that under a constant interest rate of 1%, the actuarial value of a 45-year fixed term annuity paying out 1 unit every year until the age of 110 ranges from 13.33 in West Virginia to 17.57 in New York under the SLGG model, and 14.41 in Mississippi to 16.61 in Florida under the LL model. We see higher annuity prices in the more economically growing regions of the northeastern US and observe that in the south-eastern states, where there limited economic growth, the LL model produces higher values of $\ddot{a}_{i,y}$. We conclude that the pricing of annuities has an underlying spatial dimension to it and that the SLGG model is better equipped to capture the existing economic inequalities among the neighborhoods of the US to produce more accurate estimates.

Table 5 displays the summary statistics of mean and standard deviation for the calculated values of $\ddot{a}_{i,y}$ and allows for a comparison of the values across the three fixed rates of r. Importantly, we observe that while the mean present value of the annuities calculated using the mortality rates of both models are similar, the SLGG model reveals more of the variability among these prices than the LL model, as indicated by the standard deviations. As the interest rate r increases to higher levels, the SLGG model continues to admit more regional differences in these annuity prices than the LL model.

TABLE 4 Present value of a 45-year fixed term annuity of 1 unit per year commencing at age 65 with discount rates *r* of 1%, 3%, and 5%, as defined in (2), for each state and for the LL and SLGG models.

	LL			SLGG		
State	**1%**	**3%**	**5%**	**1%**	**3%**	**5%**
Alabama	14.58	11.94	10.01	13.76	11.40	9.63
Arizona	16.51	13.28	10.98	16.52	13.26	10.94
Arkansas	14.98	12.23	10.22	13.93	11.50	9.70
California	16.53	13.30	11.00	16.97	13.57	11.16
Colorado	16.05	13.02	10.82	16.19	13.10	10.88
Connecticut	15.97	12.95	10.76	17.40	13.90	11.43
Delaware	15.40	12.54	10.46	16.68	13.37	11.03
Florida	16.61	13.34	11.02	16.94	13.54	11.14
Georgia	14.86	12.14	10.15	14.40	11.86	9.98
Idaho	15.94	12.94	10.76	15.60	12.71	10.60
Illinois	15.27	12.44	10.39	14.86	12.17	10.20
Indiana	14.90	12.19	10.20	14.71	12.05	10.11
Iowa	15.62	12.70	10.59	15.51	12.63	10.53
Kansas	15.58	12.67	10.56	15.42	12.55	10.47
Kentucky	14.43	11.84	9.94	13.68	11.33	9.58
Louisiana	14.71	12.02	10.07	14.16	11.66	9.82
Maine	15.27	12.47	10.42	16.00	12.97	10.78
Maryland	15.37	12.51	10.43	15.26	12.44	10.39
Massachusetts	15.66	12.73	10.60	16.51	13.32	11.02
Michigan	15.21	12.41	10.37	15.42	12.55	10.46
Minnesota	15.99	12.97	10.79	16.65	13.42	11.10
Mississippi	14.41	11.81	9.91	13.47	11.18	9.46
Missouri	15.06	12.30	10.29	15.65	12.67	10.53
Montana	15.72	12.78	10.64	16.24	13.11	10.86
Nebraska	15.61	12.70	10.58	15.41	12.57	10.49
Nevada	15.38	12.52	10.44	16.13	12.96	10.71
New Hampshire	15.65	12.74	10.62	15.94	12.94	10.77
New Jersey	15.58	12.69	10.56	16.34	13.16	10.89
New Mexico	16.23	13.11	10.86	16.20	13.07	10.83
New York	16.09	13.00	10.79	17.57	13.92	11.38
North Carolina	15.10	12.31	10.28	14.92	12.24	10.27
North Dakota	15.92	12.91	10.73	16.19	13.06	10.82
Ohio	15.28	12.45	10.39	14.57	11.97	10.05
Oklahoma	14.83	12.13	10.15	14.79	12.06	10.08
Oregon	15.79	12.82	10.67	15.40	12.55	10.47
Pennsylvania	15.21	12.42	10.38	15.67	12.70	10.57
Rhode Island	15.51	12.62	10.52	15.45	12.59	10.50
South Carolina	15.00	12.23	10.22	14.48	11.93	10.04
South Dakota	15.80	12.83	10.67	16.01	12.97	10.77
Tennessee	14.72	12.05	10.09	14.37	11.81	9.93
Texas	15.46	12.56	10.47	15.69	12.70	10.56

TABLE 4 (Continued)

	LL			SLGG		
State	**1%**	**3%**	**5%**	**1%**	**3%**	**5%**
Utah	16.29	13.18	10.94	16.69	13.47	11.15
Vermont	15.47	12.61	10.52	16.09	13.03	10.82
Virginia	15.19	12.39	10.35	14.44	11.91	10.03
Washington	15.93	12.92	10.74	16.46	13.27	10.99
West Virginia	14.53	11.92	10.01	13.33	11.09	9.41
Wisconsin	15.59	12.69	10.58	15.46	12.62	10.54
Wyoming	15.64	12.71	10.59	16.12	13.03	10.80

TABLE 5 Summary statistics of the present value of the annuities.

	LL			SLGG		
Discount Rate	**1%**	**3%**	**5%**	**1%**	**3%**	**5%**
Mean	15.47	12.58	10.49	15.53	12.62	10.51
Standard Deviation	0.55	0.39	0.28	1.04	0.71	0.51

5 | CONCLUSION

This study introduces the large class of models which incorporate spatial components, as reflected in mortality and GDP, into the traditional stochastic mortality modeling framework outlined by Li and Lee (2005). As such, it goes well beyond mortality models that incorporate economic growth (Boonen & Li, 2017). Also, by investigating questions about the impact of neighboring mortality on the mortality of a particular state, our study goes well beyond the current mortality modeling literature. Our findings show that there is a heterogeneous impact of GDP on mortality across space. Also, when it comes to the impact of GDP of neighboring states on a state under consideration, it is important to notice that this impact is heterogeneous across space and different given the GDP of the state under consideration. Interestingly, these considerations impact different age groups differently across space. In conclusion, this research provides an important starting point for more localized and interpretable studies of mortality, serving as a blueprint for the inclusion of spatial components and economic growth into the traditional mortality models. Further research should include investigating a variety of possible covariates that may impact mortality and their relationships across space.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the public domain and were obtained from the Bureau of Economic Analysis (at https://www.bea.gov/gdp/), as well as from the Centers for Disease Control and Prevention's (CDC) WONDER internet databases (accessed at https://wonder.cdc.gov/).

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ENDNOTES

[1] The federal district Washington DC is excluded from our analysis, because the GDP per capita in this district is very high, and uninformative as factor of economic growth for this area.

[2] State level real GDP data were obtained online (from https://www.bea.gov/).

[3] Mortality data were obtained online (from https://wonder.cdc.gov/).

[4] To reduce the model to a reasonable number of parameters, we only incorporate neighboring states.

[5] Results of these criteria can be found in Table A1 of Appendix A.

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APPENDIX A: TABLES OF SELECTION CRITERIA

TABLE A1 The optimal lag order of the VAR selected by the Akaike's Information Criteria (AIC), Hannan-Quinn Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FRE) for the individual states.

	Criterion			
State	AIC	HQ	SC	FPE
Alabama	1	1	1	1
Arizona	3	3	1	3
Arkansas	3	3	1	3
California	2	1	1	2
Colorado	3	3	1	3
Connecticut	3	1	1	2
Delaware	2	1	1	2
Florida	2	2	1	2
Georgia	3	1	1	3
Idaho	3	3	1	3
Illinois	3	1	1	1
Indiana	1	1	1	1
Iowa	3	1	1	1
Kansas	3	1	1	3
Kentucky	3	3	1	1
Louisiana	3	1	1	3
Maine	1	1	1	1
Maryland	2	1	1	2
Massachusetts	3	1	1	2
Michigan	1	1	1	1
Minnesota	3	1	1	3
Mississippi	2	1	1	1
Missouri	3	3	3	3
Montana	3	3	1	3
Nebraska	3	3	1	3
Nevada	3	1	1	1
New Hampshire	1	1	1	1
New Jersey	1	1	1	1
New Mexico	3	3	1	3
New York	3	3	1	2
North Carolina	1	1	1	1
North Dakota	3	1	1	1
Ohio	3	1	1	1
Oklahoma	3	3	1	3
Oregon	2	2	1	2
Pennsylvania	3	2	1	2
Rhode Island	2	2	1	2
South Carolina	1	1	1	1

TABLE A1 (Continued)

State	Criterion AIC	HQ	SC	FPE
South Dakota	3	3	1	3
Tennessee	2	1	1	3
Texas	1	1	1	1
Utah	3	3	1	3
Vermont	1	1	1	1
Virginia	3	3	1	3
Washington	2	1	1	2
West Virginia	3	2	1	2
Wisconsin	1	1	1	1
Wyoming	3	3	1	3

Note: For the modeling of GDP, a VAR(1) model was determined to be most suitable. For more information about these four selection criteria, we refer to Akaike (1973), Hannan and Quinn (1979), Schwarz (1978), and Hamilton (1994).