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# Exploring geographic variation in US mortality rates using a spatial Durbin approach

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## Abstract

Previous studies focused on identifying the determinants of mortality in US counties have examined the relationships between mortality and explanatory covariates within a county only, and have ignored the well-documented spatial dependence of mortality. We challenge earlier literature by arguing that the mortality rate of a certain county may also be associated with the features of its neighboring counties beyond its own features. Drawing from both the spillover (i.e., same direction effect) and social relativity (i.e., opposite direction effect) perspectives, our spatial Durbin modeling results indicate that both theoretical perspectives provide valuable frameworks to guide the modeling of mortality variation in US counties. Our empirical findings support that mortality rate of a certain county is associated with the features of its neighbors beyond its own features. Specifically, we found support for the spillover perspective in which the percentage of the Hispanic population, concentrated disadvantage, and the social capital of a specific county are negatively associated with the mortality rate in the specific county and also in neighboring counties. On the other hand, the following covariates fit the social relativity process: health insurance coverage, percentage of non-Hispanic other races, and income inequality. Their direction of the associations with mortality in the specific county is opposite to that of the relationships with mortality in neighboring counties. Methodologically, spatial Durbin modeling addresses the shortcomings of traditional analytic approaches used in ecological mortality research such as ordinary least squares, spatial error, and spatial lag regression. Our results produce new insights drawn from unbiased estimates.

### Keywords

mortality; social capital; income inequality; spatial Durbin modeling; social relativity; spatial spillover

## Introduction

Mortality is an overall assessment of the population health of an area. In the past eight decades, the United States (US) has witnessed an exceptional decrease in mortality, from almost 20 deaths per 1,000 population in 1930 to roughly 8 deaths per 1,000 population in 2010 (Hoyert 2012). Despite the significant decrease in overall mortality through the years, disparities in mortality have persisted along various dimensions, such as gender, race/ethnicity, and geographic space (Yang et al. 2011). Intersectionality of these socio-demographic characteristics of a specific area puts individuals who reside in certain geographic spaces at a greater risk of mortality, and the concentration of high mortality in specific areas in the US has been an important public health concern. Particularly, mortality disparities across space have received considerable scholarly and policy attention in recent years. For example, Cossman and colleagues (2007) have reported that the spatial patterns of all-cause mortality in US counties have persisted over the past 35 years, and suggested that “spatial autocorrelation must be explained by ecological mortality models” (p. 2149). Their statement underscores the importance of using methodologies that account for spatial structure in mortality research.

Identifying the determinants of mortality at the ecological level is not an unexplored area. Briggs and Leonard (1977) examined the role of ecological structure in predicting spatial variation in mortality, and found that characteristics at the ecological level are strongly associated with mortality. They concluded that ecological socioeconomic characteristics (i.e., socioeconomic disadvantage, and poverty) were strongly associated with mortality within a spatial unit (i.e., tract), yet a substantial portion of the mortality variation was not adequately explained by socioeconomic characteristics alone (Briggs and Leonard 1977). Despite the limited ability to explain mortality variation, socioeconomic conditions at the ecological level (e.g., poverty at the tract or county-level) have driven the majority of the subsequent mortality research following Briggs and Leonard (1977). That is, socioeconomic conditions have been found to be one of the fundamental determinants of health outcomes (Link and Phelan 1995), and other studies have shown that the socioeconomic status of a county is related to mortality (Sparks et al. 2012; Yang et al. 2012). For example, previous studies found that residents in socioeconomically disadvantaged areas have higher rates of mortality compared to their more affluent counterparts (Ezzati et al. 2008; Kaplan et al. 1996; Mansfield et al. 1999). Subsequently, scholars have begun to move beyond examining the socioeconomic conditions at the ecological level to explain mortality variation by investigating other potential factors and mechanisms that may affect mortality (Kawachi and Berkman 2003), such as income inequality (Kawachi and Kennedy 1999; Marmot 2004; Yang et al. 2012), social capital (Kawachi and Kennedy 1997; Kennedy et al. 1998; Lochner et al. 2003), and rurality (Yang et al. 2011).

Income inequality and social capital have driven the recent investigation of the effects of social characteristics on mortality (Kawachi et al. 1997; Yang et al. 2011). Previous ecological studies have also found that income inequality (i.e., unequal distribution of income a population) is strongly associated with mortality risk (Daly et al. 2001; Kaplan et al. 1996; Kennedy et al. 1996; Waldmann 1992), regardless of the measure of income inequality used (Kawachi and Kennedy 1997). It is also notable that scholars have begun to explore how relative measures of inequality (e.g., income distribution) affect mortality by moving beyond focusing on absolute measures of inequality (e.g., poverty). Similar to the effect of absolute social conditions, relative measures of inequality are positively associated with the mortality rate at the ecological level (Kaplan et al. 1996; Kawachi and Kennedy 1999; Kawachi et al. 1999; Kennedy et al. 1996; Wilkinson 1996). Several mechanisms in the literature help to explain why high income inequality is associated with an increased mortality rate, including underinvestment in human resources (Kaplan et al. 1996; Smith 1996), loss of social cohesion, disinvestment in social capital (Wilkinson 1997), and psychological consequences of inequality (Kawachi and Kennedy 1997). One of these mechanisms that has been drawing attention since the 1990s is social capital (Bourdieu 1985; Coleman 1988; Putnam 1993; 2000), and it has been rigorously applied to health research (Lochner et al. 2003; Shoff and Yang 2013; Weil et al. 2012). Social capital refers to “connections among individuals—social networks and the norms of reciprocity and trustworthiness that arise from them (p.19)” (Putnam 2000), and studies have found that social capital at the ecological level is associated with a decrease in mortality (Kawachi et al. 1997; Yang et al. 2011). Social capital has been identified as a useful framework for identifying the resources available to improve health measures within a community, including mortality disparities (Kawachi 2006), and recent studies have provided evidence to support these theoretical arguments (Kaplan et al. 1996; Kawachi 2006; Kennedy et al. 1998; Wilkinson 1994). In short, it has been demonstrated that these purely ecological variables are important to consider when predicting a purely ecologic outcome (e.g., mortality) (Kawachi et al. 1997).

## Literature Review

Although the previous studies discussed above have advanced our understanding of the determinants of mortality, they have largely overlooked two issues that could either undermine their conclusions or limit the scope of mortality research. First, although mortality is an ecological and spatial feature of a population in a specific area (Cossman et al. 2007), a large body of previous mortality research has not incorporated a spatial perspective into the investigation of the relationship between contextual characteristics and mortality rates (Sparks and Sparks 2010; Sparks et al. 2012; Yang et al. 2011). Incorporating a spatial perspective into macro-demography research is crucial as demography is inherently a spatial science (Voss 2007; Voss et al. 2006a; Voss et al. 2006b). Without a spatial perspective, which accounts for the spatial structure of ecological data, results may be biased and these biases could lead to incorrect estimates of the associations between the independent and dependent variables. As a result, biased analyses could lead to improper conclusions (Haining 2003; Voss et al. 2006b; Yang et al. 2011), and the previous findings of the determinants of mortality at the ecological level without a spatial perspective have relatively few implications for policymakers. In this study, we demonstrate the importance of incorporating a spatial perspective in the ecological level mortality research by comparing spatial Durbin model results with other conventional approaches.

Second, in addition to the methodological shortcomings, previous research investigating the determinants of mortality utilized a limited conceptualization of context to refer to the “immediate area” without investigating the impacts of the explanatory variables in “adjacent areas." Although there has been a scholarly push to expand the theoretical scope of what contributes to the local health phenomena by examining the effects of the residential context beyond the immediate residential area (Dietz 2002; Mujahid and Diez Roux 2010); most, if not all, previous mortality studies have attempted to explain the mortality rate of a given area *only* with the characteristics *within* this area—reflecting an "aspatial" perspective. This perspective may not capture the spatially clustered mortality process (James et al. 2004; Yang et al. 2011), and we argue that expanding the theoretical scope of one's residential area beyond the "immediate area" by incorporating its adjacent areas is important to advance our understanding of the mortality variation across space. That is, there is a need to incorporate a spatial perspective into mortality research both methodologically and theoretically. In this study, we challenge the literature by proposing that the determinants of the mortality rate of a certain area could be explained not only by the features of this area, but also by the characteristics of the surrounding area. As social processes are spatially embedded, geographic proximity to neighboring areas should play an important role in unveiling the spatial mortality dynamics. To our knowledge, no ecological mortality research has considered the trans-spatial relationship among analytic units and attempted to empirically test our argument, though the importance of neighbors has recently drawn researchers' attention (Auchincloss et al. 2007; Takagi et al. 2012). Our argument is grounded in two theoretical perspectives: the spatial spillover and the social relativity.

The first perspective, the spatial spillover process, is drawn from both the regional development and economics literature (Anselin 2003; Audretsch 2003). The term "spatial spillover" has a variety of meanings, such as knowledge spillover (Fischer 2006), industry spillover (Audretsch and Feldman 2004), and growth spillover (Arora and Vamvakidis 2005). Of the various meanings of spatial spillover, growth spillover has the most general meaning and implies that the change in the outcome of interest in a unit is related to the behaviors of the neighboring units (Arora and Vamvakidis 2005). Despite the various meanings of spatial spillover, the core concept is to conceptualize spatial structure and the dynamics among spatial units in which diffusion of ideas, practices, and resources occurs (Capello 2009; Rogers 1995). Following the previous studies that utilized the spatial spillover perspective to regional developmental and economic outcomes, we conceptualize a spatial unit as a geographically limited system in which all necessary resources could not be produced, but those resources exceeding local demands would spill over to nearby units for survival and growth (Capello 2009). Specifically, when a spatial unit exceeds specific resources, it may generate spillover influence to its neighbors. Thus, a spatial unit is neither self-efficient nor isolated, but it is inherently interdependent on its surroundings.

Applying this concept of spatial interdependence to mortality research, the local social and institutional resources that promote population health may exceed local needs, and hence, generate spatial spillover influences on mortality in nearby areas. While it is theoretically plausible that the spillover effect may lead to negative consequences in the area of origin (as a donor of resources and thus, suffer from declining population health), empirical research has found little evidence to support this pathway (Capello 2009).

The spatial spillover process may be relevant in understanding the role of social capital in mortality disparities. As discussed previously, social capital is negatively associated with mortality and could be treated as a resource that facilitates health within a county. Drawing from the spillover perspective, we hypothesize that high levels of social and institutional resources that promote health (e.g., social capital and accessibility to health care) in an area would spill over to its neighbors, generating a positive effect on the outcome of interest (i.e., reducing mortality) in adjacent areas. The hypothetical process here is that in a specific area, the relationship between health enhancing factors and mortality is consistent across space, and the relationships operate similarly in adjacent areas. Therefore, if social capital has a protective effect on mortality within an area, then social capital will have a protective spillover effect on mortality in neighboring areas as well.

The second perspective, the social relativity process, is drawn from social comparison theory (Festinger 1954), which suggests that comparing with others helps an evaluator to gain precise self-assessment and the discrepancy between an evaluator and others would lead to a change in actions, attitudes, and behaviors in order to reduce the discrepancy. This knowledge stream has been used to explain why income inequality matters in mortality and health research (Ben-Shlomo et al. 1996; Boyle et al. 2001; Kondo et al. 2008; Yang et al. 2012). That is, previous studies have suggested that an individual's lower social position or ranking compared with others in a society could lead to mental health issues, such as frustration, depression, and social isolation, then deteriorate physical health and eventually result in death (Kawachi and Kennedy 1999; Wilkinson 1997). The social relativity process does not ignore the importance of absolute resources in health; instead, this process introduces an additional theoretical linkage to the literature as to how the distribution of resources that is associated with social groups matters. Recent studies have found that geographic proximity is relevant to the choice of the reference group for social comparison (Firebaugh and Schroeder 2009; Kondo et al. 2008), and such a finding implies that the spatial structure underlying the ecological morality data should have a role to play. [1]

Specific to this study and extending the social comparison theory to the ecological level, the social relativity process could refer to the situation that the characteristics associated with mortality in a unit would impose the opposite effect on mortality in geographically proximate units. The reason why we hypothesize the "opposite" effect is that social comparison could be divided into upward and downward comparison (Thornton and Arrowood 1966). With the superior as the reference group, it is likely to lead to inspiration to improve, but also likely to generate the negative feelings that arise from having less than others (Turley 2002). Conversely, with the inferior as the comparison group, it is likely to create a positive impact on behaviors and health outcomes (Pham-Kanter 2009; Suls et al. 2002).

We use income inequality to illustrate how the social relativity process contributes to this study. Previous research has found that inequality is positively related to mortality "within" a specific county (Yang et al. 2012). Based on the social relativity process, should the income inequality in the specific county be higher than that of neighboring counties, a downward (the inferior as the reference group) social comparison occurs among the

[1] We note that social proximity or cyber proximity may also be crucial in the social relativity hypothesis. However, given the feature of ecological data, the discussion here is focused on geographic proximity.

neighboring counties and the high income inequality in the specific county may therefore be negatively related to the mortality of the neighboring counties. More generally, we hypothesize that the determinants associated with mortality within a specific county would create the opposite relationships with mortality in adjacent counties through the social relativity process.

The goal of this study is twofold. Substantively, we aim to test whether the spatial spillover and social relativity processes could be used to guide the modeling of geographic variation in the US county mortality rates by moving beyond the typical theoretical conceptualization of context where a county's mortality is only associated with the features of its own features. Methodologically, we address the shortcomings with spatial Durbin modeling (Anselin 1988). Specifically, we investigate whether the mortality rate of a county is associated with the features of surrounding counties after accounting for the characteristics of the specific county. Our discussion above leads to three empirical research hypotheses. First, a high level of social capital in a specific area is negatively associated with the mortality rate of that immediate area and its adjacent areas. In other words, we suspect that the social capital within an area will have a "spatial spillover effect" on its adjacent areas. Second, a high level of income inequality in a specific area is positively associated with the mortality rate of that area, but is negatively associated with the mortality rates of surrounding areas. That is, even after controlling for the absolute resources (e.g., socioeconomic status) in a county, a high level of income inequality will have the social relativity effect, triggering the opposite response in its adjacent areas. Finally, beyond social capital and income inequality, we hypothesize that the spatial spillover and/or social relativity process will be observed for other determinants of mortality. This study will directly respond to the call for actions identified by Cossman et al. (2007) by moving beyond the effects of the immediate context to those of adjacent places theoretically, and demonstrate the importance of incorporating a spatial perspective methodologically.

## Data and Measures

The county-level mortality rate in the contiguous US is the dependent variable of this study; the independent variables could be divided into six groups, namely racial/ethnic composition, rural/urban residence, health care infrastructure, socioeconomic status, social capital, and income inequality. The data sources and the operational definitions of these variables are discussed below.

### Mortality

The Compressed Mortality Files (CMF) maintained by the National Center for Health Statistics (NCHS) provides the death counts at the county-level. The five-year (2003–2007) average mortality rates were calculated in order to adjust for the annual fluctuations, and the rates were standardized with the 2005 US age-sex population structure (NCHS 2010). The mortality rate was thus measured with the total number of deaths per 1,000 population in a county. The age-sex standardized mortality rate is suitable for ecological mortality research (Kawachi and Blakely 2001) and is a common practice in demography that allows researchers to compare data across space (Preston et al. 2001). As racial/ethnic structure has been argued to be a proxy of social stratification in the US (Deaton and Lubotsky 2003), this factor was not standardized in the dependent variable. Instead, the racial/ethnic composition was included in this study as an independent variable (see below). It is suggested that the age-sex standardized mortality rate is appropriate for ecological mortality research.

### Racial/ethnic composition

Three variables were considered in the analysis to capture the racial/ethnic structure of a county: the percentage of the population who identify as non-Hispanic Black, Hispanic, and other non-Hispanic races. The percentage of the non-Hispanic White population was excluded from the analysis to avoid potential problems with multicollinearity. These variables were extracted from the 2005–2009 American Community Survey (ACS) 5-year estimates (US Census Bureau 2010). As racial/ethnic mortality differentials remain in the US (Hoyert 2012), it is essential to control for these variables in the analysis.

### Rural/urban residence

Rural/urban residence has been found to be associated with mortality in the US (McLaughlin et al. 2007; Yang et al. 2011). Specifically, while rural counties are often characterized with poor socioeconomic profiles and access to health care services, their age-sex standardized mortality rates are unexpectedly lower than those of their urban counterparts, creating the so-called “rural paradox” (McLaughlin et al. 2001; Yang et al. 2011). To capture rural/urban residence, the rural-urban continuum codes (RUCC) developed by the US Office of Management and Budget were used, with 1 indicating the most urban counties and 9 representing the most rural counties. The RUCC coding scheme has been used in recent rural mortality studies despite the fact that it only focuses on the ecological dimension of rural/urban residence (Morton 2004; Yang et al. 2012).

### Health care infrastructure

The 2009 Area Resource Files (ARF 2009), a database maintained by the US Department of Health and Human Services, provided the information on health care services in US counties. Based on ARF data, three variables were created to describe the health care infrastructure and were included in the analysis: percentage of the population aged less than 65 without health insurance, total number of medical doctors per 1,000 population, and total number of hospital beds per 1,000 population. The relationship between health care resources and mortality has been stable in the US (Poikolainen and Eskola 1988; Shi et al. 2003) and these variables would serve as a proxy for access to health care for residents within and across counties.

### Socioeconomic status

Social conditions have been found to be fundamental determinants of health outcomes (Link and Phelan 1995) and other previous studies have shown that the socioeconomic status of a county is related to mortality (Sparks et al. 2012; Yang et al. 2012). Following Sampson and colleagues (1997), this study applied factor analysis to seven variables obtained from the 2005–2009 ACS 5-year estimates and found that two factors could be generated to describe the socioeconomic status of a county, namely social affluence and concentrated disadvantage. Specifically, the former included the log of per capita income (factor loading

= 0.72), percentage of the population aged 25 or over with at least a bachelor's degree (0.91), percentage of the population working in professional, administrative, and managerial positions (0.87), and percentage of families with annual incomes higher than $75,000 (0.87); whereas the latter is comprised of the poverty rate (0.72), percentage of the population receiving public assistance (0.71), and the percentage of female-head households with children (0.81). These two factors, affluence and disadvantage explain more than 70 percent of variation (eigenvalues are 3.76 and 1.25, respectively). The regression approach was used to create the factor scores for these two socioeconomic variables.

### Social capital

Four variables were created to capture the concept of social capital proposed by Putnam (2000). The first is the social capital index (SCI) score developed by Rupasingha and colleagues (2006), which is a composite score derived from the following four variables: the number of associations per 10,000 population, the number of non-profit organizations per 10,000 population, 2000 census mail response rate, and the voting rate for 2004 presidential election. The SCI scores are obtained from Rupasingha and Goetz (2008) and a high SCI score indicates strong social capital in a county. In addition, high crime rates and frequent crime victimizations have been found to be an indicator of weak social capital of an area (Sampson et al. 1997; Takagi et al. 2012). The 2002–2004 Uniform Crime Reports (U.S. Department of Justice 2002–2004) were used to calculate the total number of violent crimes per 1,000 population and the total number of property crimes per 1,000 population, and the three year average rates were used to minimize annual fluctuations. The final variable used to capture the concept of social capital is residential stability. A recent study has shown that social capital is stronger in a more stable area than a place with high residential turnovers (Glaeser et al. 2002), and we obtained two variables from the ACS: the percentage of individuals aged 5 and older who lived at that same address for at least 5 years, and the percentage of housing units occupied by owners. As these variables are highly correlated (Pearson correlation = 0.6), they were standardized and averaged to yield a single residential stability indicator.

### Income inequality

While several indicators have been developed to measure income inequality, their associations with health measures do not vary greatly (Kawachi and Kennedy 1997). The Gini coefficient is a widely used income inequality measure in economics and government reports and ranges from 0 (total equality, everyone has the same income) to 1 (completely unequal, one person has all of the income). A larger Gini coefficient indicates higher inequality. The 2005–2009 ACS provided the household income data that allow us to calculate the Gini coefficient. We used the top-coded category of $200,000 for the maximum income value and acknowledged that the income inequality in this study may be slightly underestimated, a drawback of the publicly available ACS data.

# Methodology

## Advantages of spatial Durbin modeling

Spatial econometricians are mainly interested in modeling the spatially autoregressive process in either the dependent variable or in the error term. The former is known as the spatial lag model, while the latter refers to the spatial error model (Elhorst 2010). Following this mainstream analytic approach, mortality and health researchers have applied the two spatial modeling techniques to account for spatial dependence and to provide new insights into the existing literature (Sparks and Sparks 2010; Sparks et al. 2012; Yang et al. 2011); however, the methodological limitations of both the spatial lag and the spatial error models have not been explicitly addressed in previous research. First, three types of spatial interaction effects have been proposed to explain how the spatial autoregressive process works (Manski 1993). These include (1) an ***endogenous interaction relationship***, which indicates that the outcome of a spatial unit is dependent on the outcomes of other spatial units; (2) a ***correlated relationship*** that refers to the phenomenon where unobserved factors lead to similar outcomes across spatial units; and (3) an ***exogenous interaction relationship*** that suggests that the outcome of a spatial unit is associated with the determinants of the outcome in other spatial units. Spatial lag and spatial error models have focused on the endogenous interaction and correlated relationship, respectively; however, to the best of our knowledge, the exogenous interaction relationship has not been considered in the mortality literature.

Second, both spatial lag and spatial error models have to restrict the magnitude of the spatial effect to ensure a positive definite variance-covariance matrix for successful model estimations (LeSage and Pace 2009). This limitation may result in biased coefficient estimates if the spatial interaction effect is misclassified (i.e., a correlated relationship is handled with the spatial lag model and an endogenous interaction relationship is considered by the spatial error model). Third, the spatial effects in the spatial lag and spatial error models do not capture both local and global spillover effects (Elhorst 2010), which may undermine the understanding of why the outcome of interest is spatially correlated.

The spatial Durbin model (Anselin 1988) has been proven to outperform the spatial lag and spatial error models and to address the limitations above. Specifically, it has been demonstrated that the spatial Durbin model is “the only means of producing unbiased coefficient estimates,” regardless of the true spatial processes underlying the observed data (Elhorst 2010). In addition, under the spatial Durbin analytic framework, there is no restriction imposed on the magnitude of the spatial effects, and both global and local effects are produced (LeSage and Pace 2009). These advantages have made the spatial Durbin model the state-of-the-art method of spatial econometrics, and should be further promoted in applied research (Elhorst 2010).

## Specifications of spatial Durbin modeling

Three components comprise a spatial Durbin model (LeSage and Pace 2009): a spatial lagged dependent variable, a set of explanatory variables of a spatial unit, and a set of spatial lagged explanatory variables, which can be expressed as Equation 1:

$$y=\rho Wy+\alpha l_n+X\beta+WX\theta+\varepsilon \ \varepsilon\sim N(0,\sigma^2 I_n), \quad (1)$$

where *y* denotes an n x 1 vector of the dependent variable (i.e., mortality), *W* is the spatial weight matrix, $W_y$ represents the spatial lagged dependent variable (endogenous interaction relationships), ρ denotes the effect of $W_y$, which is known as the spatial autoregressive coefficient. $l_n$ indicates an n x 1 vector of ones associated with the intercept parameter α. *X* represents an n x k matrix of k explanatory variables, which are related to the parameters β; *WX* reflects the spatial lagged explanatory variables (exogenous interaction relationships), and θ denotes an k x 1 vector of the effects of *WX*. The error term, ε, follows a normal distribution with a mean 0 and a variance $\sigma^2 I_n$, where $I_n$ is an n x n identity matrix. The formula above clearly demonstrates that the characteristics of a specific unit (the county, in this study), and its neighbors are simultaneously considered in the analysis. This paper will use this approach to explore whether the mortality rate of a county is related to the features of its neighbors and, if so, to answer how they are associated.

The model above explicitly takes into account both the endogenous and exogenous interaction relationships, and the correlated relationship is missing in the model intentionally. Technically, the error term could be further divided into a spatially correlated error and a random error to consider unobserved factors, and the model could be estimated without problems (Manski 1993). However, when the three spatial interaction effects are considered simultaneously in analysis, the estimated coefficients will be biased and the endogenous and exogenous effects could not be distinguished (Elhorst 2010; Manski 1993). In light of this fact, LeSage and Pace (2009) suggest that the best option is to exclude the spatially correlated error term because doing so will only reduce modeling efficiency, instead of producing biased and inconsistent coefficient estimates (Greene 2005). The statistical form above, therefore, should be regarded as the most appropriate spatial regression model, especially when the spatial processes or the spatial interaction effects are unknown to researchers.

### Interpretation of the Spatial Durbin Modeling Estimates

The spatial Durbin model includes both the spatially lagged dependent and independent variables and the endogeneity in the model makes the interpretations of the estimates richer. Specifically, the spatial Durbin model allows researchers to separate the direct (within a county) impact of an independent variable on the dependent variable from the indirect (to/from neighboring counties) impact (Fischer 2010; LeSage and Pace 2009). To see this, Equation 1 could be rewritten in Equation 2:

$$(I_n-\rho W)y=\alpha l_n+X\beta+WX\theta+\varepsilon \ y=(I_n-\rho W)^{-1}\alpha l_n+(I_n-\rho W)^{-1}X\beta+(I_n-\rho W)^{-1}WX\theta+(I_n-\rho W)^{-1}\varepsilon. \quad (2)$$

The partial derivatives of *y* with respect to the *r*th independent variable ($X_r$) across the *n* observations in the study region could be expressed as follows:

$$\partial y/\partial X_r=(I_n-\rho W)^{-1}(I_n\beta_r+W\theta_r), \quad (3)$$

where $\partial ??/\partial ??_{??}$ indicates an n x n matrix, and $\beta_r$ and $\theta_r$ represent the parameter estimates associated with the independent variable in a county and in neighboring areas. Equation 3 contains important implications for the interpretations of spatial Durbin modeling estimates. That is, the change in the *r*th independent variable of a county will not only lead to the change in the dependent variable in the same county, but also affect the dependent variables in other counties. The former refers to the direct impacts (average of the main diagonal elements of $(I_n - \rho W)^{-1}(I_n\beta r + W\theta_r)$ matrix), whereas the latter is the indirect impacts (average of the off-diagonal elements). While the indirect impacts could be further understood as the impacts *to* and *from* a unit, they are numerically equivalent, and the only difference is their interpretations in practice (Elhorst 2010). With the *to a unit* perspective, the indirect impacts could be translated into how changes in an independent variable in all other units affect the dependent variable in a particular unit. By contrast, the *from a unit* aspect could be interpreted as how the changes in an independent variable of a unit influence the dependent variables in other units across the study region (LeSage and Pace 2009).

Another implication drawn from Equation 3 is that the partial derivatives of *y* is a function of $(I_n - \rho W)^{-1}$, which can be expanded as an infinite linear combination of powers of spatial weight matrix ($W$): $I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \ldots$. The powers of $W$ correspond to the counties themselves (zero-order), adjacent neighbors (first-order), neighbors of adjacent neighbors (second-order), and so on (LeSage and Pace 2009). The infinite series of $W$ makes it possible to partition both the direct and indirect impacts of the independent variables on the dependent variables by the powers of the spatial weight matrix. Note that if a spatial Durbin model could be reduced to a spatial lag model (i.e., θs are not significant), there is not an indirect impact at the zero-order and there is not a direct impact at the first-order (Jensen and Lacombe 2012). As the discussion on partitioning the direct and indirect impacts is beyond the scope of this study, we refer readers to the work by Elhorst (2010), Fischer (2010), Autant-Bernard and LeSage (2011), and Jensen and Lacombe (2012) for details. We will use the Markov chain Monte Carlo (MCMC) method to calculate the direct and indirect impacts, as well as the partitioning results, with the *spdep* package (Bivand et al. 2013) in R (R Development Core Team 2011).

## Analysis Strategy

This study will first conduct exploratory analysis to have a basic understanding of the county-level data and then implement the explanatory analysis. We will then apply the ordinary least square (OLS), spatial lag, and spatial error modeling to the county-level dataset. These models are commonly used in ecological demographic research. While the social relativity and spatial spillover processes already justify the use of spatial lag and spatial Durbin model, conducting the OLS and spatial lag models will allow us to assess if the spatial Durbin model statistically outperforms other models, particularly the spatial lag model. The Akaike Information Criterion (AIC) will be used to determine if a model is better than the other (Akaike 1974). In general, if the difference in the AIC between the two models is greater than 10, the model with a smaller AIC value should be preferred as it is more probable to minimize the information loss in contrast to the “true” model that generates the observed data (Burnham and Anderson 2002). This study will employ the first-order Queen adjacency matrix to define whether or not two counties are neighbors. That is, if the counties share a boundary or a vertex geographically, they will be defined as neighbors. The final analysis will obtain and interpret the direct, indirect, and partitioning results of the spatial Durbin modeling.

## Results

### Descriptive analysis results

The descriptive statistics of the dependent and independent variables are summarized in Table 1. The five-year average age-sex standardized mortality rates in US counties range from 2.9 to 18.9 deaths per 1,000 population, which is comparable to previous research (McLaughlin et al. 2001; Yang et al. 2011) and validates the mortality measure of this study. As for racial/ethnic composition, the standard deviations are much larger than the mean values, which imply that the distribution of minorities varies greatly across counties. The variation in the racial/ethnic structure seems to echo the argument that the racial/ethnic structure would be the underlying determinant of social stratification in an area, and may have implications for health outcomes and residential health disparities (Deaton 2003; Deaton and Lubotsky 2003). Moreover, on average, almost one out of five residents aged less than 65 in a county did not have health insurance, but this figure increases to almost one out of two in our data. Some counties had no medical doctors practicing there and the average number of medical doctors per 1,000 population was 1.2. Similarly, about 4 hospital beds are shared by 1,000 population in a county. Unsurprisingly, the ranges of the health care infrastructure variables were relatively wide, because medical resources have been found to be distributed unevenly in the US (Glasgow et al. 2004).

As the social affluence and concentrated disadvantage measures were constructed with factor analysis, they have a mean of zero and a standard deviation of one. Regarding the concept of social capital, high SCI scores indicate strong civic engagement and high density of social organization. While the average SCI score is close to zero, the variation is relatively great as Rupasingha and colleagues have suggested (Rupasingha et al. 2006). The average violent crime rate is lower than the average property crime rate, and residential stability had a mean of zero since it is an average indicator of two standardized variables. The distribution of the Gini coefficients seems to be concentrated on the mean value of 0.43 as the standard deviation is fairly small (0.04). Though these independent variables were expected to capture different dimensions of a county, they are somewhat correlated with one another and it becomes essential to inspect whether these independent variables introduce multicollinearity into our explanatory analysis, which may undermine the findings and conclusions of this study. The variance inflation factor (VIF) was used to answer this question (Kutner et al. 2004). As a rule of thumb, a VIF value greater than 10 suggests that multicollinearity may lead to imprecise coefficient estimates. The last column of Table 1 provides evidence that multicollinearity is not a concern in this study. The largest VIF value in our data was 2.76, which is substantially lower than the more strict cut-off VIF threshold of 4 (Kutner et al. 2004).

### Conventional spatial analysis results

Following the proposed analytic strategy, four regression models were implemented (i.e., OLS, spatial lag, spatial error, and spatial Durbin) and the results were presented in Table 2. Two findings are notable.[2]

First, the OLS model shows the highest value (8,752.7) and the spatial Durbin model has the lowest AIC value (8,066.4). This finding confirms the argument that the conventional analytic approach does not take the features of ecological data into account and may misestimate the associations between the independent variables and the dependent variable (Voss et al. 2006b). The differences in the AIC values between the OLS and other spatial models were all greater than 10, indicating that the OLS modeling approach should no longer be considered for these data. As the social relativity and spatial spillover processes are mainly captured by spatial lag and spatial Durbin models, the AIC comparison between them suggested that the spatial Durbin model fits the data better than does the spatial lag model. Explicitly, we obtained preliminary support that neighbors' characteristics may contribute to the mortality of a county. Though OLS and spatial error models are commonly used in ecological mortality research, our results indicated that the spatial Durbin model fits our data best, both statistically and substantively.

Second, the spatial lag effects (Rho in Table 2) demonstrate that the endogenous interaction relationship accounts for the mortality variation across US counties and the estimates of the spatial lag effect were similar in the spatial lag (0.43) and spatial Durbin (0.44) models. That is, if the average mortality rate of neighboring counties increases by one percent, the mortality rate of a particular county increases more than 0.4 percent. This relationship is net of other explanatory covariates. As for the statistically significant spatial error effect (Lambda in Table 2), it suggests that there may be variables that contribute to county-level mortality rates, but are not included in the analysis. However, based on the Lagrange Multiplier (LM) testing results, the residuals from the spatial Durbin model are not spatially autocorrelated (LM value=3.456). That said, the correlated relationships caused by omitted variables in the spatial error model can be explained by the lagged covariates included in spatial Durbin model.

### Direct and indirect effects of spatial Durbin modeling estimates

As discussed previously, the interpretations of the spatial Durbin modeling results are richer than other conventional analytic approaches. Table 3 shows the decomposition estimates and we summarized the key findings as follows.[3]

First, the significant indirect effects provided strong evidence to support our argument that the features of surrounding counties are important determinants of mortality. Four variables demonstrated the "spillover effect" on mortality, namely the SCI score, the percentage of the Hispanic population, hospital beds per 1,000 population, and concentrated disadvantage.

[2]The coefficient estimates of explanatory variables in spatial Durbin model in Table 2 cannot be directly interpreted (LeSage and Pace 2009). The interpretations are in the next subsection.

[3]Note that the decomposition estimates will not be the same with the estimates shown in Table 2 as the results in Table 3 are based on simulations (Fischer 2010; Jensen and Lacombe 2012; LeSage and Pace 2009).

More specifically, a one unit increase in the average SCI score in other counties was associated with roughly 0.31 deaths per 1,000 population decrease in the mortality rate. Somewhat surprisingly, the relationship between the SCI score and mortality within a county (direct effect) was much weaker than the spillover effect. The same increase in the SCI was only related to 0.04 deaths per 1,000 population decrease within a county. While this direct impact is smaller than those found in other models, e.g., −0.099 in spatial lag model (see Table 2), the total impact of social capital on mortality (−0.35) is the strongest among all modeling approaches. In addition, the mortality literature has documented the “Hispanic paradox” (Abraido-Lanza et al. 1999; Lara et al. 2005), which refers to the phenomenon that the Hispanic population has a lower mortality rate in contrast to other race/ ethnicity groups (especially non-Hispanic white), despite their relatively poor socioeconomic status. Spatial Durbin modeling not only echoes this literature, but also reveals the spillover impact. That is, within a county, every 10 percent increase in the Hispanic population was associated with about 0.11 deaths per 1,000 population decrease in mortality (−1.086*0.1= −0.1086). More importantly, the same level of change in the Hispanic population in other counties would further reduce mortality in a county by 0.32 deaths per 1,000 population (−3.231*0.1= −0.3231).

Interpreting the direct and indirect effects of hospital beds per 1,000 population on mortality in the same vein, we found that a 10-beds increase per 1,000 population was associated with roughly 0.2 deaths increase within a county and about 0.3 deaths in neighbors. Concentrated disadvantage, as expected, was positively related to mortality within a county (Link and Phelan 1995), and this effect spills over to neighbors as a one unit increase in concentrated disadvantage score in a specific county is related to a 0.25 deaths per 1,000 population increase in neighbors.

Second, we also obtained evidence to support the social relativity argument for non-Hispanic other races, percent of population without health insurance, and the Gini coefficient. Taking the Gini coefficient for example, within a particular county, every 0.1 unit increase in income inequality was found to increase the mortality rate by 0.18 deaths per 1,000 population (direct effect). Nonetheless, should the average Gini coefficient arise by 0.1 unit in other counties, the mortality rate of this particular county would decrease by more than 0.4 deaths per 1,000 population. Explicitly, the magnitude of the direct impact is comparable to those estimated by spatial lag and spatial error models and the positive relationship between inequality and mortality within a county echoes recent findings in mortality research (Kawachi and Kennedy 1999; Kawachi et al. 1999; Yang et al. 2012). The indirect effect of the Gini coefficient bolsters the proposition that if a county experiences stronger inequality than its neighbors, the mortality rates of its neighbors would be lower due to the social relativity mechanism (Firebaugh and Schroeder 2009).

The total impact of the percentage of the population without health insurance on mortality is positive, suggesting that, on average, every 10 percent increase in the population without health insurance is associated with roughly 0.3 (0.029*10=0.29) deaths per 1,000 population increase in mortality across the contiguous US. The results in Table 3 indicate that the relationship between the percent of the population without insurance and mortality within a county (direct) is only about 60 percent as strong as the indirect association

(0.038/0.066=0.58). This ratio is similar to the direct and indirect impact of the percentage of non-Hispanic other races on mortality (2.207/3.952= 0.56). The total impact suggests that 10 percent increase in non-Hispanic other races in a county may reduce mortality by 0.17 deaths per 1,000 population overall.

Third, the percentage of non-Hispanic Black was found to be positively related to mortality in the conventional approaches (see Table 2); however, the spatial Durbin modeling did not provide statistical support for this finding. Several scholars argued that the percentage of non-Hispanic Black is a proxy for social stratification in a community and will account for the impact of income inequality on mortality (Deaton 2001;2003; Deaton and Lubotsky 2003). Our analytic results seem to challenge this argument, and suggest that the features of neighboring areas need to be considered.

Fourth, recent studies concluded that rural residence was negatively related to mortality in US counties (McLaughlin et al. 2007; Yang et al. 2011). Our spatial Durbin modeling results, to some extent, support this literature and indicate that the relationship between rural residence and mortality may be largely driven by the rural status in neighboring areas. Specifically, we did not find a significant direct impact of rural residence on mortality but the indirect (and negative) effect accounts for more than 80 percent of the total impact (0.051/0.061= 0.84). One explanation for this finding is that being adjacent to rural areas could be translated into easy access to natural amenities without sacrificing access to health care services, which will benefit the mortality in a county.

Finally, the impact of social affluence on mortality was found to matter the most locally. The direct impact accounts for more than 90 percent of the total impact (0.531/0.573=0.927) and the indirect impact was not statistically significant. That said, the change in social affluence would only affect the mortality within a county. This phenomenon may be understood as the consequence of internal migration. Specifically, people with diseases or health issues may prefer to live close to health providers to avoid the additional burden and inconvenience that comes with travelling. However, only those who are socioeconomically advantaged can afford moving/relocation due to illness, which leads to a selection process that generates the direct impact found by the spatial Durbin modeling. It seems to be a plausible explanation as we found a spillover impact of concentrated disadvantage on mortality. Those who are socioeconomically disadvantaged can only travel to receive treatments or services and the interactions across county boundaries produce interdependence as discussed previously (Capello 2009).

### Partitioning the direct and indirect effects:

The findings of the direct and indirect results did not answer the question of how important the immediate neighbors are for county mortality. Using the partitioning techniques (LeSage and Pace 2009), we calculated the coefficient estimates by different neighboring orders in Table 4 to address this question. Before discussing the findings, we would like to reemphasize that due to the significant spatially lagged covariates, the estimates at zero-order ($W_0$) for indirect impacts and those at first-order ($W_1$) for direct impacts will not be just zero (Jensen and Lacombe 2012).

The partitioning direct impacts provide evidence for spatial feedback. That said, for significant direct impacts beyond the zero-order neighboring ($W_1$~$W_4$) could be understood as the fact that a county is a first-order (or higher) neighbor to itself (LeSage and Pace 2009), which contributes to the direct impacts (the diagonal elements in the spatial weight matrix). For instance, over 95 percent of the direct impact of concentrated disadvantage comes from a county itself (0.316/0.330 = 0.957) and only 4 percent could be attributed to the spatial dynamics across county boundaries. In this case, the immediate neighbors ($W_1$) do not matter at all. As for income inequality, the absolute magnitude of the direct impact dropped by almost 90 percent from zero-to first-order neighbors. The dramatic changes in the direct impacts between $W_0$ and $W_1$ are observed for all variables that follow either the spillover or the social relativity argument. The significant estimates beyond the second-order neighbors were relatively trivial in contrast to the zero- and first-order estimates. That is, for direct impacts, the immediate neighbors play a more important role than do other neighbors at higher orders.

With respect to the indirect impacts, the estimates decreased from the first order to the higher orders. Take the percentage of the Hispanic population for example, the estimate dropped by more than 55 percent from $W_1$ to $W_2$ and further decreased by another 55 percent to $W_3$. This diminishing pattern could be observed in other covariates, such as rural residence and hospital beds per 1,000 population. Note that even in the indirect impacts, the estimates at the zero-order remained much larger than those at higher orders. This is again due to the sophisticated spatial dynamics and significant spatially lagged independent covariates across the US counties.

The partitioning results convey two important messages. On the one hand, some of the direct impacts, yet relatively small, are attributable to the spatial feedback drawn from the spatial structure. The immediate (first-order) neighbors are more crucial than those neighbors at higher orders. On the other hand, but for the significant spatially lagged covariates, the indirect impacts would be mainly from the immediate neighbors (Jensen and Lacombe 2012) and the diminishing patterns from first- to higher orders were relatively smooth in contrast to the patterns found in the direct effects. That is, most of the direct impacts were found under the second-order, whereas the indirect impacts may last till the fourth-order.

## Discussion and Conclusion

We examined our three hypotheses with the findings above. We first hypothesized that the social capital of a specific county is not only beneficial to the mortality of this county, but also to the mortality of its neighbors. The direct and indirect impacts of the SCI score on mortality were both significant and negative, which provides solid empirical evidence to support the first hypothesis. Other social capital measures were not related to mortality in US counties. Second, based on the social relativity perspective, we hypothesized that income inequality is positively associated with mortality within a county, but negatively related to neighbors' mortality. As we found a positive direct impact and a negative indirect impact of the Gini coefficient on mortality (both significant), the second hypothesis was supported. It should be emphasized that the effects of social capital and income inequality are independent of other social conditions, such as social affluence and racial composition. We finally hypothesized that the spillover and/or social relativity effects would be observed in other determinants of mortality. Table 5 summarized the evidence for the spillover and social relativity effects for all explanatory covariates. According to Table 5, we found five other variables that demonstrate either spillover or social relativity effects. The former includes the percentage of the Hispanic population, hospital beds per 1,000 population, and concentrated disadvantage; whereas the latter embraces the percentage of non-Hispanic other races and the percentage of the population without health insurance. We observed spillover or social relativity effects in 7 out of the 14 explanatory variables, providing decent support for the third hypothesis. Overall, the spatial Durbin modeling results bolster the three main hypotheses of this study, and highlight that the features of neighboring areas are important in modeling the geographic mortality variation in the US.

Spatial Durbin modeling allows for the partitioning of the direct and indirect effects by neighboring orders. By doing so, we found that the immediate (first-order) neighbors are more important than those farther away and that spatial feedback commonly exists due to the complex spatial structure underlying the data. The partitioning results echo the first law of Geography: “Everything is related to everything else, but near things are more related than distant things” (Tobler 1970:236). More importantly, we found that the directions of the relationships between mortality and its determinants may change across boundaries if the social relativity process is in play. Our findings suggest that spatial structure should not merely be treated as white noise in mortality research. Instead, spatial structure can be used in order to better understand why and how neighbors contribute to the mortality of a particular area.

The findings of this study have important implications for both policymaking and future research. First, the identification of the spillover and social relativity effects of social factors on mortality suggests that by improving social conditions, such as increasing the level of social capital in a particular area may not only promote the health of the local population, but also that of the residents nearby. Second, income inequality demonstrates the social relativity effect and the overall negative impact of income inequality on mortality identified in this study corresponds to a recent ecological study by Blanchard et al. (2008). This finding may be somewhat troubling from a policymaking perspective. That said, reducing income inequality of a county may directly decrease the mortality of the county, but it may, in turn, increase the mortality in neighboring areas. These counter effects lead to the third implication. Explicitly, future research should pay extra attention to uncovering the mechanisms of the social relativity effects on mortality. To our knowledge, no study has attempted to use spatial structure to explain the geographic mortality variation in US counties. This study provided arguments to theorize why neighboring counties should be important and confirmed the importance of the characteristics of neighbors with spatial Durbin modeling. More efforts are warranted to investigate the mechanisms underlying the spillover and social relativity effects.

While this study contributed substantively and methodologically to the mortality literature, it has limitations. First, there have been many definitions of social capital identified in the literature, and the measures used here may not capture all dimensions of this complex concept. This may be a reason why crime rates and residential stability were not significant in our analysis. Second, as this was a county-level analysis, caution should be used when interpreting the results of this study in order to avoid committing the ecological fallacy by generalizing the findings to the individual-level (Piantadosi et al. 1988). As social capital, income inequality, and mortality are ecological constructs (Kawachi et al. 1997), we feel confident in our aggregate-level analysis. The third limitation, the modifiable areal unit problem (Openshaw 1984), is universally shared by published ecological studies and this study is not an exception. As the CMF data are not allowed to be aggregated into finer geographic scales (e.g., tracts), the findings and conclusions of this study are limited to the county-level. However, there is no guarantee that the same results would hold for other spatial scales. For instance, if one aggregates deaths into census tracts and conduct analysis accordingly, the conclusions may change. Future efforts are warranted to investigate if the social relativity and spatial spillover processes found in this study exist in a finer spatial scale than county. Finally, the effect of social affluence is largely limited to a local population (within a county), but the effect of concentrated disadvantage spilled over to neighboring counties. While this finding corresponds to the argument that social conditions are fundamental causes of diseases (Link and Phelan 1995), it remains unclear why the spillover effect is only observed for concentrated disadvantage. Future efforts are necessary to explain this phenomenon.

The three spatial models used in this study are mainly focused on spatial dependence and it is not clear if spatial non-stationarity exists in our data. Spatial non-stationarity indicates that the relationship between a dependent variable and an independent variable varies across space (Fotheringham et al. 2003) and it is not limited to the arbitrarily defined boundaries. While, to some extent, the spatial Durbin modeling addresses spatial non-stationarity (LeSage and Pace 2009), the spatially varying associations may not be visualized with this approach. The social relativity and spatial spillover processes may be further tested with other spatial models that are designed for capturing spatial non-stationarity, such as geographically weighted regression (Fotheringham et al. 2003) and spatially varying coefficient modeling (Gelfand et al. 2003).

In sum, as mentioned earlier, mortality is an important population indicator that assesses the population health in an area. Despite the decrease in mortality in the past few decades, disparities in mortality rates continue to persist along various dimensions including geographic space. To reduce the geographic disparity in the mortality rate in US counties, it is imperative to identify the determinants of mortality as well as specific mechanisms. Even though researchers have recently began to apply a spatial perspective to county-level mortality research (Sparks and Sparks 2010; Sparks et al. 2012), the spatial structure has been mainly treated as white noise and could not help to explain the mortality variation. This study explicitly utilized the county-level spatial structure to understand mortality differentials across space. We confirmed that the spatial Durbin model outperforms other methods and that considering the features of neighboring counties (via spatial structure) helps to explain the county-level mortality variation. Our empirical findings indicate that the spillover perspective and social relativity perspective are valuable frameworks for approaching a comprehensive understanding of how different socio-demographic and economic characteristics are at work in mortality research.

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**Table 1**

Descriptive statistics for the mortality rate and independent variables (N=3,107)

| | **Mean** | **Std. Dev.** | **Minimum** | **Maximum** | **VIF**† |
|---|---|---|---|---|---|
| Mortality Rate | 8.913 | 1.453 | 2.904 | 18.889 | N.A. |
| **Racial/Ethnic Composition** | | | | | |
| Non-Hispanic Black | 0.089 | 0.144 | 0.000 | 0.868 | 1.847 |
| Hispanic | 0.076 | 0.128 | 0.000 | 0.986 | 1.619 |
| Non-Hispanic Other Races | 0.040 | 0.069 | 0.000 | 0.910 | 1.714 |
| **Rural/Urban Residence** | | | | | |
| RUCC | 5.109 | 2.680 | 1.000 | 9.000 | 2.101 |
| **Health Care Infrastructure** | | | | | |
| % w/o Health Insurance | 18.029 | 6.108 | 7.100 | 47.000 | 1.750 |
| MD per 1,000 pop. | 1.215 | 1.510 | 0.000 | 29.353 | 1.738 |
| Hospital Beds per 1,000 pop. | 3.630 | 5.545 | 0.000 | 104.157 | 1.206 |
| **Socioeconomic Status** | | | | | |
| Social Affluence | 0.000 | 1.000 | −7.676 | 5.382 | 2.139 |
| Concentrated Disadvantage | 0.000 | 1.000 | −2.842 | 10.166 | 2.761 |
| **Social Capital** | | | | | |
| SCI Score | −0.002 | 1.642 | −3.804 | 15.222 | 1.848 |
| Violent Crime Rate | 1.317 | 1.158 | 0.000 | 11.844 | 1.587 |
| Property Crime Rate | 3.900 | 2.852 | 0.000 | 27.696 | 1.525 |
| Residential Stability | 0.000 | 0.887 | −5.430 | 2.238 | 1.503 |
| **Income Inequality** | | | | | |
| Gini Coefficient | 0.431 | 0.037 | 0.272 | 0.621 | 1.565 |

Notes:

†Variance inflation factor is a measure of multicollinearity among the independent variables; N.A.: Not applicable.

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## Table 2

Coefficient estimates of different regression approaches (N=3,107)

| | OLS Model | Spatial Lag Model | Spatial Error Model | Spatial Durbin Model‡ | |
|---|---|---|---|---|---|
| | Estimate | Estimate | Estimate | Estimate | Lag Estimate |
| Intercept | 7.969$^{***}$ | 4.825$^{***}$ | 8.703$^{***}$ | 5.625$^{***}$ | |
| **Racial/Ethnic Composition** | | | | | |
| Non-Hispanic Black | 1.393$^{***}$ | 0.849$^{***}$ | 1.342$^{***}$ | 0.421 | −0.045 |
| Hispanic | −3.019$^{***}$ | −1.449$^{***}$ | −1.769$^{***}$ | −0.904$^{**}$ | −1.516$^{***}$ |
| Non-Hispanic Other Races | 0.679$^{*}$ | 1.498$^{***}$ | 1.922$^{***}$ | 2.429$^{***}$ | −3.407$^{***}$ |
| **Rural/Urban Residence** | | | | | |
| RUCC | −0.055$^{***}$ | −0.040$^{***}$ | −0.030$^{**}$ | −0.007 | −0.027 |
| **Health Care Infrastructure** | | | | | |
| % w/o Health Insurance | −0.001 | −0.014$^{***}$ | −0.030$^{***}$ | −0.041$^{***}$ | 0.057$^{***}$ |
| MD per 1,000 pop. | −0.035$^{*}$ | −0.032$^{*}$ | −0.032$^{*}$ | −0.043$^{**}$ | −0.019 |
| Hospital Beds per 1,000 pop. | 0.021$^{***}$ | 0.017$^{***}$ | 0.014$^{***}$ | 0.015$^{***}$ | 0.010 |
| **Socioeconomic Status** | | | | | |
| Social Affluence | −0.658$^{***}$ | −0.495$^{***}$ | −0.591$^{***}$ | −0.529$^{***}$ | 0.208$^{***}$ |
| Concentrated Disadvantage | 0.390$^{***}$ | 0.294$^{***}$ | 0.333$^{***}$ | 0.316$^{***}$ | 0.006 |
| **Social Capital** | | | | | |
| SCI Score | −0.189$^{***}$ | −0.099$^{***}$ | −0.078$^{***}$ | −0.027 | −0.169$^{***}$ |
| Violent Crime Rate | 0.039$^{*}$ | 0.017 | 0.025 | 0.016 | 0.026 |
| Property Crime Rate | 0.003 | 0.003 | 0.003 | −0.001 | −0.012 |
| Residential Stability | −0.040 | −0.028 | −0.015 | 0.003 | −0.027 |
| **Income Inequality** | | | | | |
| Gini Coefficient | 2.840$^{***}$ | 1.496$^{**}$ | 1.782$^{**}$ | 2.071$^{***}$ | −3.409$^{***}$ |
| **Spatial Effect** | | | | | |
| Rho (Spatial Lag) | | 0.428$^{***}$ | | 0.439$^{***}$ | |
| Lambda (Spatial Error) | | | 0.586$^{***}$ | | |

| | OLS Model | Spatial Lag Model | Spatial Error Model | Spatial Durbin Model‡ |
|---|---|---|---|---|
| **Model Diagnostics** | | | | |
| AIC | 8,752.7 | 8,243.6 | 8,229.4 | 8,066.4 |
| Lagrange Multiplier Test (residuals' autocorrelation) | 562.4522*** | 11.234*** | N.A. | 3.456 |

* $p \le 0.05$;

** $p \le 0.01$;

*** $p \le 0.001$;

‡ The coefficient estimates should be interpreted with direct and indirect impacts as shown in Table 3.

**Table 3**

Decomposition estimates of the direct and indirect effects of selected conditions on mortality

| | Direct | Indirect | Total |
|---|---|---|---|
| **Racial/Ethnic Composition** | | | |
| Non-Hispanic Black | 0.434 | 0.236 | 0.670 |
| Hispanic | **−1.086** | **−3.231** | **−4.316** |
| Non-Hispanic Other Races | **2.207** | **−3.952** | **−1.745** |
| **Rural/Urban Residence** | | | |
| RUCC | −0.010 | **−0.051** | **−0.061** |
| **Health Care Infrastructure** | | | |
| % w/o Health Insurance | **−0.038** | **0.066** | **0.029** |
| MD per 1,000 pop. | **−0.047** | −0.064 | −0.111 |
| Hospital Beds per 1,000 pop. | **0.017** | **0.029** | **0.046** |
| **Socioeconomic Status** | | | |
| Social Affluence | **−0.531** | −0.042 | **−0.573** |
| Concentrated Disadvantage | **0.330** | **0.245** | **0.576** |
| **Social Capital** | | | |
| SCI Score | **−0.044** | **−0.305** | **−0.350** |
| Violent Crime Rate | 0.019 | 0.056 | 0.075 |
| Property Crime Rate | −0.003 | −0.022 | −0.024 |
| Residential Stability | 0.001 | −0.044 | −0.043 |
| **Income Inequality** | | | |
| Gini Coefficient | **1.833** | **−4.219** | −2.386 |

Note: Bold numbers indicate that the variable is associated with the dependent variable at the 95% level.

**Table 4**

Spatial partitioning results of direct and indirect effects of selected conditions on mortality

| | Direct | | | | | Indirect | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **$W_0$** | **$W_1$** | **$W_2$** | **$W_3$** | **$W_4$** | **$W_0$** | **$W_1$** | **$W_2$** | **$W_3$** | **$W_4$** |
| **Racial/Ethnic Composition** | | | | | | | | | | |
| Non-Hispanic Black | 0.421 | −0.003 | 0.014 | 0.002 | **0.001** | −0.045 | **0.269** | 0.059 | 0.030 | 0.013 |
| Hispanic | **−0.904** | **−0.115** | **−0.046** | **−0.013** | **−0.005** | **−1.516** | **−0.949** | **−0.421** | **−0.192** | **−0.085** |
| Non-Hispanic Other Races | **2.429** | **−0.258** | **0.045** | **−0.010** | 0.001 | **−3.407** | −0.172 | **−0.234** | −0.073 | −0.037 |
| **Rural/Urban Residence** | | | | | | | | | | |
| RUCC | −0.007 | −0.002 | −0.001 | **0.000** | **0.000** | −0.027 | **−0.013** | **−0.006** | **−0.003** | **−0.001** |
| **Health Care Infrastructure** | | | | | | | | | | |
| % w/o Health Insurance | **−0.041** | **0.004** | **−0.001** | **0.000** | 0.000 | **0.057** | 0.003 | **0.004** | **0.001** | **0.001** |
| MD per 1,000 pop. | **−0.043** | −0.001 | **−0.002** | 0.000 | **0.000** | −0.019 | **−0.026** | −0.010 | −0.005 | −0.002 |
| Hospital Beds per 1,000 pop. | **0.015** | 0.001 | **0.001** | **0.000** | **0.000** | 0.010 | **0.010** | **0.004** | **0.002** | **0.001** |
| **Socioeconomic Status** | | | | | | | | | | |
| Social Affluence | **−0.529** | **0.016** | **−0.015** | **−0.001** | **−0.001** | **0.208** | **−0.157** | **−0.047** | **−0.026** | **−0.011** |
| Concentrated Disadvantage | **0.316** | 0.000 | **0.011** | **0.001** | **0.001** | 0.006 | **0.141** | **0.052** | **0.026** | **0.011** |
| **Social Capital** | | | | | | | | | | |
| SCI Score | −0.017 | **−0.013** | **−0.003** | **−0.001** | **0.000** | **−0.169** | **−0.073** | **−0.035** | **−0.015** | **−0.007** |
| Violent Crime Rate | 0.016 | 0.002 | 0.001 | 0.000 | 0.000 | 0.026 | 0.017 | 0.007 | 0.003 | 0.001 |
| Property Crime Rate | −0.001 | −0.001 | 0.000 | 0.000 | 0.000 | −0.012 | −0.005 | −0.002 | −0.001 | 0.000 |
| Residential Stability | 0.003 | −0.002 | 0.000 | 0.000 | 0.000 | −0.027 | −0.009 | −0.004 | −0.002 | −0.001 |
| **Income Inequality** | | | | | | | | | | |
| Gini Coefficient | **2.071** | **−0.258** | 0.033 | −0.011 | 0.000 | **−3.409** | −0.330 | −0.292 | −0.102 | −0.050 |

Note: Bold numbers indicate that the variable is associated with the dependent variable at the 95% level.

**Table 5**

Summary of support for spillover and social relativity processes

| | Spatial Spillover (same directions) | Social Relativity (opposite directions) |
|---|---|---|
| **Racial/Ethnic Composition** | | |
| Non-Hispanic Black | NS | NS |
| Hispanic | **Yes** | |
| Non-Hispanic Other Races | | **Yes** |
| **Rural/Urban Residence** | | |
| RUCC | NS | NS |
| **Health Care Infrastructure** | | |
| % w/o Health Insurance | | **Yes** |
| MD per 1,000 pop. | NS | NS |
| Hospital Beds per 1,000 pop. | **Yes** | |
| **Socioeconomic Status** | | |
| Social Affluence | NS | NS |
| Concentrated Disadvantage | **Yes** | |
| **Social Capital** | | |
| SCI Score | **Yes** | |
| Violent Crime Rate | NS | NS |
| Property Crime Rate | NS | NS |
| Residential Stability | NS | NS |
| **Income Inequality** | | |
| Gini Coefficient | | **Yes** |

NS=Not statistically significant; Yes=Supported by analytic results