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Social Capital and Human Mortality: Explaining the Rural Paradox with County-Level Mortality Data

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Abstract

The “rural paradox” refers to standardized mortality rates in rural areas that are unexpectedly low in view of well-known economic and infrastructural disadvantages there. We explore this paradox by incorporating social capital, a promising explanatory factor that has seldom been incorporated into residential mortality research. We do so while being attentive to spatial dependence, a statistical problem often ignored in mortality research. Analyzing data for counties in the contiguous United States, we find that: (1) the rural paradox is confirmed with both metro/non-metro and rural-urban continuum codes, (2) social capital significantly reduces the impacts of residence on mortality after controlling for race/ethnicity and socioeconomic covariates, (3) this attenuation is greater when a spatial perspective is imposed on the analysis, (4) social capital is negatively associated with mortality at the county level, and (5) spatial dependence is strongly in evidence. A spatial approach is necessary in county-level analyses such as ours to yield unbiased estimates and optimal model fit.

Keywords

Rural paradox; spatial analysis; mortality; social capital

Introduction

Several factors would suggest that rural populations in the United States should suffer from higher mortality rates.¹ Rural residents are generally characterized by higher poverty rates, a

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¹We use the term rural for convenience. The Census Bureau defines a metropolitan area as a large population nucleus and its adjacent communities that are highly integrated. The places that are not classified as metropolitan are non-metropolitan, a common definition of rural.

lower prevalence of health insurance coverage, generally inferior access to preventive medical services, a higher proportion of people with chronic diseases, more restricted activity days for the elderly, and worse self-assessed health conditions (Miller, Stokes, and Clifford 1987; Norton and McManus 1989; Oh 2001; Rogers, Hummer, and Nam 2000). However, these disadvantages do not seem to affect overall mortality. Though rural areas exhibit higher crude death rates, adjustment for demographic composition (age, sex, and race) eliminates and often reverses this rural disadvantage (Clifford and Brannon 1985; Clifford, Miller, and Stokes 1986; Keppel 1981; Miller, Stokes, and Clifford 1987). Regardless of how “rural” is operationalized, several recent studies confirm that mortality rates are lower in rural than urban areas (McLaughlin, Stokes, and Nonoyama 2001; McLaughlin, Stokes, Smith, and Nonoyama 2007).

A complete understanding of this so-called “rural paradox” has been elusive. In this paper we offer a theoretical and empirical assessment of whether the protective effect of social capital on health (Song, Son, and Lin 2010), combined with the higher level of social capital in rural areas (Beaudoin and Thorson 2004; Beggs, Haines, and Hurlbert 1996), helps to account for the rural paradox. While the concept of social capital has been linked to mortality, little is known about whether it can explain the residential mortality differentials. Our second goal is to offer a methodological contribution. While mortality research often uses ecological designs and area-level analysis of the associations between mortality rates and other contextual characteristics, the spatial dependence in areal data is seldom accounted for. It has been well documented that spatial dependence is a common problem in ecological research and may bias statistical estimates (Banerjee, Carlin, and Gelfand 2004). Accordingly, we employ and compare results across various sophisticated and traditional spatial modeling techniques.

The twin goals of this study are therefore to explore whether social capital can be used as an explanation for residential mortality differentials, and to do so with appropriate spatial analysis methods. In so doing, we seek to answer the following questions: (1) Are mortality rates lower in rural than urban places? (2) If yes, can social capital account for some of the association between residence and mortality even after controlling for socioeconomic and demographic covariates? (3) Does spatial dependence exist in ecological mortality data at the county level? (4) If it does, can spatial analysis be employed to yield better models than those commonly seen in the literature?

Literature Review

What is Social Capital?

The intellectual origin of the concept of social capital is debatable (Islam, Merlo, Kawachi, Lindström, and Gerdtham 2006). Sociologists can trace back to Emile Durkheim, Karl Marx, and Max Weber (Portes 1998); whereas economists may quote Alfred Marshall, John Hicks and Adam Smith (Woolcock 1998). However, the rapid surge of interest in social capital since the 1990s has been attributed to Bourdieu (1985), Coleman (1988; 1990), and Putnam (1993; 2000).

Bourdieu (1985) defined social capital as the sum of the resources embedded in an individual's social relationships and held that social capital could be converted from personal economic and cultural capital and vice versa. By contrast, Coleman (1990) emphasized that social capital should be defined by its functions and its role in facilitating an individual's actions within the social structure. These approaches to conceptualizing social capital came from a micro perspective and focused on the individual benefits or productivity of social capital. Putnam (1993; 2000) extended this to the ecological level and conceptualized social capital as a feature of social organizations and a community asset. Though this conceptual leap from the individual to the community level has been criticized for the lack of theoretical rigor and attention to issues of cause and effect (Portes 2000), a growing body of literature, especially in health research, has emerged from Putnam's conceptualization (Song, Son, and Lin 2010).

The fact that Bourdieu and Coleman did not specify how to measure social capital contributes to the popularity of Putnam's efforts. While Putnam proposed that bridging and bonding social capital connects heterogeneous and homogeneous groups respectively, he only created a single state-level social capital index and provided evidence that his social capital measures were significantly related to many aspects of society such as population health and economic development (Putnam 2000). We follow this approach in our empirical analysis, and offer caveats in this regard in the conclusion.

Operationalizing Social Capital in this Study

The term social capital debuted in an article on a rural school community center (Hanifan 1916). Social capital was defined to be developed collectively by people in the same social units and in turn they would be benefitted from social capital (Hanifan 1916). This definition is similar to Putnam's perspective and relevant to the rural sociology literature. Hence, inheriting this legacy, we define social capital as “connections among individuals – social networks and the norms of reciprocity and trustworthiness that arise from them (Putnam 2000, p.19).” The social connections refer to participation in formal and/or informal organizations and activities, such as political meetings and leisure activities. It is noteworthy that social capital here is equated to networks, social trust, honesty, and other consequences derived from these concepts, e.g., volunteering (Putnam 2000). This definition is operationalized at the aggregate level and has been adopted in ecological research since at least 1997 (Moore, Shiell, Hawe, and Haines 2005).

In the economic growth and development literature, it has been argued that not all social-capital-related organizations and activities are associated with regional economic performance in the same way (Olson 1971; Olson 1982; Woolcock 1998). Hence, civic organizations have been further divided into Putnam- and Olson-type groups, with the former (e.g., churches and sports clubs) involving social interactions that promote trust within organizations and the latter (e.g., unions and political parties) drawing on external resources to benefit members (Knack 2002). Although these two types of groups have been theorized to have countervailing associations with economic growth (Olson 1982; Putnam 1993),² there is little evidence of divergent associations with health. Indeed, there is reason to believe that participation on both Putnam- and Olson-type groups will have positive

implications for population health. Both types of civic organizations pursue both public and private goods for each member. For instance, Putnam-type groups could provide a well-knit safety net and support network for those with health problems, while Olson-type groups may strive for better public health policies and indirectly facilitate human health.

Social Capital and Health

The linking of social connections and institutions to health outcomes has a long history in social science. Durkheim ([1897] 2002) analyzed suicide data and suggested that self-destructive behaviors varied by social integration and institutional memberships. His legacy has been extended to various areas of health research over the years and enlightened recent works exploring the association between religion and mortality (Berkman and Syme 1979; Blanchard, Bartkowski, Matthews, and Kerley 2008; Reynolds and Kaplan 1990).

Numerous studies have taken advantage of longitudinal data collected in Alameda County, California, since 1965 and confirmed the preventive effects of social connectedness (Berkman and Syme 1979; Reynolds and Kaplan 1990; Seeman, Kaplan, Knudsen, Cohen, and Guralnik 1987). Social and community ties were believed to be crucial determinants for human health. Even after taking individual lifestyles (e.g., smoking and alcohol consumption), self-reported health status, and socioeconomic status into consideration, the most socially isolated men and women still had higher risks of death compared to their counterparts who were socially integrated (Berkman and Syme 1979; Seeman et al. 1987). The Tecumseh (MI) County Health Study, initiated in 1959 and designed to examine health and disease determinants in Michigan, also supported the positive effects of social capital. Adjusting for age and other risk factors, men having more social relationships and participating in more activities were less likely to die during the follow-up period (House, Robbins, and Metzner 1982). More recently, Klinenberg (2003) attributed the excess mortality caused by a severe 1995 heat wave to the social isolation of the elderly in some Chicago neighborhoods.

Although an association between health and social connections is well documented, one might question the causal relationship. That is, might not physical or mental illness lead to social isolation? However, longitudinal data sets, like those of the Alameda and Tecumseh studies, suggest that indeed social isolation compromises health. It was suggested that people who were socially disconnected had over twice the probability of dying of all causes in contrast to matched individuals who were tightly connected with friends, families, and communities (Berkman and Glass 2000). The beneficial effects of individual social involvement on health are significant; however, since social capital is to some degree a community rather than individual-level attribute, evidence from higher analytic units is needed.

A cohesive and relatively stable Italian-American community in Roseto, Pennsylvania, has drawn researchers' attention since the 1950s. Compared to its geographical neighbors, Roseto demonstrated a lower mortality of cardiovascular diseases. Roseto's age-adjusted

²Olson-type groups (social capital) are theorized to have a negative impact on economic growth, while Putnam-type social capital is thought to be positively correlated with economic development. Mixed findings are reported in the literature, however.

heart attack rate was less than half of that of its neighbors, and not a single Roseto resident below forty-seven died from cardiovascular diseases over a seven-year investigation. Important predictors of heart disease, like diet, exercise, weight, and genetic factors, had been considered but none of them could explain why Rosetans were healthier. Indeed, they had greater risk factors than did residents of other towns (Bruhn and Wolf 1979).

Digging deeper, the researchers discovered the distinct social processes among residents of Roseto. Due to the more homogeneous backgrounds of residents, many public facilities or institutions where residents could interact or communicate were created, such as churches, sports clubs, a labor union, a newspaper, a park, and an athletic field. Not only was the conspicuous display of wealth disdained, but also stronger family values and good behaviors were encouraged. Therefore, Rosetans established a community with both physical and emotional support, and the stronger linkage among inhabitants explained the lower heart attack rate (Egolf, Lasker, Wolf, and Potvin 1992; Wolf and Bruhn 1998).

Recently, Putnam's social capital has been linked to various health outcomes. Using a survey sample from 40 U.S. communities, a study found that the odds of reporting poor/fair self-rated health was negatively associated with the formal group involvement (Kim, Subramanian, and Kawachi 2006). Another study concluded that better individual self-rated health was related to higher social trust, more associational involvement, more organized group interactions and informal social interaction, and volunteer activities (Schultz, O'Brien, and Tadesse 2008). Adolescent alcohol or drug use and dependency were found to be negatively associated with civil participation, a measure of social capital (Winstanley, Steinwachs, Ensminger, Latkin, Stitzer, and Olsen 2008). Similar findings have been reported elsewhere (Lindström 2008; Petrou and Kupek 2008; Viswanath, Randolph Steele, and Finnegan 2006).

In addition to the classic individual-level longitudinal studies noted above, the past decade has witnessed increased interest in the association between mortality and social capital at the cross-sectional and ecological level. Kawachi and his colleagues found that per capita group membership and social trust are negatively associated with total mortality in a study of 39 U.S. states (Kawachi, Kennedy, Lochner, and Prothrow-Stith 1997). Another study concluded that age-adjusted mortality across the 48 contiguous states is negatively related to social capital, which is measured by community organization life, public engagement, community voluntarism, social trust, and informal sociability (Weaver and Rivello 2007). A recent U.S. county-level mortality analysis suggested that social capital is inversely correlated with infant mortality after controlling for population composition and other socioeconomic measures (Yang, Teng, and Haran 2009). Blanchard and colleagues (2008) emphasized the theological distinction between religions at the county level, and found that tightly bonded Conservative Protestant communities are less supportive of health-related social services and have higher mortality rates than those where Mainline Protestants or Catholic predominate. As religious environment partly reflects Putnam's social capital, Blanchard et al.'s finding implies that social capital's detrimental consequences may be understated.

It should be noted that studies comparing national-level data across countries provide weaker evidence for the presumed beneficial effect of social capital on population health. One study of 16 wealthy countries concluded that cause-specific mortality is more strongly associated with inequality than social capital (Muntaner, Lynch, Hillemeier, Lee, David, Benach, and Borrell 2002), while another analysis of 19 nations found that social trust, membership in organizations and volunteering were unrelated to a wide range of health outcomes, such as infant mortality and perinatal mortality (Kennelly, O'Shea, and Garvey 2003). The mixed findings above suggest that more studies at the ecological level are needed to clarify the association of social capital with health, particularly at the county level, a widely used analytic unit in ecological research.

How Social Capital Affects Health

Previous research points toward a significant relationship between social capital and health outcomes. However, exactly how social capital might improve health is still unclear. Though a definitive explanation is needed, several plausible theories are noteworthy (Song, Son, and Lin 2010). First, social capital enhances both tangible and intangible assistance, such as money, food, convalescent care, or health information (Kawachi, Kennedy, and Glass 1999; Putnam 2000). For instance, the diffusion of innovations is found to be more rapid in a community where residents know and trust one another and that are more tightly bounded (Rogers 1983). Once a new medical service is created, more people will adopt it due to the information diffusion, thereby improving population health.

Second, social capital reinforces healthy behaviors and exerts control over deviant ones. People who are socially isolated tend to have more unhealthy behaviors, like diet disorders, heavy smoking, and excessive alcohol consumption (Berkman 1985; Kawachi, Kennedy, and Glass 1999). The stronger bonds that social capital represents will discourage the occurrence of unhealthy behaviors because of the potential damage to the group caused by these risk factors. On the other hand, beneficial behaviors such as regular exercise are encouraged. Communities with higher social capital may also have greater political influence and the wherewithal to procure and maintain proper access to health care. The degree of mutual trust within a neighborhood determines the extent of social capital (Kawachi, Kennedy, and Glass 1999).³

Third, social capital can promote health through its psychosocial benefits. In the case of Roseto, flaunting personal wealth was scorned, while offering help was valued. In this circumstance, social capital can be regarded as the source of self-esteem, reciprocal regard, and mutual respect. Social ties and networks, for instance, help explain why socially isolated individuals living in a more cohesive society demonstrate fewer symptoms of psychological illness than their counterparts in a less cohesive community (Seeman, et al., 1993; Schoenbach, et al., 1986; Reed, et al., 1983).

³A reviewer raised the issue that high social capital may also encourage unhealthy behaviors within gangs or among drug addicts. We acknowledge this possibility. However, the negative effects of social capital in such circumstances are manifest within counterculture groups, which are beyond the scope of this study.

Finally, in line with positive psychosocial effects, social capital can serve as a catalyst for better immune systems, which fight diseases more efficiently and help the body recover sooner. According to current biomedical theory, low social capital and high isolation is a stressful condition that can compromise immune responses (Glaser, Rabin, Chesney, and Cohen 1999; Ross and Mirowsky 2001). Rural Areas Have Stronger Social Capital

Rural sociologists have demonstrated significant differences in social capital between rural and urban areas (Coward and Eathbone-McCuan 1985; Wilkinson 1991). Defining rural places as non-metropolitan (non-metro) areas, a study found that non-metro dwellers reported a longer time in a location and more mutual interactions in personal networks than their metro counterparts (Beggs, Haines, and Hurlbert 1996). Another report examined social exchanges (in dollars) in rural and urban areas, and found that rural families were more likely to have exchanges with kin than were their urban counterparts. Specifically, compared to the urban dwellers, rural families were more likely to receive money from kin, and younger rural householders were inclined to give greater support to kin (Hofferth and Iceland 1998). A study investigating the effect of mass media on social capital in rural and urban communities also indicated that rural community trust was higher than urban community (Beaudoin and Thorson 2004).

Other evidence indicated that social capital depends on the size of the community. Altruism, volunteering, and philanthropy, participating in community projects, helping strangers, charitable giving, and even blood donation were all more common in small towns than in metropolitan areas (Putnam 2000). Returning overpayment when shopping in stores, or assisting a wrong number phone call were more likely to be observed in smaller communities. Conversely, it was three times more likely for city residents to cheat on taxes, insurance claims, and bank loan applications. Even in small towns, fewer unnecessary automobile repairs were performed (Blumberg 1989; Brehm and Rahn 1997; Scholz 1998).

Urban inhabitants are more likely to be less socially engaged in their communities. People residing in central cities attended 10-15 percent fewer group membership organizations and club meetings than their rural counterparts. Rural inhabitants went to church about 10-20 percent more frequently, and were 30-40 percent more likely to serve as officers or committee members of local organizations. After controlling for a wide range of individual features including parental status, financial circumstances, and homeownership, Putnam (2000) concluded, "Metropolitans are less engaged because of where they are, not who they are (p.206)."

In sum, social capital is found to promote human health via both tangible help and psychosocial pathways, despite the concern about the understatement of social capital's negative effects (Blanchard, Bartkowski, Matthews, and Kerley 2008; Song, Son, and Lin 2010). In addition, rural residents share stronger social capital than do their urban counterparts. These characteristics make social capital a plausible explanation for mortality rates that are lower in rural than urban areas – the rural paradox.

Methods, Measures, and Data Sources

In this paper, we analyze the five-year average mortality rates of counties in the contiguous U.S. along with a wide range of county-level covariates in order to document and explain mortality differentials across space. Here, we describe the data and measures, and detail the statistical techniques in the subsequent section.

Mortality

We use the *Compressed Mortality Files* (CMF), 1989-1998 and 1999-2003, from the National Center for Health Statistics (NCHS) to calculate five-year (1998-2002) mortality rates (NCHS 2003; NCHS 2006) standardized with 2000 U.S. age-sex population structure. Race/ethnicity is not included because the CMFs only categorize races into three groups: white, black, and others. We have chosen therefore to keep the rate unstandardized by race, and to control for a race/ethnic variable that includes Blacks, Hispanics, and Other as separate categories.

Social Capital

As noted, social capital in this study is regarded as social “connections among individuals – social networks and the norms of reciprocity and trustworthiness that arise from them” (Putnam 2000). We first draw on recent endeavors by Rupasingha, Goetz, and Freshwater (2006), who have followed Putnam's work and developed a social capital index for U.S. counties that pulls together a number of widely accepted indicators. They developed a county-based social capital index, which includes the following variables. Putnam-type association density is measured as the total number of the following establishments per 10,000 people in a county: civic organizations, bowling centers, golf clubs, fitness centers, sports organizations, and religious organizations. Similarly, Olson-type association density includes political organizations, labor organizations, business organizations, and professional organizations. Furthermore, Rupasingha and colleagues also adopted recently developed social capital measures, including the percentage of voters participating in presidential elections (Alesina and La Ferrara 2000), the county-level response rate to the decennial census (Knack 2002), and the number of tax-exempt non-profit organizations. A principal component analysis of these indicators formed the basis of a single social capital index (Rupasingha, Goetz, and Freshwater 2006).

Along with this index, we use two additional measures of social capital: safety, and residential stability. Safety is a factor score based on the incidence of a variety of crimes, and is used to reflect the absence of mutual trust and the sense of safety (and thus weaker social capital). To reduce random variation, five-year average rates are calculated for 1998-2002 from the *Uniform Crime Reports*. As we measured this concept inversely, it is expected to be positively correlated with mortality.

Finally, a recent study suggests social capital is higher among homeowners (Glaeser, Laibson, and Sacerdote 2002), implying that a stable neighborhood is good for residents' interaction and facilitates the development of social capital. Hence, we include a residential stability index that is created by combining the percent of a county population living at the

same address in 1995, the percent of owner-occupied housing units, and the percent of people living in mobile homes, respectively, and then averaging the three z-scores. *The 2000 Census of Population and Housing SF3 Files* enables the calculation of residential stability.

Population Composition and Socioeconomic Environment

Following prior research (Sampson, Raudenbush, and Earls 1997; Yang, Teng, and Haran 2009), we begin to describe the social structure of a county with social affluence and concentrated disadvantage.⁴ The former is comprised of the following variables: log of per capita income (factor loading is .88), percent of population age 25 with a bachelor's degree or more (.93), percent of population employed in professional, administrative, and managerial positions (.78), and percent of families with incomes over 75,000 (.92). A principal components factor analysis yielded one factor that explained 78 percent of the variance and the resulting factor score is used measure social affluence.

In contrast to social affluence, concentrated disadvantage consists of the following covariates: poverty rate (.89), percent of persons receiving public assistance (.85), unemployment rate (.87), and percent of female-headed households with children (.78). Principal components factor analysis of these variables found that one factor emerged (Eigen value 2.85) that explained 72 percent of the common variance. The main purpose of dividing all the socioeconomic variables above into two factor scores is to explore the countervailing effects of affluence and disadvantage on human health.

In addition to the absolute measures of socioeconomic status above, we calculate the Gini index with household income data from the 2000 Census to capture the concept of income inequality. The Gini index ranges between 0 (total equality) and 100 (complete inequality), and its positive association with mortality has been discussed elsewhere (McLaughlin, Stokes, and Nonoyama 2001; Wilkinson and Pickett 2006). The Gini index is treated as a continuous variable. As it may be an extraneous variable that affects both mortality and social capital, including income inequality in the analysis should further validate the role of social capital in explaining rural paradox.

As pointed out earlier, the prevalence of race/ethnic groups is included as a predictor of mortality. The percent of the county population that is Hispanic, the percent black, and the percent non-Hispanic Others are used in the analysis. The percent of non-Hispanic white is not included to avoid perfect collinearity. While Latinos and African Americans are known to be deprived relative to whites, prevailing literature suggests that Hispanics have lower mortality than whites, referred to as the Hispanic Paradox⁵ (Abraido-Lanza, Dohrenwend, Ng-Mak, and Turner 1999), while blacks have higher mortality.

⁴We implemented a principal component analysis with all socioeconomic variables and the results suggested that two components should be extracted.

⁵The Hispanic Paradox refers to the low mortality of U.S. Hispanics relative to other racial groups, especially in view of their comparatively low socioeconomic status.

Rural/urban residence

While there is no consensus on how to measure rural at the county level, two operationalizations of rurality are: metro/non-metro, and rural-urban continuum codes (RUC) developed by Economic Research Service (ERS). These two measures are interrelated. All US counties and county equivalents are first dichotomized into metro and non-metro according to population size and worker commuting criteria. Metro areas consist of counties with cities of 50,000 or more or total urbanized areas of 100,000 or more, plus adjacent counties tied economically to the central county via employment commuting. RUC further distinguishes metro counties by the population size of the metro area (over 1 million, between 250,000 and 1 million, and fewer than 250,000), and stratifies non-metro counties by urban population (over 20,000, between 2,500 and 19,999, and fewer than 2,500) and adjacency to a metro area. Thus, the metro and non-metro categories can be further divided into 3 and 6 subgroups, respectively, resulting in a nine-category coding scheme (ERS 2004). These two conventional measures of rurality capture the ecological aspect of rurality, but they do not consider other dimensions of rurality, such as occupation and culture. While rural sociologists attempted to establish a composite rurality index that can fully embrace the concept of rurality, little success was found in the literature (Bealer, Willits, and Kuvlesky 1978). Therefore, metro/non-metro and RUC are widely accepted and we examine the rural paradox using both of these operationalizations of rural.

One dummy variable captures the metro/non-metro dichotomy, with non-metro counties as the reference group. While the ERS rural-urban continuum codes (RUC) range from 1 (most urban) to 9 (most rural), we create 8 dummy variables with the most rural category of counties serving as the reference. If the rural paradox exists, those counties that are *not* in the reference groups should have higher mortality rates than those in the reference groups. Moreover, if social capital helps to account for the rural advantage, then its inclusion should attenuate the associations of residence and mortality.

Exploratory Spatial Data Analysis—In this analysis we employ exploratory spatial data analysis (ESDA). The objectives of ESDA are to detect the spatial association in data and assess the need for advanced spatial modeling. ESDA embraces a range of techniques to visualize data, capture spatial autocorrelations, unveil spatial clusters, and help researchers prepare for explanatory analysis. Moran's I is a correlation coefficient weighted by the spatial structure of areal data and used to measure the departures from randomness. The Moran's I usually falls between -1 and 1 with positive values indicating positive spatial autocorrelation – that nearby areas have similar attributes. Negative values suggest heterogeneity of a certain characteristic within an area (Moran 1950).

To detect if a spatial clustering of mortality (and other independent variables) exists, we use the local indicator of spatial association (LISA). LISA consists of a series of statistics that assess spatial clustering and whether the clustering happens by chance. Four types of spatial clusters are identified: high-high, low-low, high-low, and low-high. In this application, high-high clusters refer to places with high mortality clustering spatially (Anselin 1995). Obviously the high-high and low-low clusters exhibit the expected spatial clustering

whereby areas with similar characteristics tend to be closer to each other. High-low and low-high clusters are considered spatial outliers.

If both global and local spatial association indicators confirm the existence of spatial dependence across counties, the usual regression tool, OLS – which assumes independent and homoskedastic errors – fails to account for spatial dependence. To rectify this statistical shortcoming, we use LeSage's Spatial Econometrics Toolbox for MATLAB to implement both spatial and non-spatial modeling (LeSage 1998).

Explanatory Spatial Modeling—To fully explore the importance of spatial dependence, the following analytic strategies are designed:

First, we begin with a first-order spatial autoregressive (FAR) model:

$$\begin{aligned} M &= \rho W M + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I), \end{aligned} \quad (1)$$

where M is a vector containing county-level mortality data and W is a standardized square matrix reflecting the first-order spatial relationships among counties. That is, W is a symmetric matrix where the diagonal elements are all zeros and those non-zero elements represent the adjacent relationship between two counties. The scalar ρ is a spatial autoregressive parameter. If it is significant, the spatial dependence found by ESDA is reconfirmed.

Second, we estimate OLS models where no spatial relationship is considered and conduct a multi-collinearity diagnosis, using the variance inflation factor (VIF) for predictors to ensure that our estimates are not biased:

$$\begin{aligned} M &= \beta X + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I), \end{aligned} \quad (2)$$

where X is a matrix including all independent variables and β represents the parameters to be estimated for the explanatory variables. Next, the spatial autoregressive (SAR) model handles spatial dependence by adding a spatial lag to the OLS model:

$$\begin{aligned} M &= \rho W M + \beta X + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I) \end{aligned} \quad (3)$$

The SAR model takes the mortality rate weighted by adjacent neighbors as one explanatory variable and assumes there is no spatial dependence in the error term.

In addition to spatial lag, the spatial error model (SEM) is considered, which captures the spatial dependence through the disturbance term:

$$\begin{aligned}
 M &= \beta X + u \\
 u &= \lambda W u + \varepsilon \\
 \varepsilon &\sim N(0, \sigma^2 I)
 \end{aligned} \quad (4)$$

where λ is a scalar spatial error parameter and u is a disturbance term. This disturbance term is used to estimate the effects of unknown factors which are not included in our models.

If both spatial lag and error parameters are found significant in equations 3 and 4, we should employ the general spatial model (GSM). According to LeSage (1998), the GSM model should be used if the error structure from a SAR model still demonstrates spatial dependence. The GSM model should include both lag and error parameters:

$$\begin{aligned}
 M &= \rho W_1 M + \beta X + u \\
 u &= \lambda W_2 u + \varepsilon \\
 \varepsilon &\sim N(0, \sigma^2 I)
 \end{aligned} \quad (5)$$

It should be noted that W_1 and W_2 can be the same but a potential identification problem could exist in that case. The estimated spatial parameters (ρ and λ) might be biased and would not be restricted within the spatial structure represented by the matrix (LeSage 1998). To avoid this problem, we will employ the first-order and the second-order contiguity matrix for W_1 and W_2 respectively, if this generalized model is necessary. The first-order contiguity matrix defines a county's neighbors as those with a directly shared boundary or a vertex, whereas the second-order contiguity matrix regards two counties as neighbors if they share a border or a vertex directly *or* if they have a common county where they both directly share a boundary or a vertex.

After estimating these models, we need to know which model is the most preferable. While the value of log-likelihood is a commonly used indicator of model fit, the total number of parameters used in the model is not accounted for. Therefore, we will employ Akaike information criterion (AIC) for model selection (Akaike 1974).

Results and Discussion

Table 1 shows descriptive statistics for variables used in the analysis along with their expected associations with mortality. All the measures of social capital (safety is measured conversely), concentrated affluence, and the percent Latino are expected to be negatively correlated with mortality. Conversely, percent black and others, disadvantaged groups, and income inequality are expected to have positive (detrimental) effects on mortality. Among the measures of rurality, mortality is expected to be higher among the metro counties than non-metro. When using RUC, in contrast to the reference group, all other counties should have higher mortality rates. It is anticipated that the inclusion of social capital in regression models will reduce, if not eliminate, the impacts of rurality measures on mortality.

The ESDA results indicate a strong spatial association of mortality across the country. The Moran's I is .53 and significant beyond .001 level. Figure 1 is the LISA map in which the four spatial clustering types are shown. Clearly, the standardized mortality rates do not

distribute evenly in the U.S. The red counties represent the high-high group in which counties with high mortality rates are surrounded by those also having high mortality. The high-high cluster is concentrated on the southeastern region and includes areas of well-known disadvantage. These areas include the Black Belt, Appalachia, and the Mississippi Valley and Delta regions. On the other hand, the low-low groups (those in blue), low-mortality counties close to one another, sit in the Great Plains, Mid-West region, and along the US/Mexico border. This spatial clustering pattern is consistent with the literature on the Hispanic Paradox and the rural/urban mortality differential. More importantly, the LISA map demonstrates a crucial distinction in the rural paradox. Specifically, the rural Mid-West counties have low mortality but the rural counties in the South and Appalachia show high mortality. This heterogeneity within the rural counties would not be revealed without a spatial perspective as used in this study. The spatial patterns of mortality imply that it is important to account for race/ethnic composition and other social factors in order to explore how mortality varies in the U.S.

Not only the dependent variable but also other covariates have the problem of spatial dependence. In Table 1, residential stability has the weakest spatial dependence but its Moran's I is .31 and significant at .001. The findings here further assure the need for a spatial investigation of mortality and bolster our argument that the spatial dependence commonly exists in areal data.

Table 2 and Table 3 show the regression results with different measures of rurality. Due to the similarity between the two tables, we draw the important findings from the tables as follows. First of all, the FAR model yields a strong spatial lag coefficient which, again, confirms that spatial dependence is an important issue that should not be overlooked. Without any other explanatory variables, over 40 percent of variance has been explained by lagged mortality (adjusted R^2 is .43). Next, the OLS model seems to work well with our data and the variance inflation factor (VIF) indicates multicollinearity is not biasing the estimates. Generally, a VIF greater than 10 is problematic. Regardless of the measures of rural, all VIFs are much smaller than this cut-off value.

Our base OLS model includes only rurality measures with no covariates (Model I) to which we add population composition and socioeconomic environment variables (Model II). First, we briefly compare the two measures of rurality in their relationship with mortality (Models I in Tables 2 and 3). Taken together, metro counties have slightly lower mortality than non-metro counties (Model I, Table 2), mildly refuting the rural paradox. The more refined rurality measure (RUC) yields results more in line with the rural paradox (Model I, Table 3). Specifically, the most rural counties – those non-metro, with no one in settlements of 2,500 population or more, and not adjacent to a metro area (RUC code 9) – have the lowest age-sex standardized mortality compared to counties that are more urban in character. More specifically, without controlling for other covariates, the mortality of the more urban counties (RUC code 1~8) is, on average, approximately 4~9 deaths per 10,000 population more than that of the most rural counties. Based on the adjusted R^2 and AIC, the RUC provides a better fit to the data and explains more variation in county mortality rates than the metro/non-metro dichotomy.

These results underscore how the metro/non-metro dichotomy obscures within-group heterogeneity as found in the LISA map. However, even here, once population composition and socioeconomic environment covariates are taken into account, metro counties are found to have higher mortality than non-metro counties (Table 2, Model II), thus supporting the existence of the rural paradox. In Table 3, the rural paradox becomes more conspicuous in Model II with a decreasing trend along the urban-rural continuum. That is, in contrast to the most rural counties, the largest residential mortality differential is seen among the most urban counties, and this gap steadily declines as the RUC codes increase.

The coefficient estimates for the other covariates in Model II (in both Table 2 and 3) are consistent with expectation, those for race/ethnicity being notable among these. A high concentration of African Americans is related to higher mortality. However, consistent with the idea of a Hispanic paradox, Hispanic concentration is associated with lower mortality. Moreover, the effect of residence remains significant and the adjusted R^2 increases dramatically. About 50 percent of the variance can be explained by Model II and the rural paradox holds in both tables. The relationships of social affluence and concentrated disadvantage with mortality are consistent with expectation and with arguments in the literature (Link and Phelan 1995). The positive association between the Gini index and mortality indicates that the uneven distribution of income within a county is detrimental for human health. This finding echoes previous ecological studies (McLaughlin, Stokes, and Nonoyama 2001; McLaughlin and Stokes 2002). It should be noted that several earlier studies on residential mortality differentials only compared mortality rates by rurality and failed to include other potential explanations into analysis (Clifford and Brannon 1985; Clifford, Miller, and Stokes 1986; Miller, Stokes, and Clifford 1987; Morton 2004). Our Model II (in both Tables) basically controls for key competing explanations for why mortality varies across counties, positioning us to determine whether social capital may help account for the rural paradox.

In Model III, the social capital index, safety, and residential stability all have protective effects and explain the residential mortality differential. In comparison to Model II, the inclusion of social capital diminishes the magnitude of the rural/urban effects, while their statistical significance remains. For instance, the effect of metro drops more than 40 percent from Model II to Model III. Similarly, all the impacts of RUC codifications on mortality decrease by roughly 35 percent (RUC 1) to almost 60 percent (RUC 5). In addition, the adjusted R^2 increases by more than 5 percent and AIC declines significantly, suggesting a superior model fit. As the literature suggested and as measured here, rural areas have greater social capital,⁶ an advantage that has implications for the rural paradox. With the inclusion of social capital, the associations between rurality and mortality are attenuated. Moreover, the counties where residents are more engaged in public affairs tend to have lower mortality. The negative effect of residential stability indicates that places with proportionately more long-term residents have greater social capital and lower mortality. Safety is also associated with lower mortality. High crime rates hinder the development of mutual trust, assistance,

⁶The most rural counties have the highest social capital index and stability scores and the lowest safety (crime) score. Results are available upon request.

and reciprocity among people and turn out to adversely affect health, as evidenced by higher mortality.

In contrast to earlier studies (Kawachi, Kennedy, and Glass 1999; Kawachi, Kennedy, Lochner, and Prothrow-Stith 1997), the beneficial effect of social capital on mortality found in this study fills a gap in a literature that has, to date, provided little evidence at the county level. In addition, the more nuanced measures of social capital used here provide a clearer picture of how social capital affects health. Counties featuring high cohesion, residential stability and safety benefit by having lower mortality than counties with less social capital, other variables controlled.

While the OLS models conform to expectation, a lingering question is whether a spatial approach can improve the models. Following our analytic strategy, we first introduce the SAR model where a spatial lag parameter, ρ , is estimated. The AIC improves greatly from OLS Model III to SAR, the adjusted R^2 increasing by more than 10 percent (the trend is the same in Tables 2 and 3). Compared with the FAR model, the magnitude of ρ decreases but remains significant. That is, though the inclusion of all the predictors minimizes the “spatial spillover” effect, the mortality rate of a county is still related to that of neighboring counties. In general, an average increase of 10 deaths per 1,000 population in the neighboring counties is associated with an increase of almost 4 deaths per 1,000 population in a county. This spatial spillover relationship holds even accounting for other covariates.

The SEM Model considers a spatial error parameter, λ , in the regression. In contrast to the OLS Model III, both AIC and the adjusted R^2 improved greatly. The magnitude of the effect of metro reduces by more than 50 percent but the RUC seems to be affected relatively slightly, with the exception of the most urban counties (RUC=1). Statistically, λ is used to capture all other unattended variables that are spatially correlated. As found earlier, the dichotomous rurality measure disguises much variation among counties so introducing a spatial error parameter into the analysis should have a greater impact on metro/non-metro than RUC. Clearly, a spatial perspective can help us better understand residential mortality differentials.

To further confirm the necessity of a more complex model, we follow LeSage's suggestion and impose a Lagrange Multiplier (LM) test on the residual structure of SAR. The LM values of both SAR Models do indicate that a general statistical model where both spatial lag and error are integrated is required (results not shown but available upon request). The GSM Models have the smallest AIC statistics (7589.962 and 7540.922 in Table 2 and 3, respectively) and the highest R^2 (roughly 65 percent) among various models and hence we have confidence that it is the most appropriate model for our data.

Both coefficients of spatial lag and error in the GSM Model are significant. The significant spatial dependence in the mortality (spatial lag) indicates that the standardized mortality in a particular county associates with the mortality rates in surrounding counties. Controlling for other predictors and spatial errors, a 10 percent increase in the standardized death rates in neighboring counties will correlate with a 2 percent increase in county-level mortality. This spillover effect of GSM is similar in both Tables. Note that the estimated effects of rurality

are smaller in the GSM Model than in the OLS Model III because the GSM Model takes into account the spatial dependence embedded in both mortality and error terms. Simply put, a spatial analysis can handle spatial autocorrelation well, result in superior model fit, and in part account for the associations between rural/urban residence and mortality. It is noteworthy that the rural paradox still holds even with a sophisticated analytic approach accounting for spatial dependence. The GSM models in Table 2 and 3 provide us stronger evidence for the rural paradox and social capital's role in accounting for it.

Conclusion

We have sought to advance the literature on residential mortality differentials by incorporating social capital into an analysis of mortality. And we have employed advanced techniques in spatial data analysis that corrected for statistical weaknesses in previously used methods that would have led to biased results. Based on the findings above, the questions raised in the introduction section are answered: First, rural mortality rates are lower than urban. Specifically, after accounting for population composition and socioeconomic variables, mortality is lower in non-metro than metro counties. Moreover, the most rural counties in the RUC coding scheme share the lowest age-sex standardized mortality relative to other counties. Second, the rural paradox shown above can be explained *partially* by the concept of social capital. Including the measures of social capital into the model attenuates the effects of metro and RUC on mortality by at least 35 percent and improves model fit as indicated by the adjusted R^2 and AIC. In addition, a spatial perspective can further minimize the residential mortality differential, indicating that certain unattended variables that are spatially correlated can explain the rural paradox. Third, this study also demonstrates that spatial dependence is a common problem in ecological studies. Multiple data sources were used to create a wide range of county-level variables. All of them are spatially correlated (Table 1). Spatial dependence, especially in ecological research where areal data are employed, has not been adequately accounted for in social science research or rural health studies. Fourth, we do find evidence that spatial analysis improves the analytic results and yields unbiased estimates. Over 60 percent of the total variation of county mortality is explained with a spatial approach and the AIC of the GSM Model is the smallest among various models. Our conclusion here also echoes recent argument that spatial modeling is necessary especially in the ecological level mortality analysis (Sparks and Sparks 2010; Yang, Teng, and Haran 2009).

We also provide evidence that social capital has a negative association with mortality at an intermediate level between the state and individual, after accounting for other covariates. The literature on the relationship between social capital and health mainly focuses on either the state level (Kaplan and Reynolds 1988; Kawachi, Kennedy, and Glass 1999; Kawachi, Kennedy, Lochner, and Prothrow-Stith 1997; Putnam 2000) or the individual level (Rose 2000; Veenstra 2000). When a place has a low turnover rate and safe living environment, residents have more opportunities to know each other, devote themselves to community development, organize voluntary activities, and cultivate common interests. Accordingly, the degree of mutual trust and reciprocity in a place will rise and conduce to high civic engagement, and a strong collective conscience. In turn, these may be related to more tangible resource support, better mental health, stronger immune systems and other

proximate determinants of physical health and mortality. Another key conclusion of our analysis is that net of other factors, places with greater social capital do have lower mortality, which in part explains the rural paradox (regardless how to measure rurality). Just which of these possible intervening mechanisms is at play is left to future research.

We noted three limitations and caveats of this study. First, we did not examine the associations of bridging and bonding social capital with mortality and rurality due to a lack of appropriate measures. Reliable and valid county-level indicators for these two subtypes of Putnam's social capital are needed to address this question. Second, while we acknowledged the possibly detrimental consequences of social capital (*c.f.*, Olson's work), additional theoretical exploration would serve to advance a comprehensive research framework needed for future studies of social capital and health. Third, the social capital index used in this study comprised a wide range of social groups, such as religious and political organizations. Within-group heterogeneity is glossed over which might otherwise yield more nuanced findings. For example, using the detailed classifications of religious organizations has shed new light in the area of religion and health (Blanchard, Bartkowski, Matthews, and Kerley 2008). Future work may explore the associations between certain social groups and mortality under the social capital framework. It is, of course, worth noting the standard statistics caveats that one must be cautious when interpreting regression coefficients in such analyses, even in the context of models that incorporate spatial dependence (Hughes and Haran 2010; Reich, Hodges, and Zadnik 2006).

Several policy implications evolve from the role of social capital in rural paradox. Our results suggest that building up solid social capital at the county level may enhance population health. While additional confirmatory research is certainly needed, to the extent our findings hold, health policy might expand to include efforts to strengthen civil involvement and society engagement among residents, especially in *urban* counties. First, funding community activities would encourage residents to participate in public affairs and produce opportunities for community solidarity to develop. Second, providing assistance to the groups that support social services and address social problems would facilitate population health because the strong relationships in the groups may provide additional resources to protect their members' health. Third, given the importance of residential stability found in this study, providing affordable housing – either through subsidies or low-interest loans – may engender community stability and strong social capital and hence decrease mortality. Finally, promoting and maintaining a sense of safety could enhance mutual trust and increase reciprocal help among people, likewise contributing to human health.

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Figure 1.
Spatial Cluster of Mortality in the U.S. Counties.

Table 1
Descriptive Statistics, Moran's I, and Expected Directionality of Effects (N=3,072)

Variables	Expected Effect	Moran's I	Minimum	Maximum	Mean	Std. Deviation
Mortality (per 1,000)	N.A.	0.53***	0.00	19.78	8.89	1.36
Rural/urban						
Metro	+	N.A.	0.00	1.00	0.34	0.48
Non-metro (reference group)	N.A.	N.A.	--	--	0.66	0.48
Rural-Urban Continuum						
RUC (code 1)	+	N.A.	0.00	1.00	0.13	0.34
RUC (code 2)	+	N.A.	0.00	1.00	0.10	0.31
RUC (code 3)	+	N.A.	0.00	1.00	0.11	0.31
RUC (code 4)	+	N.A.	0.00	1.00	0.07	0.26
RUC (code 5)	+	N.A.	0.00	1.00	0.03	0.18
RUC (code 6)	+	N.A.	0.00	1.00	0.20	0.40
RUC (code 7)	+	N.A.	0.00	1.00	0.14	0.35
RUC (code 8)	+	N.A.	0.00	1.00	0.08	0.26
RUC (code 9, reference group)	N.A.	N.A.	--	--	0.14	0.34
Population Composition						
Black (percent)	+	0.80***	0.00	86.08	8.54	14.35
Hispanic (percent)	-	0.83***	0.00	98.10	6.18	12.18
Others (percent)	+	0.39***	0.00	93.58	3.49	6.79
Socioeconomic Environment						
Affluence	-	0.51***	-2.43	5.75	-0.01	0.99
Disadvantage	+	0.52***	-2.54	9.06	-0.01	1.00
Inequality (Gini index)	+	0.50***	33.33	60.50	43.42	3.75
Social Capital						
Social Capital Index	-	0.62***	-4.06	7.66	-0.01	1.27
Neighborhood Safety	+	0.33***	-1.37	9.20	-0.03	0.93
Residential Stability	-	0.31***	-5.67	2.76	0.03	0.97

 p<0.001

Table 2
Regression Results of Age-sex Standardized Mortality with Metro/non-metro Classification[†]

Variables	VIF ^a	FAR Model	OLS Model I	OLS Model II	OLS Model III	SAR Model	SEM Model	GSM Model
Rural/urban								
Constant			8.921 ***	7.670 ***	7.882 ***	5.521 ***	9.006 ***	7.390 ***
Metro	1.538		-0.104 *	0.519 ***	0.281 ***	0.202 ***	0.137 **	0.130 ***
Population Composition								
% Black	2.052			0.019 ***	0.012 ***	0.008 ***	0.010 ***	0.006 ***
% Hispanic	1.345			-0.023 ***	-0.029 ***	-0.019 ***	-0.022 ***	-0.017 ***
% Others	1.725			0.008 *	0.008 **	0.014 ***	0.019 ***	0.023 ***
Socioeconomic Environment								
Affluence	2.835			-0.501 ***	-0.461 ***	-0.390 ***	-0.453 ***	-0.39 ***
Disadvantage	4.241			0.440 ***	0.340 ***	0.312 ***	0.402 ***	0.389 ***
Inequality (Gini index)	1.862			0.023 ***	0.022 ***	-0.003	-0.004	-0.011
Social Capital								
Social capital index	1.616				-0.246 ***	-0.126 ***	-0.094 ***	-0.058 ***
Residential Stability	1.862				-0.095 ***	-0.122 ***	-0.107 ***	-0.110 ***
Neighborhood Safety	1.314				0.141 ***	0.096 ***	0.133 ***	0.107 ***
Spatial Parameters								
rho		0.677 ***				0.384 ***		0.214 ***
lambda							0.556 ***	0.642 ***
Adjusted R-square		0.431	0.001	0.493	0.541	0.607	0.629	0.646
AIC		25310.414	10602.020	8256.160	8225.071	7850.076	7777.102	7589.962

[†] **FAR:** first-order autoregressive; **OLS:** ordinary least squares; **SAR:** spatial autoregressive; **SEM:** spatial error model; **GSM:** general spatial model where both spatial lag and spatial error are considered

^a The VIF values are calculated based on OLS Model III

* p<0.05
** p<0.01

1000>d

Table 3
Regression Results of Age-sex Standardized Mortality with Rural-urban Continuum Codes (RUC)[†]

Variables	VIF ^a	FAR Model	OLS Model I	OLS Model II	OLS Model III	SAR Model	SEM Model	GSM Model
Constant			8.404 ***	6.412 ***	7.081 ***	4.896 ***	8.365 ***	6.779 ***
Rural/urban								
RUC 1	2.765		0.386 ***	1.414 ***	0.958 ***	0.792 ***	0.714 ***	0.618 ***
RUC 2	2.036		0.430 ***	0.899 ***	0.509 ***	0.389 ***	0.420 ***	0.360 ***
RUC 3	1.956		0.429 ***	0.681 ***	0.332 ***	0.217 ***	0.248 ***	0.147 *
RUC 4	1.639		0.514 ***	0.624 ***	0.268 ***	0.216 ***	0.243 ***	0.157 *
RUC 5	1.355		0.445 **	0.533 ***	0.214 *	0.159	0.206 *	0.107
RUC 6	2.209		0.872 ***	0.619 ***	0.367 ***	0.307 ***	0.310 ***	0.245 ***
RUC 7	1.897		0.515 ***	0.392 ***	0.234 ***	0.168 **	0.144 *	0.131 *
RUC 8	1.466		0.579 ***	0.337 ***	0.218 ***	0.183 **	0.191 **	0.172 *
Population Composition								
%Black	2.088			0.015 ***	0.010 ***	0.007 ***	0.009 ***	0.005 *
%Hispanic	1.349			-0.025 ***	-0.029 ***	-0.019 ***	-0.023 ***	-0.018 ***
%Others	1.767			0.010 **	0.009 **	0.014 ***	0.019 **	0.022 ***
Socioeconomic Environment								
Affluence	3.143			-0.585 ***	-0.541 ***	-0.465 ***	-0.500 ***	-0.446 ***
Disadvantage	4.333			0.388 ***	0.329 ***	0.306 ***	0.391 ***	0.383 ***
Inequality (Gini index)	1.977			0.042 ***	0.035 ***	0.009	0.006	-0.003
Social Capital								
Social capital index	1.779				-0.198 ***	-0.086 ***	-0.079 ***	-0.039 *
Stability	2.001				-0.097 ***	-0.126 ***	-0.110 ***	-0.123 ***
Safety	1.388				0.134 ***	0.093 ***	0.124 ***	0.102 ***
Spatial Parameters								
rho		0.677 ***				0.376 ***		0.225 ***
lambda							0.530 ***	0.614 ***

Variables	VIF ^a	FAR Model	OLS Model I	OLS Model II	OLS Model III	SAR Model	SEM Model	GSM Model
Adjusted R-square		0.431	0.035	0.526	0.556	0.619	0.634	0.652
AIC		25310.414	10510.548	8326.121	8126.83	7740.942	7731.810	7540.922

^a **FAR**: first-order autoregressive; **OLS**: ordinary least squares; **SAR**: spatial autoregressive; **SEM**: spatial error model; **GSM**: general spatial model where both spatial lag and spatial error are considered

^a The VIF values are calculated based on OLS Model III

* p<0.05
** p<0.01
*** p<0.001