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The Impacts of Social Capital on Infant Mortality in the U.S.: A Spatial Investigation

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Abstract One of the leading health mysteries in the U.S. is why the infant mortality rate is one of the highest among industrialized countries. Although the relationships of both maternal health and socioeconomic characteristics to infant mortality rates are well documented, little is known about whether the social environment is associated with infant health. Moreover, few ecological studies of infant mortality in the literature have adopted a spatial approach to handle the spatial dependence embedded in the data. This study is designed to fill these gaps by connecting the concept of social capital with infant mortality in the U.S. at the county level. In so doing, it employs a spatial Poisson methodology to manage spatial dependence. The major conclusions are: (1) Though structural social capital index alone is predictive of infant health, this effect disappears when residential stability and neighborhood safety (cognitive social capital) are considered. Both could better explain why infant mortality varies by county. (2) The adverse effect of low birth weight on infant health could be attenuated by social capital and other socioeconomic conditions. (3) Our study illustrates that a spatial approach is necessary, especially for ecological studies; otherwise, spatial dependence would lead to biased estimates and incorrect conclusions.

Keywords Infant mortality · Social capital · Spatial Poisson regression · Low birth weight

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Introduction

At the beginning of the twentieth century, the life expectancy at birth in the U.S. was a mere 47 years, but that had increased to 78 by the year 2009 (Department of Health and Human Services [DHHS] 2000; CIA 2009). Contributing significantly to this were major improvements in hygiene, technology, and medicine. In spite of this fact, life expectancy in the U.S. is notably lower than that of most other industrialized nations (i.e. Sweden, Canada, and other 13 other countries all have a life expectancy over 80). This is primarily due to the relatively high rate of infant mortality at a national level (Paneth 1995). Admittedly, individual health improvement, maternal health in particular, could lower infant mortality. However, community intervention (i.e. better hygiene and higher adoption rates of screening services) have just as much potential to promote public health, if not more.

Infant mortality has been used to predict the success of the state's ability to serve the people (King and Zeng 2001). Although infant mortality rates decreased steadily in the last two decades of the twentieth century, the rates of infant death in the U.S. remain the highest among industrialized countries (National Center for Health Statistics [NCHS] 1999). According to the World Factbook (CIA 2009), the 2009 estimated infant mortality rate is 6.26 per 1,000 live births in the U.S., which is much higher than that of Sweden (2.75), Norway (3.58), Canada (5.04), and even Cuba (5.82). Therefore, one of the goals of Healthy People 2010, a national initiative by the U.S. government, is to reduce infant mortality rates (DHHS 2000).

To reach this goal effectively and efficiently, the determinants of infant mortality in both social and physical environments need to be identified. At the individual level, previous research has been focused on the effects of the following factors on infant mortality: low birth weight, nutrition intake, and maternal behavior (McCormick 1985; Barker and Osmond 1986; Kleinman et al. 1988). From an ecological perspective, air pollution (district level) and inequality (country level) have had an unfavorable influence on health (Wilkinson 1996, 1997; Wilkinson and Pickett 2009); lower social class has been found to be correlated to infant mortality (Bobak and Leon 1992; Loomis et al. 1999; Waldmann 1992; Hogue and Hargraves 1993).

The last decade has witnessed an increasing interest in the impact of social capital on human health (Kawachi et al. 1999; Kennelly et al. 2003). While social capital has been found to have beneficial effects on various mortality rates, such as all-cause and cancer mortality (Lochner et al. 2003), little is known about its influence on infant mortality. This study aims to bridge this gap by: (1) investigating whether social capital exerts an independent and favorable impact on infant mortality, and (2) exploring whether social capital attenuates the negative effect of low birth weight on child health.

Background and Literature Review

In this study, three factors are regarded as the major determinants of infant mortality: low birth weight, social conditions, and social capital. Social conditions are defined as the demographic and socioeconomic structure of a place, whereas social capital in this study refers to the social interaction, norms, mutual trust, and social organizations that serve as resources. This section will provide a systematic review on how these factors affect infant health and why they play crucial roles in understanding infant mortality. Since the impact of social capital on infant mortality is under-explored, this will be our focus.

Low Birth Weight

Low birth weight (defined as a birth weight lower than 2,500 g, or 5 lbs 8 oz) has been found to contribute to infant mortality and childhood morbidity (McCormick 1985; Buehler et al. 1987). Infection, respiratory distress, and congenital defects are the three major causes of death among low birth weight infants (Barton et al. 1999). Not only is low birth weight an outcome that can be used to make inferences regarding the gestation process, but it is also the chief predictor of infant death in the U.S. Indeed, the correlation between low birth weight rate and infant mortality rate in the 50 states and the District of Columbia can approach 0.8 (Paneth 1995).

In addition, infants born to mothers of lower social class and worse economic conditions are more likely to be underweight (Bergner and Susser 1970). This is partly explained by the fact that mothers of lower socioeconomic status are more likely to be malnourished and practice unhealthy behaviors, such as smoking and excessive alcohol consumption during pregnancy (Rush and Cassano 1983).

At first glance, low birth weight seems to be a simple concept that could be linked to infant death directly without other confounders. Nonetheless, birth weight should be regarded as the fruit of both maternal and social conditions. Without fully considering other factors, the pure impact of low birth weight on infant health might be biased. The subsequent section will elaborate on how social conditions influence infant health.

Social Conditions

Community socioeconomic characteristics have been identified as important determinants of mortality. Well-educated residents and wealthy neighborhoods are both negatively correlated with mortality (Curtiss and Grahn 1980; Rogers et al. 2000). The degree of a population's affluence reflects its ability to access preventive health-care, get health insurance, and acknowledge the severity of illness. Similarly, the prevalence of poverty, unemployment, and female-headed families indicate a poor standard of living, qualified by such effects as malnutrition, overcrowded or uncomfortable housing, and insufficient resources related to health-care. As suggested by Link and Phelan (1995), social conditions should be regarded as the fundamental causes of disease because socioeconomic disparities endure regardless of the underlying mechanisms.

Clearly, social conditions should be included in the analysis as they are embedded in both the social and physical environments. People with more education generally have more income and can thus afford better housing and health insurance. They are also more receptive to professional consultation and are more capable of seeking and adopting innovative treatments. In terms of infant mortality rates, better social conditions could be translated into better nutrition, cleaner and safer neighborhoods, and better available health care services for kids. Similarly, mothers should have less financial stress, receive better prenatal care, and have more thorough examinations. All of these advantages would lead to a lower infant mortality rate. As discussed above, social conditions could be defined by various indicators, such as unemployment, poverty, household income, and education level. It is difficult to determine which indicator is the most important and thus a composite indicator is commonly used (Sampson et al. 1997).

What Is Social Capital?

In addition to social conditions, the concept of social capital has drawn increasing attention in recent decades in the health literature (Schoenbach et al. 1986; Kawachi et al. 1999; Kawachi et al. 1997; McKenzie et al. 2002). One of the many components that make up a community is human interaction (Flora and Flora 2003; Wilkinson 1991). Social capital can be accumulated by frequent interactions or diminished through isolation and indifference. Bourdieu (1986) discussed various forms of capital, and defined social capital as "the aggregate of the actual or potential resources which are linked to the possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition." In addition, norms of reciprocity and mutual trust were the marrow of social capital as defined by Coleman (1988), who writes that social interactions, like collective action, group forming, and collaboration, could consolidate social norms. Moreover, the book by Putnam et al. (1993), "*Making Democracy Work,*" one of the most important works in political economy since Pareto and Weber, referred to social capital as "features of social organization, such as networks, norms, and trust, that facilitate coordination and cooperation for mutual benefit. Social capital enhances the benefits of investment in physical and human capital." Social norms and interactions link individuals to the broader social context, and when someone falls on hard times, the close-knit network is available to provide important social resources. Clearly, social capital is a collective characteristic and can widely affect various social outcomes, such as health, economic development, and social equity (McKenzie et al. 2002; Woolcock and Narayan 2000).

Social capital is an asset of places or organizations rather than of individuals. It constitutes a support system enabling the participants to act effectively to achieve shared goals. This ecological feature distinguishes social capital from the concepts of social networks and support, which are regarded as individuals' properties (McKenzie et al. 2002; Putnam 1996). Social networks are woven by social ties surrounding a person and can be used to explain one's behaviors (Berkman 1984). It should be noted that social networks do not necessarily lead to social support involving the exchanges of emotion, instrumental aid, or information (Wellman 1981; House 1981).

Colletta and Cullen (2000) further broke the concept of social capital into "cognitive" and "structural" ones. The former describes the shared values and attitudes that promote cooperation within a community, and the latter refers to rules, precedents, and institutions that bond members together, that lead to social inclusion, and that integrate different groups in a society (McKenzie et al. 2002). To fully explore the role of social capital in health literature, both components should be considered in research.

The Effects of Social Capital on Infant Health

The review above suggests a significant relationship between social capital and various social dimensions. Yet, comprehensive understanding of the specific manner by which social capital improves health is limited. Though a definitive explanation is still lacking, several plausible theories are worthy of discussion. First, social capital enhances both tangible and invisible assistance, such as money, food, convalescent care, or health information (Putnam 2000; Kawachi et al. 1999). For example, the diffusion of innovations is found to be more rapid in a community where residents know and trust one another and are tightly bonded. Once a new preventive medical service is introduced, more people will adopt it due to the diffusion of information, thereby improving population health. Moreover, if an individual goes to church regularly, her absence due to illness is more easily noticed and hence she is more likely to gain help. Similarly, when a new preventive medicine or technology which could decrease infant mortality rates is implemented, children or mothers from communities with stronger social capital are more likely to benefit than their counterparts from neighborhoods with weak social capital.

Second, social capital reinforces healthy behavior and exerts control over deviant incidences. People who are socially isolated tend to exhibit more unhealthy behavior patterns, such as dietary disorders, heavy smoking, and excessive alcohol consumption (Berkman 1985; Kaplan et al. 1977; Kawachi et al. 1999). Stronger bonding social capital will discourage the occurrence of unhealthy behavior because of the potential damages to the group caused by these risk factors. On the other hand, good behavior, like regular exercise, is encouraged thanks to the possible benefits. A community with higher social capital is more likely to fight for its rights, such as ensuring that budget cuts will not affect their access to health care or other amenities. The degree of mutual trust within a neighborhood determines the extent of social capital. The higher a community's social capital, the more likely that crime and deviant behavior, like adolescent drinking and smoking, are monitored (Sampson et al. 1997; Kawachi et al. 1999). In terms of infant mortality rates, the behaviors of mothers certainly affect the health of infants. Once deviant behaviors, such as substance abuse, are discouraged and healthy ones, like exercising regularly, are encouraged, infant mortality rates are likely to be lowered.

Third, social capital could advance health through psychosocial progress. Social capital could be regarded as the source of self-esteem, reciprocal regard, and mutual respect. Social ties and networks, for instance, have been identified as imperative factors in explaining why socially isolated individuals living in a more cohesive society demonstrate fewer symptoms of psychological illness than their counterparts in less cohesive communities (Reed et al. 1983; Schoenbach et al. 1986; Seeman et al. 1993). During pregnancy, maternal happiness and self-satisfaction makes for healthy infants and ultimately leads to lower infant mortality rates.

Traditionally, the public health and epidemiology literature has explained the socioeconomic health disparities in the following two ways. First, the lower socioeconomic classes have more risky behaviors, which leads to greater health disparities. Second, the material deprivation caused by social inequality makes the people in low social classes unhealthy. However, the evidence for these two arguments is tenuous (Lomas 1998). Several studies by Wilkinson (1996, 1997) and his colleagues (2009) have asserted that relative deprivation is the reason why inequality is positively associated with mortality among developed countries. In addition, Kawachi et al. (1997) further untangled the relationships between inequality and social capital with the state level data, and concluded that "inequality leads to increased mortality via disinvestment in social capital." Clearly, weak social capital is the product of high inequality. The recent works by Wilkinson, Kawachi, and others not only emphasized the impacts of social context on human health, but also underpinned the argument that psychosocial process can affect infant health

In sum, the effects of social capital on infant mortality have not yet been carefully explored. Based on the discussion above, we expect that higher social capital should lead to lower infant mortality due to the availability of greater resources, less maternal deviant behavior, and a better psychosocial environment.

Data and Methodology

Units of Analysis

Counties in the U.S. are the analytic units of this study. Though many studies have investigated the impacts of smaller units of analysis on health outcomes, such as zip codes and census tracts, considering geographic units smaller than county level may lead to flawed conclusions. First and foremost, the administrative hierarchy capable of effectuating policy solutions is the federal, state, and county.[1] The policy making structure does not always extend to the units below county (c.f. city health boards). That is, county is the smallest analytic unit with useful policy implications, therefore other smaller units would not be as practical as the county (Allen 2001). Second, the data are more readily available at county level than for other smaller units. Not only are they prepared by the Census Bureau, but they are also accessible to many governmental offices, like the EPA or FBI. For instance, health-related data are difficult to obtain at lower levels due to confidentiality issues. Based on these reasons, counties are considered the most appropriate unit of analysis for this study.

Data Sources and Measures

Following standard practice in analyses of public health data, infant deaths are studied as counts rather than as continuous outcomes. Almost 70% of the contiguous U.S. counties have fewer than 4 infant deaths per year. For rare diseases, it is common to use the Poisson approximation to the binomial distribution in modeling count variables (Waller and Gotway 2004). Therefore, in this study, the designated

[1] While county is an imperative unit directly involved in health care policies, there are numerous governmental units below the county scale in the U.S., such as municipalities and school districts. These can be used as the units of analysis, however, the county is the lowest level in the administration hierarchy that contains national infant health information.

dependent variable is the number of infant deaths before the first birthday, and the number of infants weighing less than 2,500 g is used as one of the explanatory variables. The Bureau of Health Professions *Area Resource File* (ARF) 2003 provides the needed data: three-year (1998–2000) average number of infant deaths, three-year average number of live births, and three-year average number of low birth weight infants.

As reviewed in the previous section, socioeconomic status and other related measures of social conditions are associated with infant mortality. Following earlier studies (Massey and Denton 1993; Sampson et al. 1999), we describe the social structure of a county with concentrated disadvantage and social affluence. We use factor analysis and extract one composite score to represent "concentrated disadvantage," which consisted of the following covariates: poverty rate (factor loading is .89), percent of persons receiving public assistance (.85), unemployment rate (.87), and percent of female-headed households with children (.78). We consider these to be indicators of concentrated disadvantage because the principal factor analysis indicates that 72% of the variance is shared by these variables.

On the other hand, social affluence comprises the subsequent variables: log of per capita income (factor loading is .88), percent of population age 25 with a bachelor degree or over (.93), and percent of population employed in professional, administrative, and managerial positions (.78), and percent of families with incomes over 75,000 (.92). They are used in a principal components factor analysis for the purpose of reducing variables and eliminating multi-collinearity. Like concentrated disadvantage, one single factor emerges that explained 78% of the variance and hence a single factor score is used to represent the degree of social affluence. All the variables used in social affluence and concentrated disadvantage are calculated based on *The 2000 Census of Population and Housing SF3 Files.*[2]

As discussed previously, social capital can be divided into structural and cognitive components. We attempt to measure them with the following three indicators. With respect to structural social capital, we draw on recent endeavors by Rupasingha et al. (2006), who have developed a social capital index for U.S. counties that pulls together a number of widely recognized indicators of this concept. They developed a county-based social capital index, which focuses on institutions and civil engagement and includes four variables. (1) "Association density:" the total number of the following establishments per 10,000 people in a county— civic organizations, bowling centers, golf clubs, fitness centers, sports organizations, religious organizations, political organizations, labor organizations, business organizations, and professional organizations. (2) The percentage of voters participating in presidential elections (Alesina and La Ferrara 2000). (3) The county-level response rate to the decennial census (Knack 2002). (4) The number of tax-exempt non-profit organizations. Rupasingha et al. (2006) create a single social capital index by extracting the first principal component scores out of these four variables.

[2] While the Pearson correlation coefficient between social affluence and concentrated disadvantage is -.47 ($p<.001$), the variance inflation factor (VIF) in Table 1 indicates that multi-collinearity is not a problem in our models.

Along with the index, we use two additional measures to capture the cognitive component of social capital: neighborhood safety and residential stability. Neighborhood 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).[3] To reduce random variation, five-year average rates are calculated for 1998–2002 from the FBI's *Uniform Crime Reports*. Since this concept is measured in the inverse, it is expected to have a positive effect on infant mortality.[4]

A recent study suggests that social capital is higher among homeowners (Glaeser et al. 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 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.[5] These three variables are standardized and the average of the three standardized scores is used as the residential stability index. *The 2000 Census of Population and Housing SF3 Files* enables the calculation of residential stability.

Analytic Process and Statistical Model

The first step of the analytic process is to conduct a descriptive analysis in order to have a thorough picture of how the data appear. Furthermore, we employ a Geographic Information System (GIS) to cartographically visualize the spatial variation of infant mortality rates in the U.S. The purpose is to reveal the spatial pattern and hence pinpoint the need for spatial modeling.

To explore the effects of social capital on infant mortality, we use the spatial Poisson regression with conditionally autoregressive (CAR) error terms introduced by Besag (1974). With the emergence of Markov chain Monte Carlo (MCMC) methods, CAR models have enjoyed an increase in usage in the past decade (Banerjee et al. 2004). Greater detail of the CAR model in an applied context could be found in Besag et al's work (1991). In this study, for county i, Y_i records the infant deaths, E_i is the total live births, w_i is the spatial error, and $x_{i1}, \ldots, x_{ip}$ are predictors of interest. The total live births are treated as the offset variable in the Poisson model because they are usually proportional to the infant deaths.[6] Explicitly, our model is

$$\begin{aligned} Y_i &= Poisson(\mu_i) \\ log\,\mu_i &= log(E_i) + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + w_i, \end{aligned}$$

[3] The crimes and factor loadings are: embezzlement (.59), forgery/counterfeiting (.82), fraud (.60), and total part I property crimes (.76). Though total part I violent crimes are correlated to neighborhood safety, its factor loading is less than .5 and thus we exclude it in the analysis.

[4] Table 1 shows the expected sign for all predictors.

[5] We included the percent of people living in mobile homes to account for the potential turnover rates of counties.

[6] The offset variable, total births (E_i), is not a precise population at risk used in epidemiology. However, according to Waller and Gotway (2004), the spatial epidemiology literature widely employs the number of incident cases per person instead of per unit of person-time to estimate disease rates. The difference between these two measures is minimal if the fluctuation in population is low. This study has used the three-year average infant health data to obtain a stable population and control the fluctuation.

where w_i given the spatial errors for the rest of counties, w_{-i}, is distributed as

$$w_i | w_{-i} N\left(\frac{\sum_{j\sim i} w_j}{n_i}, \frac{1}{n_i \tau_c}\right),$$

with τ_c being the precision parameter. $j \sim i$ denotes that county j is a neighbor of county i, and n_i is the number of neighbors for the county i. The coefficients ($\beta_1, \ldots, \beta_p$) should be interpreted exponentially. For instance, holding others equal, one unit of change in x_{i1} will lead to the ($e^{\beta 1}$-1) percent (multiplied by 100) increase or decrease of the total infant total deaths.

With respect to model comparisons, we used the Deviance Information Criterion (DIC) developed by Spiegelhalter et al. (2002). DIC is particularly useful in Bayesian model selection in which MCMC methods are used to obtain the posterior distributions of parameters. DIC also penalizes the total number of parameters and hence the model with the most parameters does not necessarily have the smallest DIC. Generally, a model with a lower DIC should be preferred to a model with a higher DIC. In contrast to other information criterion indices (i.e. Akaike information criterion), DIC is easily calculated from the MCMC samplers (Spiegelhalter et al. 2002; Gelman et al. 2004).

To our knowledge, few studies on infant health have used Poisson regression in the research design, and even fewer employed a spatial perspective to explain the variation of infant mortality across space (cf. Kalipeni 1993; Gemperli et al. 2004; and Rushton et al. 1996). This study is among the first to consider both methodological issues at the same time. With respect to the model specification, the total number of live births of a county would be used as the offset variable and the total number of low birth weight babies was considered in the first statistical model. Social condition and social capital covariates were added subsequently.

Analytic Results, Findings, and Discussion

Table 1 demonstrates the descriptive statistics of the variables used in this study and their expected impacts on infant deaths. The average number of infant deaths among U.S. counties is almost 9 with a mean live births of 1,273 per year. On average, each county has 97 infants weighing less than 2,500 g. As discussed previously, the total number of live births will be used as the offset variable in future analysis so that we do not impose any expected impact on this variable. With respect to race/ethnicity, a report by the Center of Disease Control and Prevention (Mathews et al. 2003) indicated that non-Hispanic Blacks have higher infant mortality rates than do non-Hispanic Whites, which leads us to expect a positive (increase) impact of the percent of black population on infant deaths. Nonetheless, the same report also reveals a paradox— Latinos show lower infant mortality rates than do non-Hispanic Whites despite their comparable socioeconomic profiles with respect to Blacks. Therefore, we anticipate that a higher percentage of Hispanics would result in lower number of infant deaths.

We further visualize the infant mortality rates (the number of infant deaths per 1,000 live births) as shown in Fig. 1. The largest and most conspicuous spatial cluster lies in the southeastern part of the nation. The counties in the Black Belt,

Table 1 Descriptive statistics and multicollinearity diagnostics of variables and expected effects on infant mortality, 1998–2000

Variables (N=3109)	Effect[a]	VIF[b]	Min.	1st Quartile	Median	3rd Quartile	Mean	Max.	S.D
Infant Deaths	N.A.	N.A.	0.00	1.00	2.00	6.00	8.98	861.00	31.68
Total Live Births	N.A.	N.A.	0.00	136.00	323.00	814.50	1273.48	157430	4650.28
Low Birth Weight Infants	+	1.24	0.00	10.00	24.00	62.00	96.58	10233	344.38
Social Conditions									
Percent Black	+	1.69	0.00	0.00	0.02	0.10	0.09	0.86	0.15
Percent Hispanic	–	1.27	0.00	0.01	0.02	0.05	0.06	0.98	0.12
Social Affluence	–	2.26	−2.43	−0.66	−0.19	0.36	0.00	6.01	1.00
Concentrated Disadvantage	+	2.12	−2.54	−0.68	−0.18	0.45	0.00	9.06	1.00
Social Capital									
Structural Social Capital Index	−	1.43	−4.06	−0.90	−0.12	0.74	0.00	7.66	1.00
Residential Stability	–	1.91	−5.67	−0.51	0.13	0.67	0.00	2.76	1.00
Neighborhood Safety	+	1.31	−1.37	−0.66	−0.20	0.41	0.00	12.12	1.00

[a] This column demonstrates the expected impact of each variable. N.A.: not applicable;+: positive effect on (increase) infant deaths; −: negative effect on (decrease) infant deaths

[b] Variance inflation factor (VIF) is a diagnostics of multi-collinearity. With a stricter threshold, the VIF greater than 4 indicates that a multi-collinearity problem exists in the model (see Kutner et al. 2005)

Appalachia, the Mississippi Valley, and Delta region comprise the spatial cluster of high infant mortality rates. In the Great Plains, several significant clusters are observed around Montana and both North and South Dakota, in which several Indian reservations are situated. On the other hand, the counties with lower infant mortality rates are concentrated in the Midwestern U.S. and New England area. As is evident in Fig. 1, infant mortality rates are not evenly distributed across space, and hence a spatial perspective should be employed to yield more accurate inference.

Table 2 contains the non-spatial Poisson regression results. Across models, the effect of low infant birth weight remains the strongest, but is attenuated with the inclusion of social condition variables. In contrast to Model I, the other three models do have lower DICs, indicating a better model fit. Model II reconfirms the findings in the literature. A higher percentage of black population is associated with more infant deaths across the country; while the concentration of Latinos is correlated with fewer deaths. Social affluence does improve infant health in terms of decreasing the incidences, and, as expected, concentrated disadvantage increases the number of infant deaths in a county. We further include the structural social capital index in Model III. While significant, compared to the effects of social conditions, the structural index has a relatively weak impact on infant death.

Although the inclusion of the cognitive component of social capital in Model IV yields the smallest DIC (the DIC difference between Model III and IV is not greater

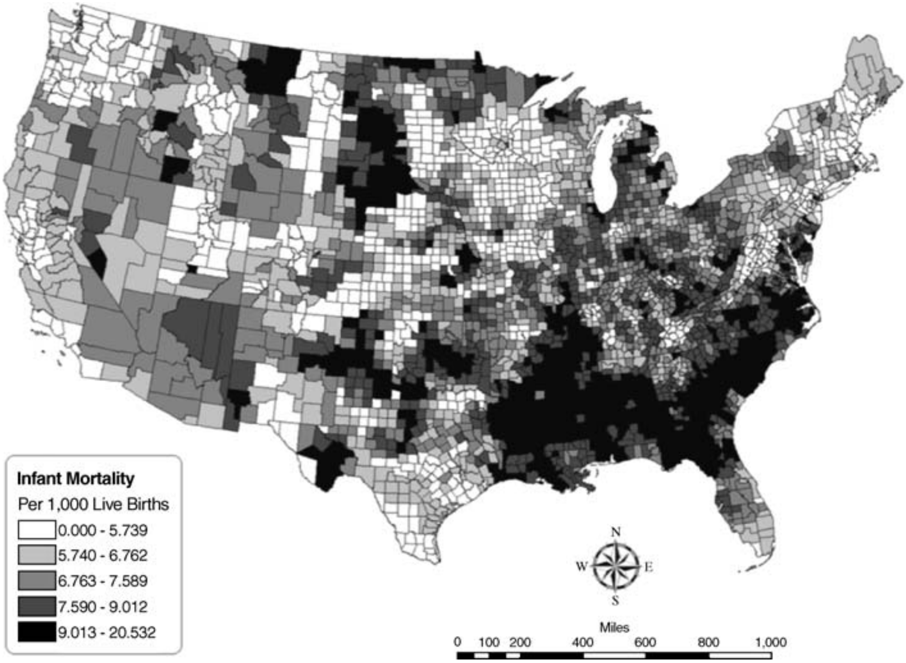

Fig. 1 Spatial distribution of infant mortality rates in U.S. counties

than 10), the effects of all three social capital indicators on infant health become insignificant. It seems the cognitive social capital confounds with the structural index, which is an important predictor of infant death in Model III. Note that the results in Table 2 are from non-spatial Poisson modeling. The insignificant impacts of social capital could be understood with the following reason: The spatial clustering pattern of social capital has been documented (Rupasingha et al. 2006) but the non-spatial approach here fails to consider the known phenomenon. Hence, the untreated spatially correlated errors might disguise the real effects of social capital. We anticipate that a spatial perspective would advance our knowledge by demonstrating the beneficial impacts of social capital on infant health. If the spatial Poisson regression not only improves the DIC but also shows the significant coefficients of social capital indicators, we should be confident of the findings.

The spatial Poisson regression results are shown in Table 3. Compared with Table 2, we summarize several important findings as below. First and foremost, the concept of social capital becomes an important determinant of infant health with a spatial perspective. The evidence is two-fold. One is that the inclusion of social capital variables reduces DICs significantly from Model II to Model IV, indicating that social capital helps to improve predictions. The other is that two out of three social capital variables in the final model of Table 3 become significant predictors of infant death, which are not found in Table 2. As discussed previously, the paper by Rupasingha et al. (2006) illustrated a strong spatial clustering pattern of social capital. It seems, without spatial modeling, the influences of social capital on infant health would not be disclosed. Second, the DICs of spatial models are consistently

Table 2 Non-spatial Poisson regression results of infant deaths in the U.S. counties

Variables	Model I		Model II		Model III		Model IV	
	Coefficient	MC Error	Coefficient	MC Error	Coefficient	MC Error	Coefficient	MC Error
Intercept	−0.24		−2.13		−2.18		−1.87	
	(0.02)[a]	<0.01	(0.16)[a]	<0.01	(0.25)[a]	0.02	(0.20)[a]	<0.01
Low Birth Weight Infants	3.34		1.96		1.96		2.15	
	(0.08)[a]	<0.001	(0.11)[a]	<0.01	(0.17)[a]	0.01	(0.14)[a]	<0.01
Social Conditions								
Percent Black			0.41		0.48		0.36	
			(0.07)[a]	<0.01	(0.08)[a]	<0.01	(0.07)[a]	<0.01
Percent Hispanic			−0.42		−0.31		−0.33	
			(0.05)[a]	<0.01	(0.06)[a]	0.06	(0.06)[a]	<0.01
Social Affluence			−0.05		−0.06		−0.07	
			(0.01)[a]	< 0.001	(0.01)[a]	<0.01	(0.01)[a]	<0.001
Concentrated Disadvantage			0.02		0.01		0.01	
			(0.01)	< 0.001	(0.01)	<0.001	(0.01)	<0.001
Social Capital								
Structural Social Capital Index					0.03		0.03	
					(0.01)[a]	<0.001	(0.02)	<0.001
Residential Stability							−0.01	
							(0.01)	<0.001
Neighborhood Safety							0.014	
							(0.007)	<0.001
Deviance Index Criterion	10,599		10,378		10,370		10,364	

[a] Zero is not included in the 95% credible region

Sample standard deviations are given in parentheses. MC error stands for Monte Carlo error

lower than those of non-spatial models. Our spatial perspective is better than the traditional approach with respect to model fit. While there is no absolute standard of comparing different DICs, the rule of thumb is that a difference of more than 10 would definitely rule out the model with a larger DIC (Spiegelhalter et al. 2002). The differences between non-spatial and spatial models are 238, 121, 119 and 120, respectively. They are all greater than 10 and we have sufficient evidence to favor spatial models.

Third, in contrast to Table 2, the spatial Poisson regression results suggest that residential stability and neighborhood safety are imperative factors in determining the number of infant deaths. Generally, one residential stability score would avoid 2% of the total infant deaths ($\exp(-0.02) - 1 = -0.02$). However, the total infant deaths will be raised by 2% with one neighborhood safety score increase ($\exp(0.016) - 1 = 0.02$). While the structural social capital index by Rupasingha et al. is not predictive of infant health in the full model, it alone in model III (in both

Table 3 Spatial Poisson regression with conditionally autoregressive errors results in the U.S. counties, 1998–2000

Variables	Model I		Model II		Model III		Model IV	
	Coefficient	MC Error	Coefficient	MC Error	Coefficient	MC Error	Coefficient	MC Error
Intercept	−0.50		−1.93		−2.01		−2.37	
	(0.04)[a]	<0.001	(0.20)[a]	<0.01	(0.35)[a]	0.03	(0.28)[a]	<0.01
Low Birth Weight Infants	3.40		2.10		2.05		1.80	
	(0.34)[a]	<0.001	(0.14)[a]	<0.01	(0.24)[a]	0.03	(0.20)[a]	<0.01
Social Conditions								
Percent Black			0.30		0.32		0.33	
			(0.10)[a]	<0.01	(0.11)[a]	<0.01	(0.10)[a]	<0.01
Percent Hispanic			−0.40		−0.35		−0.41	
			(0.09)[a]	<0.01	(0.09)[a]	0.06	(0.10)[a]	<0.01
Social Affluence			−0.04		−0.04		−0.05	
			(0.01)[a]	< 0.001	(0.01)[a]	<0.001	(0.01)[a]	<0.001
Concentrated Disadvantage			0.05		0.05		0.4	
			(0.01)[a]	< 0.001	(0.01)[a]	<0.001	(0.01)[a]	<0.001
Social Capital								
Structural Social Capital Index					0.02		0.01	
					(0.01)[a]	<0.001	(0.01)	<0.001
Residential Stability							−0.02	
							(0.01)[a]	<0.001
Neighborhood Safety							0.02	
							(0.01)[a]	<0.001
Deviance Index Criterion	10,361		10,257		10,251		10,244	

[a] Zero is not included in the 95% credible region

Sample standard deviations are given in parentheses. MC error stands for Monte Carlo error

Table 2 and 3) demonstrates a significant effect on infant death. The explanation for this finding is that the structural component of social capital could not really carry an effect on infant health because it takes time to develop mutual trust and to produce cooperative behaviors among residents. When the models include cognitive social capital, the effect of structural social capital index disappears. Our finding echoes a recent study (Boardman 2004) reporting that residential stability at the neighborhood level had a beneficial effect on the adults' physical health. Coupled with our findings, residential stability not only benefits the residents directly, but also establishes a healthy environment for infants and women during pregnancy.

Finally, according to Table 3, the effect of low birth weight on infant health decreases gradually from Model I to Model IV. In other words, the relationship between low birth weight and infant death could be mediated by both social conditions and social capital, echoing our hypothesis that social capital plays a role in understanding the variation of infant mortality rates across space. The causal relationships between social capital, social conditions, low birth weight, and infant mortality could be further untangled with structural equation modeling. Based on the finding here, social capital and social conditions not only exert their direct influence on infant mortality, but also indirectly through low birth weight. Apparently, social conditions and capital can be regarded as the exogenous variables that affect both low birth weight and infant death, the proximate determinant and endogenous variable. It should be noted that structural equation modeling might not be able to account for the spatial dependency and more efforts are required to clarify the intertwined causal associations among these concepts.

With respect to the parameter estimations, we would like to emphasize that the MC errors need to be very small numbers in order to assure researchers that the simulation based estimation is precise enough (see, for instance, Jones et al. 2006 and Flegal et al. 2008). Otherwise, the estimates generated by the MCMC would be questionable. Explicitly, the MC error is an estimate of the difference between the estimated posterior mean of each parameter and the true posterior mean. All the MC errors in Table 2 and 3 are very small, enabling us to have confidence in parameter estimations.

This study is among the first to provide evidence at the county level that social capital is beneficial for infant health. While the adverse effect of low birth weight on infant health is well documented, our finding explores another way to offset the undesirable impact and hence promotes both community and individual health. The next section will provide our conclusions and potential policy implications.

Implications and Conclusions

In our opinion, the most significant contribution of this study is to confirm the theoretical relationship between infant health and social capital with empirical evidence. Residential stability is found to promote infant health. As discussed earlier, stronger social capital exists in more stable neighborhoods. Social capital brings both invisible and tangible resources, encourages healthy behaviors, and provides an enjoyable environment in which to live. Therefore, to improve community health, one approach is to establish a stable neighborhood and increase home ownership. For example, providing affordable housing through either low-interest loans or subsidies would increase residential stability. Accordingly, residents would have more opportunities to become acquainted with each other, devote themselves to community development and voluntary activities, and so forth. In turn, social capital within the community will be stronger and lead to better maternal and infant health.

Neighborhood safety is also crucial. The degree of mutual trust, reciprocity, and sense of safety needs to be strengthened in a community. These may be related to more tangible resource support when needed, less mental stress and more psychosocial support for mothers during pregnancy. As a result, infant health would be enhanced and thus fewer infant deaths will occur. To increase neighborhood safety, developing community solidarity by funding community activities and encouraging public affairs participation are possible actions that could be taken.

While the structural social capital index demonstrates a significant impact on infant health, this effect disappears when the cognitive component of social capital is included. The existence of various institutions and organizations, indeed, provides residents more opportunities to engage in the community; however, without sufficient time or a safe environment, it would be difficult to produce social capital or promote cooperative behaviors among residents.

Methodologically, this study confirms that a spatial perspective is necessary for ecological analysis because it provides better model fit than the non-spatial approach. Failing to do so can result in biased estimates and incorrect assessments of the variability of our estimates, which can lead to incorrect conclusions as well as the camouflaging of the impacts of interest, such as social capital in this study.

In closing, we believe this study has advanced the literature on infant health by incorporating social capital and spatial modeling techniques into an analysis of infant death at the county level. The concept of social capital plays a role in understanding the variation of infant health among U.S. counties. Its impacts follow the theoretical expectation and carry beneficial effects on infant deaths. In addition, the spatial perspective is crucial and necessary to explore the relationship between social capital and infant health at the ecological level. Our study clearly illustrates that spatial Poisson regression can significantly improve model fit and provide reliable conclusions by accounting for the effects of spatial dependence. We not only reconfirm the significance of social conditions found in the earlier studies, but also provide the evidence that social capital could be utilized to reduce infant mortality rates, which is among the most urgent public health concerns in the U.S. today.

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