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Looking through a different lens: Examining the inequality-mortality association in U.S. counties using spatial panel models

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Abstract

Two areas still need further examination in the ecological study of inequality and mortality. First, the evidence for the relationship between income inequality and mortality remains inconclusive, particularly when the analytic unit is small (e.g., county in the U.S.). Second, most previous studies are cross-sectional and are unable to address the recent diverging patterns whereby mortality has decreased and income inequality increased. This study aims to contribute to both topic areas by studying the relationship between inequality and mortality via a spatiotemporal approach that simultaneously considers the spatial structure and the temporal trends of inequality and mortality using county panel data between 1990 and 2010 for the conterminous U.S. Using both spatial panel random effect model and spatial panel fixed effect models, we found that (a) income inequality was not a significant factor for mortality after taking into account the spatiotemporal structure and the most salient factors for mortality (e.g., socioeconomic status); (b) the spatial panel fixed effect model indicated that income inequality was negatively associated with mortality over the time, a relationship mirroring the diverging patterns; and (c) the significant spatial and temporal fixed effects suggested that both dimensions are critical factors in understanding the inequality-mortality relationship in the U.S. Our findings extend support to the argument that income inequality does not affect mortality and suggest that the cross-sectional findings may be a consequence of ignoring the temporal trends.

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1. Introduction

One unsettled debate in mortality research is whether or not income inequality (hereafter, inequality) positively affects mortality in the United States (U.S.) (A Deaton, 2003; Kawachi & Blakely, 2001; J. Lynch, Smith, Harper, & Hillemeier, 2004; J. Lynch, Smith, Harper, Hillemeier, et al., 2004; J.M. Mellor & Milyo, 2001). Several county-level studies provide evidence supporting the positive inequality-mortality relationship (R. E. Cossman, Cossman, Cosby, & Reavis, 2008; McLaughlin, Stokes, & Nonoyama, 2001; McLaughlin, Stokes, Smith, & Nonoyama, 2007; T.C. Yang, Chen, Shoff, & Matthews, 2012); however, some scholars argued that the association between inequality and mortality is spurious (A. Deaton & Lubotsky, 2003; Laporte, 2002; J.M. Mellor & Milyo, 2001; Muller, 2002) or is negatively related (A. S. Deaton & Paxson, 2001) due to both methodological shortcomings (e.g., endogeneity), and substantive weaknesses (e.g., the underexplored mediation mechanisms through which inequality affects mortality).

The mixed findings have led researchers to examine the inequality-mortality relationship with more rigorous analytic methods. As inequality and mortality are both aggregate measures, it is suggested that the potential dependency among analytic units should be controlled (Matthews & Parker, 2013). Several studies used spatial econometrics methods to control for spatial dependency with findings supporting the inequality-mortality relationship (Sparks & Sparks, 2010; T.-C. Yang & Jensen, 2014). Despite this research, the extant literature on ecological mortality research lacks a longitudinal perspective. This study is motivated to fill these gaps.

Why is a longitudinal perspective important? The answer to this question is two-fold. From a substantive viewpoint, should the claim that inequality affects mortality in the cross-sectional research stand, one would expect that the fluctuations in mortality are reflected in the fluctuations in inequality. That is, if inequality increases/decreases, mortality should increase/decrease accordingly or at least show a pattern reflecting latency over time. However, the U.S. mortality and inequality trends in the past few decades have diverged. On the one hand, the U.S. mortality has declined from roughly 11 deaths per 1,000 population in 1980 to 7.5 deaths per 1,000 population in 2010 (Hoyert, 2012). The downward trend holds for both crude and age-adjusted death rates. On the other hand, over the same time period, income inequality has increased remarkably (Piketty & Saez, 2004). Using a range of adjusted Gini indices, one study (Burkhauser, Feng, Jenkins, & Larrimore, 2011) reported that income inequality has been trending upward since the 1970s, with a significant increase observed around 1990.¹ Though the inequality trend seems to have slowed down in recent years, the overall upward trend is evident. From a longitudinal perspective, the two opposite trends would seem to suggest that income inequality and mortality are either unrelated or negatively related, which challenges the common belief that inequality is bad for mortality (*c.f.* Deaton and Paxson, 2011; Clough-Gorr, Egger, and Spoerri, 2015).

From a methodological standpoint, the cross-sectional analysis fails to take into account the temporal correlations and/or time-persistence of unobserved factors within the same unit,

¹While these trends are nationwide, they are confirmed with county-level descriptive statistics reported in this study.

which introduces bias to coefficient estimations (Baltagi, Song, Jung, & Koh, 2007; Baltagi, Song, & Koh, 2003). Mellor and Milyo (2001), for example, used time series analyses to argue that the inequality-mortality relationship at the aggregate level does not hold as the intra-unit variation in inequality in cross-sectional analyses could undermine the relationship between inequality and mortality. While several economists have proposed new space-time analysis frameworks (Anselin, Le Gallo, & Jayet, 2008; Elhorst, 2014; Lee & Yu, 2010), the availability of user-friendly programs has been limited (Millo & Piras, 2012) and as such few studies have adopted a space-time approach to explore the association between inequality and mortality.

There are two negative consequences when space and time are ignored. First, the intra-county dynamics across time cannot be captured, which may bias the estimate of the inequality-mortality relationship. Specifically, a cross-sectional design fails to consider serial correlation bias (i.e., the temporally correlation) within a county. Second, without spatiotemporal analysis the spatial relationships between analytic units cannot be used to explain why spatial patterns in mortality perpetuate over time.

This study is motivated by the observed divergence of mortality and inequality trends, the methodological significance, and the potential consequences of ignoring space and time. The aims are to answer the following related questions as they pertain to a study of U.S. counties and explore whether/how inequality and mortality are related after considering the spatiotemporal structure: (1) Does inequality remain a significant factor for mortality after considering the spatiotemporal structure and other fundamental mortality covariates? (2) If the answer to the first question is yes, does income inequality positively affect mortality or does their relationship mirror the diverging trend? And (3) what is the role of the spatiotemporal structure in understanding the inequality-mortality relationship?

The remainder of this paper is organized as follows: we begin with a review of the literature on mortality and inequality and discuss whether inequality matters. Next we describe the methods and data, followed by the presentation of findings. We close with a discussion section.

2. Literature Review

2.1 Why does/should Inequality Matter?

Before discussing why inequality matters, it is important to acknowledge that the inequality and mortality levels in the US are higher than those in other developed countries. More specifically, income inequality (as measured by the Gini coefficient) in the US, a liberal welfare state (Esping-Andersen, 2002), ranged from 0.40 to almost 0.5 between 1990 and 2010; however, over the same time span, other welfare state countries (e.g., Netherland and Nordic countries) had a Gini coefficient varying between 0.25 to 0.30 (The World Bank, 2016). Coupled with the higher mortality rates, the inequality-mortality relationship in the US has been a unique phenomenon among developed countries.

As mortality is a commonly used health indicator to assess population health, the theoretical arguments as to why inequality matters in mortality research are largely built upon the

association between inequality and health. The first theoretical linkage between inequality and mortality is drawn from the relative deprivation literature. That is, within a given area, the unequal distribution of wealth causes the sense of relative deprivation, which may in turn become psychosocial stressors that eventually undermine health (M. G. Marmot, 2004; R.G. Wilkinson, 2006). This *psychosocial pathway* has been used to explain why inequality is a factor for mortality among developed countries. Specifically, unlike the poor in developing countries, the impoverished population in developed countries may still have access to electricity, water, adequate housing and other durables. If only the absolute standard of living mattered, income inequality should not matter in developed countries. As Wilkinson (2006) pointed out, the sense of relative deprivation helps us understand the relationship of inequality with health. This perspective has received support from a range of studies. For example, several scholars (Kawachi, Levine, Miller, Lasch, & Amick, 1994; R. Wilkinson, 1997; R. G. Wilkinson & Pickett, 2009) have found that living in an area with a high level of inequality leads to stress, frustration, depression, anxiety, among other mental illnesses. These psychosocial discomforts could make individuals engage in risk behaviors, such as smoking, binge drinking, drug use, and antisocial behaviors, and consequently hinder individual health and increase the risk of death. It should be noted that this relative deprivation argument can also be applied to individuals near the top rungs of the social hierarchy (J. W. Lynch & Kaplan, 1997).

The other bridge between inequality and health suggests that high income inequality causes unequal distributions of resources and underinvestment in physical, cultural, and civic infrastructures (Daly, Duncan, Kaplan, & Lynch, 1998; Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997; J. Lynch, Smith, Harper, & Hillemeier, 2004; J. Lynch, Smith, Harper, Hillemeier, et al., 2004; J. W. Lynch & Kaplan, 1997). Kaplan and colleagues (1996) analyzed the data from the 50 U.S. states and found that higher levels of income inequality were associated with lower educational expenditure per capita, fewer investments in library resources, lower levels of health insurance coverage, higher exposure to crimes, and higher rates of incarceration. Their findings support the argument that high inequality may limit one's life chances (e.g., access to public services and resources) and are more likely to lead to an environment with poor infrastructure and social conditions. As Link and Phelan (1995) suggested, these social conditions are the fundamental causes of diseases and have substantial impacts on health. Thus, high income inequality may cause high mortality through an *underinvestment pathway*. The underinvestment and psychosocial pathway are interrelated: investment in social programs or infrastructures redistributes wealth and the provision of public services may minimize the sense of relative deprivation and the negative impact on health. Without the investment, the social dynamics among residents in an area, such as mutual trust and reciprocity, may be further damaged (Kawachi et al., 1997; R.G. Wilkinson, 2006).

A recent study (Pickett & Wilkinson, 2015) found that the relative deprivation argument received stronger support than the underinvestment argument (Elgar, 2010). Pickett and Wilkinson noted that it is more difficult to test the underinvestment linkage because many existing social welfare regimes, such as social security and Medicare, may mask the association between inequality and health. They further concluded that the literature provided strong support for the argument that high inequality causes poor health; however,

they criticized that no study, particularly time-series and panel, measured inequality at different time points, which is a key methodological limitation.

2.2 Why does/should Inequality *not* Matter?

While the two pathways linking inequality to health/mortality, as well as the causality between them, have gained empirical support (Pickett & Wilkinson, 2015; R.G. Wilkinson, 2006), scholars cast doubt on the findings. It has been argued that income inequality itself is only a proxy of the U.S. social structure, such as stratification and power relationships among race/ethnicity groups, and thus an important reason for finding the association between inequality and health is that researchers did not consider other variables that capture social structure. For example, Deaton (2003) argued that “it is *not* true that income inequality itself is a major determinant of population health... and the correlation across the states and cities of the United States is almost certainly the result of something that is correlated with income inequality, but that is not income inequality itself (p.151).” To support this argument, Deaton and Lubotsky (2003) analyzed the state and metropolitan data in the U.S. and reported that the inequality-mortality relationship can be fully explained by the proportion of African Americans in an area. Following Deaton’s argument, the mediation mechanism between inequality and mortality has not been well studied, which may yield mixed findings.

In general, there are two main reasons to examine more closely the relationship of inequality with mortality. First, the validity and reliability of the evidence drawn from aggregate analysis have been questioned and several studies show that individual-level analyses does not yield support for the positive inequality-mortality relationship (A. S. Deaton & Paxson, 2001; J.M. Mellor & Milyo, 2001; Jennifer M Mellor & Milyo, 2002; Sturm & Gresenz, 2002). More importantly, the support for the inequality-mortality relationship changes by the unit of analysis (the next subsection will discuss this issue). Second, in the cross-sectional ecological studies little attention has been paid to endogeneity and causal inference (J.M. Mellor & Milyo, 2001; Jennifer M Mellor & Milyo, 2002). This criticism is, to some extent, similar to Deaton’s argument that researchers should consider additional factors, particularly those associated with inequality as unobserved covariates may lead to endogeneity and biased results.

2.3 Unit of Analysis

The evidence for the inequality-mortality relationship varies by the unit of analysis. The strongest support for the inequality-mortality relationship comes from state or national studies (R.G. Wilkinson, 2006). Below the state level (e.g., county) there seems to be little evidence of the adverse association between inequality and health. Some argue that the homogeneity in a small unit of analysis undermines the inequality-mortality relationship (R.G. Wilkinson, 2006) and it is implied that it may not be necessary to investigate at small areas. However, several county-level studies found that inequality was associated with mortality after controlling for potential sources of bias (Sparks & Sparks, 2010; T.-C. Yang & Jensen, 2014). More importantly, there are several reasons why county *is* an appropriate unit of analysis. First, in contrast to states or labor market areas, counties are less likely to obscure within-area variations and lead to the loss of information (L. Lobao & Hooks,

2003). Second, as an administrative unit, most federal or state policy interventions are implemented through county-based offices (Kraybill & Lobao, 2001). Importantly, since 1980s, counties have gained more authority and discretion to make policies related to non-traditional social services related to population health, such as health care and pollution control (Benton, 2002; Percival, Johnson, & Neiman, 2009). That is, from the public administration perspective, county has become a critical unit for a wide range of policies that promote health. Finally, there is a growing interest in exploring the social-spatial relationships across all scales, including counties. Counties have been referred to as the “missing middle” (L. M. Lobao, Hooks, & Tickamyer, 2007) and are increasingly used to test the theoretical frameworks and social questions (Baller & Richardson, 2002; Howell, Porter, & Matthews, 2015). For these reasons, we argue it is important to examine the inequality-mortality relationship at the county-level. Note that we excluded counties in Alaska and Hawaii.

2.4 What is Missing in the Literature?

In brief, we have identified three underexplored aspects in the literature. First, even though the inequality-mortality relationship receives relatively little support from the county-level studies (R.G. Wilkinson, 2006), controlling for potential sources of bias has yielded empirical support in several cross-sectional studies (Sparks & Sparks, 2010; T.-C. Yang & Jensen, 2014). To our knowledge, no county-level study has measured inequality in across time while investigating the inequality-mortality relationship (Pickett & Wilkinson, 2015).

Second, somewhat related to the first point, some have argued that county is too small to capture the association between inequality and health (R.G. Wilkinson, 2006). However, a recent study (Peters, 2013) showed that inequality is heterogeneous within each state, indicating that state-level analysis of the inequality-mortality relationship may overlook the within-state variation.

Third, the diverging mortality and inequality trends in the U.S. in the past few decades seem to provide auxiliary support to Deaton’s argument and his work (A. S. Deaton & Paxson, 2001). To our knowledge, no county-level study has attempted to investigate whether inequality matters using a longitudinal perspective. Finally, the concerns about model specifications and endogeneity in multivariate analysis should be considered in order to generate unbiased estimates and robust conclusions.

The contribution of this study is to address these gaps by analyzing the U.S. county panel data from 1990 to 2010 with spatial panel modeling techniques (Elhorst, 2003; Millo, 2014) that take into account various sources of potential bias. As such, the findings may shed new light on the debate of whether inequality matters. We discuss our data, measures, and analytic approaches next.

3. Methodology

3.1 Data Sources and Measures

Mortality—Our dependent variable, the age-sex standardized mortality rate, was derived from three restricted Compressed Mortality Files (CMF) maintained by National Center for

Health Statistics (NCHS, 2000, 2003, 2012). The CMF includes all deaths in the US and the following variables associated with a death are available: county where a death occurred (at the county level), year of death, race (white, black and other), sex (male and female), age at death (17 age-groups), and cause of death (international classification of diseases codes).² To account for the annual fluctuations, we used the five-year average mortality rate, a commonly used approach in mortality research (McLaughlin & Stokes, 2002; T.-C. Yang & Jensen, 2014). For example, we averaged 1988–1992 mortality rates in the 1990 wave. The latest mortality data available to us is for the year 2010 and so we use 2006–2010 average mortality for our third wave; a time period corresponding with the American Community Survey (ACS) 2006–2010 five-year estimates. We did not standardize mortality by race/ethnicity because the CMF did not include detailed race/ethnicity measures until 1999. To address this issue, we include racial/ethnic composition of a county in the analysis.

Our independent variables can be categorized into four groups—income inequality, racial/ethnic composition, social conditions, and housing vacancy and tenure—and we discussed them as follows:

Income inequality—The *Gini index* was used to measure income inequality. This measure gauges the level to which the actual income distribution deviates from an equal income distribution. The Gini index ranges from 0 (no income inequality) to 1 (completely unequal income distribution). The publicly available decennial Census (and ACS) used household income data to calculate the Gini index. Note that this inequality measure has been regularly offered by the Census Bureau, which allows us to compare across time periods. There are other income inequality measures (e.g., Robin Hood index and 90/10 decile ratio), but as Kawachi and Kennedy (1997) found that all inequality measures are strongly correlated (the lowest Pearson correlation was 0.94) and that the choice of an inequality indicator does not change the relationship with mortality.

Racial/ethnic composition—as racial/ethnic composition of an area may confound the relationship of inequality with mortality (A Deaton, 2003; A. Deaton & Lubotsky, 2003) and the CMF data did not provide ethnicity information in 1990, we included *proportion of non-Hispanic Blacks* and *proportion of Hispanics* in our analysis. Doing so helps us to explore whether racial/ethnic composition matters and to control for potential confounders.

Social conditions—Six social condition variables were derived from Census and ACS data and included in our analysis, namely *proportion of household without a car*, *poverty*,³ *unemployment rate*, *proportion of households receiving public assistance*, *proportion of female-headed families*, and *proportion of population aged 25 and above who have at least a bachelor degree*. Note that in the US a family is defined as two or more people who live together and are related by birth, marriage, or adoption. A female-headed family is a family headed by a female without a husband present. With respect to poverty, the Census Bureau

²Despite the fact that deaths are individual level, CMF users are only allowed to aggregate deaths to county (or higher administrative levels, such as states and regions)

³Poverty is an absolute measure of one's resources and inequality is a relative measure that assesses how the overall resources are distributed in a population. They are two substantively different concepts and both are included in previous studies to separate the effect of poverty from the effect of inequality.

uses income before tax to determine a set of income thresholds varying by family size and if a family is in poverty, every individual in the family is classed as impoverished. These variables are the fundamental factors that contribute to health disparities (Link & Phelan, 1995; M. Marmot & Wilkinson, 2005) and have been found to affect geographic mortality patterns (Sparks & Sparks, 2010; T.-C. Yang & Jensen, 2014).

Housing vacancy and tenure—Two variables were included in this study: *the housing vacancy rate*, and *the proportion of owner occupied housing units*. These variables serve as the proxy for social cohesion and potential interactions among residents within a county (Sampson, Morenoff, & Gannon-Rowley, 2002).

Note that between 1990 and 2010 the boundaries changed for a handful of U.S. counties. To address this issue, our data have been normalized (i.e., boundaries are the same) to the 2010 Census boundaries and we use the Federal Information Processing Standards (FIPS) county codes to merge county data. Moreover, all of our analytic variables are available for 1990, 2000 and 2006–2010, generating a complete coterminous spatial panel dataset for the lower states plus the District of Columbia.

3.2 Analytic Strategies and Methods

Our analytic approach has three stages. We start with descriptive analysis, both spatial and non-spatial, to help better understand the main facets of the analytical data set and cross-sectional analyses (i.e., each census year) to understand if and how inequality and mortality are related without considering the spatial and temporal dependency (i.e., cross-sectional conventional regression). The second stage focuses on spatial panel modeling with random and fixed effects and compares them with the spatial Hausman test that helps us to determine if fixed effect modeling is preferred (details below). The final stage includes the application of exploratory spatial data analysis techniques, such as visualization, to the spatial panel modeling results to facilitate the interpretation of our main findings. All statistical analyses use the *splm* package (Millo & Piras, 2012) in R (The R Core Development Team, 2014).

As the proposed methods used in the first stage are standard approaches, we begin the discussion with a focus on the spatial panel fixed (and random) effect modeling approaches used in the second stage. To account for potential sources of bias, we followed a spatially and serially correlated panel modeling approach (Elhorst, 2014; Millo, 2014). The general analytic framework can be expressed as follows (assume that there are N spatial units across T time periods with $k-1$ independent variables):

$$y = \lambda(I_T \otimes W_N)y + X\beta + u$$

, where y is an $NT \times 1$ vector of our dependent variable, age-sex standardized mortality rates. $\otimes$ is the Kronecker product and X is a $NT \times k$ matrix of independent variables (including intercept), β is a $k \times 1$ vector containing the estimated coefficients for the independent variables, I_T represents an identity matrix of dimension T , W_N indicates the $N \times N$ spatial weight matrix. A spatial weight matrix is an interaction matrix that defines the spatial relationships between N counties. We used the first-order Queen method to define the spatial

relationships between counties (i.e., if two counties share the same boundary or vertex, they are defined as neighbors). In our spatial weight matrix, the diagonal elements are all zeros and the off-diagonal elements contain the spatial relationships. λ indicates the corresponding parameter of the spatial lag term. u is a composite error term and can be written as

$$u = (I_T \otimes I_N)\mu + \varepsilon$$

, where I_T is a $T \times 1$ vector of ones and I_N is an $N \times N$ matrix. μ is a vector of effects specific to spatial units. ε is a vector of spatially correlated errors that follow a spatial autoregressive process, which can be expressed as

$$\varepsilon = \rho(I_T \otimes W_N)\varepsilon + \nu$$

, where ρ is the corresponding parameter of the spatial error term. ν is a generalized error structure in which the errors are serially (i.e., temporally) correlated, and at each time period this error structure can be expressed as

$$\nu_T = \psi\nu_{T-1} + e_T$$

, where ψ is the corresponding parameter of the serially correlated errors and e_T is assumed to follow an independent and identical normal distribution with a mean of 0 and a standard deviation of deviation of σ_{eT}

The general analytic framework accounts for four sources of potential bias: spatial spillover (i.e., spatial lag) from the dependent variable (λ), spatial diffusion effect of unobserved variables (ρ), heterogeneity among spatial units (μ), and potential time-invariant effect of unobserved variables within the same unit (ψ). The discussion of the technical details is beyond the scope of this paper and can be found elsewhere (Elhorst, 2003, 2014; Millo, 2014).

A strength of spatial panel modeling is to allow researchers to explore whether the effect specific to each spatial unit (μ) can be assumed to be uncorrelated with the independent variables included in the analysis (Millo, 2014). If the effects specific to spatial units are not related to the independent variables, the effects can be treated as part of the composite errors; known as spatial panel random effect modeling. If the effects are related to the independent variables, these effects then have to be estimated individually or removed from the analysis; known as spatial panel fixed effect modeling. Elhorst (2014) summarized the advantages and shortcomings of each modeling approach and suggested the spatial Hausman test (Hausman, 1978) be used to examine the independence assumption. Following Elhorst, we implement both random and fixed effect models and use the spatial Hausman test to select the results for discussion.

4. Results

The descriptive statistics of the variables used in this study were presented in Table 1. Here we summarize several important observations. First, the mean of the age-sex standardized mortality rates decreased from 9.23 deaths per 1,000 population in 1990 to 8.17 deaths per 1,000 population in 2010. Our average county-level mortality rates are comparable with those reported elsewhere (Hoyert, 2012) and the declining trend in mortality reflects the increase in life expectancy over the same time period (Murray et al., 2013). With respect to income inequality, we found that between 1990 and 2000, average county inequality increased from 0.423 to 0.434 and after 2000, inequality seems to become stable. This county-level pattern follows the finding reported by Burkhauser and colleagues (2011). After comparing our Gini coefficient with those reported in the literature, we found that, as expected, our measures tend to be lower than those calculated with individual data (DeNavas-Walt, Proctor, & Smith, 2014) but are generally comparable. For example, the average inequality in 1990 was 0.423 in our data, in contrast to 0.428 calculated by U.S. Census Bureau.

Other independent variables also demonstrated the sociodemographic changes between 1990 and 2010. For example, the average proportion of the Hispanics within a county increased from 4.4 percent to almost 8 percent. The average county poverty rate decreased from 1990 to 2000 due to economic growth but poverty increased between 2000 and 2010, mostly reflecting the post-2007 economic recession. Similarly, the percentage of female-headed families increased over the study period, reflecting changes in the diversity of family structures in the U.S. Other notable changes at the county level include the increasing proportion of population with at least a bachelor degree between 1990 and 2010 and the dwindling housing markets in the first decade of the 21st century.

Beyond the non-spatial descriptive data analysis, we also mapped the key variables to understand the spatial patterns between 1990 and 2010 with a cross-sectional lens. Figure 1 shows the mortality and inequality maps (by quintiles) at the three time points, respectively (maps of other variables are available upon request). It is clear that the spatial distributions of mortality and inequality have been persistent. Specifically, similar to Cossman et al (2007), we found that counties with high mortality rates were clustered in the south (parts of the Black Belt, the Mississippi Valley, and southern Atlantic seaboard, excluding Florida), in central Appalachia, and by 2010, in parts of Texas. Other high mortality counties were sparsely distributed in parts of the northern plains and the desert Southwest. Counties with low mortality rates were concentrated on the Great Plains, Midwest, and New England. The spatial patterns have been persistent across decades, despite the decreasing trend in mortality. The spatial patterns of income inequality as measured by the Gini coefficients parallel those of mortality. Counties with high inequality were, in general, featured with high mortality with some clear exceptions in parts of California. Also, counties with Indian reservations tend to have high inequality and high mortality, such as the counties at the North/South Dakota border and the counties in South Dakota that are adjacent to Nebraska. Specific to the spatial distributions of inequality, the lowest and highest quintiles cover wider data ranges than the middle quintiles, indicating large variation across counties.

When we use the same cut-points for the three time periods (see Appendix A), it is clear that a greater number of counties moved into the low-mortality categories (i.e., blue) from 1990 to 2010, showing a declining mortality trend. Similarly, a smaller number of counties were in the low-inequality (i.e., green) categories in the same time span. The additional descriptive analyses (results not shown, available upon request) suggested that in general the within-state variation in inequality increases with the size of a state.

Following the analytic strategies, we tested cross-sectional models without considering spatial and temporal dependency. The results in Table 2 suggest that inequality and mortality were positively related and this association was significant in Model 2 (2000) and Model 3 (2010), a finding which is consistent with previous cross-sectional studies at the state or national level.⁴ However, the non-significant association of inequality with mortality in 1990 (Model 1) seems to support the argument that inequality does not matter. The cross-sectional analysis results at the three time points seem to reflect the mixed evidence in the literature.

Tables 1 and 2 convey three important messages relevant to our spatial panel data analysis. First and foremost, the descriptive statistics in Table 1 indicate that our panel data are reliable and valid for multivariate analysis as they properly capture the main sociodemographic changes in the U.S. Second, the cross-sectional spatial patterns of inequality and mortality seemed to suggest inequality is positively related to mortality; however, the diverging temporal trends from 1990 to 2010 in inequality and mortality (see Table 1) did not tell a similar story. Finally, the cross-sectional regression results provide a synopsis of the mixed findings in the literature, highlighting why a spatiotemporal investigation should be considered.

Next we estimated spatial panel models with random effects (i.e., the county-specific effects are not related to the independent variables). The results are shown in Table 3. Three findings are notable. First, under the random effect assumption, income inequality was not a significant determinant of mortality, even though the estimated relationship of inequality with mortality was positive. Regardless of how we specified the potential sources of bias, this finding holds (see Models 4–6 in Table 3). The differences across these three models lie in the specifications of random effect variance (Model 4) and the serially correlated errors (Model 6). Changing these specifications help researchers to understand whether the coefficient estimates are consistent (Millo, 2014). In addition to the inequality-mortality relationship, the associations of other independent variables followed the theoretical expectations. For example, after accounting for the spatiotemporal structure of mortality, higher proportions of Hispanic in a county were associated with lower county mortality rates; perhaps reflecting the Hispanic Paradox (Abraido-Lanza, Dohrenwend, Ng-Mak, & Turner, 1999). Similarly, poorer social conditions within a county were indicative of higher mortality; evident for poverty and unemployment. Counties with more stable populations (e.g., home owners) and fewer vacant housing units tended to have lower mortality.

Second, we found that the spatiotemporal structure underlying our data plays an important role in understanding the relationship between inequality and mortality. The serially

⁴We only discuss the inequality-mortality relationship as other variables will be discussed later.

correlated errors (ψ) were found to be a significant component, suggesting that within the same county, the unobserved variables have a temporally persistent impact on mortality. It should be emphasized that the non-significant estimate of ρ indicates the lack of a spatial spillover effect from the unobserved variables in neighboring counties. As for the spatial lag effect (λ), we found that every ten-percent increase in the mortality of neighboring counties leads to a two-percent increase in mortality of a given county. Third, we found relatively weak evidence for the random effect assumption. Specifically, Models 5 and 6 in Table 3 estimated that the variance of the random effects (Φ) was not more than 2.2 percent of the overall errors. This proportion is fairly trivial and challenges the independence assumption (Millo, 2014) and indicates that a fixed effect modeling approach may be preferred.

As the random effect assumption is not strongly supported in Table 3, we then implemented the fixed effect models with both time period fixed effects and county fixed effects (results in Table 4). In Table 4, Model 7 considers the time period fixed effects model only with a spatial lag effect, and Model 8 considers the county fixed effects (without a spatial lag). Model 9 is similar to Model 7 except for the exclusion of the spatial lag effect. In contrast to the results from the random fixed effects models, the most conspicuous difference is that the estimated associations of inequality with mortality became negative. While Model 8 found a significant (and negative) association of inequality with mortality, the spatial panel modeling results, in general, suggested that inequality is not a significant factor for mortality; consistent with the findings of the random effect models.

Moreover, the time period fixed effects were found significant, particularly in 2010. That said, in contrast to 1990 and 2000, the mortality rates in 2010 were statistically lower. Note that the time period fixed effects were stronger when the spatial lag effect was considered (Model 7) compared to when these were excluded (Model 9). More specifically, the time period effects decreased by approximately 30–40 percent and the changes between these two models may be due to the spatiotemporal interactions.

As the county fixed effects were estimated for each county in Model 8 and that roughly one third of U.S. counties had significant fixed effects, it is effective to visualize them (see Figure 2). These maps indicate that the positive county fixed effects were commonly found in the high mortality clusters in Figure 1 (i.e., across the South, Mississippi Valley and Appalachia) as well as in west Texas, New Mexico and the northern Mountain states. The negative fixed effects were commonly found in the low mortality clusters (e.g., the northern Great Plains).

The fixed effects shown in Figure 2 correspond to the income inequality patterns reported by Peters (2013). Though the county fixed effects seem to capture the persistent geographic mortality patterns, two variables, unemployment and female-headed families, changed sign from significant positive (Model 7) to significant negative (Model 8). One possible explanation is that income inequality may be correlated with these variables after the county fixed effects were estimated. Except for these differences, other independent variables were consistent across models.

To better determine whether the fixed effect modeling is favored, we used spatial Hausman tests (results not shown) and confirmed that the independence assumption does not hold. In other words, the random effect modeling approach imposes a relatively restrictive assumption on model specifications (Elhorst, 2014) and the results in our fixed effect models are preferable. The fixed effect modeling controls for unobserved heterogeneity and the potential correlation between errors and independent variables. Our discussion below mainly focuses on results from Table 4.

5. Discussion and Conclusions

Here we address the three research questions outlined in the introduction to this study. Our first two questions were concerned with whether income inequality is a significant factor for mortality after considering the spatiotemporal structure and other covariates, and if yes, whether income inequality has a positive relationship with mortality. Based on the results in Table 4, the answer to this question is that income inequality is not a significant predictor for mortality and it is possible that inequality has a negative relationship with mortality, a controversial finding that echoes the work by Deaton and Paxson (2001). This finding is not unique to the U.S. as a recent study in Switzerland reported that mortality and municipal-level inequality were negatively associated (Clough-Gorr, Egger, & Spoerri, 2015). There are three plausible explanations for our findings.

First, it has been found that the evidence for the inequality-mortality relationship is weak when the analytic unit is a small geographic unit such as county (R.G. Wilkinson, 2006; Zheng, 2012). However, as noted, there are many reasons why county is a desirable unit of analysis and several cross-sectional studies using county-level data reported a significant inequality-mortality relationship, even after accounting for the bias introduced by spatial structure (McLaughlin & Stokes, 2002; Sparks & Sparks, 2010; T.-C. Yang & Jensen, 2014; Tse-Chuan Yang, Noah, & Shoff, 2015). Putting our finding (i.e., non-significant association) into perspective and assuming that use of county as the analytic unit is appropriate, we find that controlling for the temporal trend eliminates the relationship of inequality with mortality or that the variation in inequality in the past few decades is too little to show a significant relationship with mortality. The spatial patterns of inequality and mortality seem to be persistent when viewed through a cross-sectional lens, whereas when examining through a temporal lens the trends in these two factors appear to be diverging.⁵ The implication of Model 8 (Table 4) is that inequality has a negative association with mortality, a relationship resembling the diverging trends from 1990 to 2010. To our knowledge, this study is among the first to investigate the inequality-mortality relationship with a spatiotemporal approach. Our finding warrants more research using this perspective.

The second explanation for the non-significant inequality-mortality relationship is that the analysis includes variables that may mediate or moderate the association between inequality and mortality as control variables, such as alcohol and tobacco consumption and health infrastructure (Pickett & Wilkinson, 2015). One problem with this explanation is that little is

⁵We noted that both cross-sectional and panel data analysis contribute to our understanding of how inequality is associated with mortality at the ecological level and many findings related to social conditions are consistent across different analytic perspectives.

known about what variables are mediating or moderating the relationship between inequality and mortality, particularly at any ecological level (T.-C. Yang & Jensen, 2014). While we argued that our analysis did not include potential mediators, we cannot guarantee that all the independent variables did not mediate the inequality-mortality relationship.

The third explanation is rooted in the fact that not all social groups are influenced by inequality equally (Currie & Schwandt, 2016). Explicitly, the widening inequality in the past few decades tends to make the rich richer and the poor poorer, which may be translated into lower risks of death among the rich and higher mortality among the poor. While our mortality data do not allow us to conduct detailed analysis with respect to the socioeconomic status of the deceased, a recent study found that life expectancy increases with income and the gap between the rich and the poor increased between 2001 and 2014, a time span when income inequality increases (Chetty et al., 2016). Their findings, to some extent, support the third explanation. As a result, the overall relationship of inequality with mortality may be offset or negative as shown in our results. This uneven distribution of the association between inequality and mortality may contribute to our findings.

Our third and last question asked about the role of spatiotemporal structure in understanding the inequality-mortality relationship. The spatial panel models with fixed effects suggested that both spatial and temporal structures are relevant. More specifically, we found the spatially correlated errors were significant in fixed effect models and even in the random effect models, the significant spatial lag effect indicated that the average mortality of neighboring counties contributes to the mortality of a given county. As for the temporal structure, we found that mortality rates in 2010 were significantly lower and those in 1990 are higher than other time periods, providing the statistical evidence to support the temporal trends in Table 1. When considering the spatiotemporal structure, the inequality-mortality relationship disappeared, indicating that temporal structure may account for the cross-sectional association of inequality with mortality. This finding seems to add a new argument to the methodological shortcomings identified by others (J.M. Mellor & Milyo, 2001; Jennifer M Mellor & Milyo, 2002; Milyo & Mellor, 2003). and reinforces the value of analyzing spatial panel data (Vitali, Aassve, & Lappegård, 2015).

In addition to the findings that directly answered our research questions, this study also speak to the literature in several ways. First, racial/ethnic composition is an important factor for mortality but contrary to Deaton (2003) it does not explain the county-level inequality-mortality association. That is, when the proportions of Blacks and Hispanics were excluded in our analysis, inequality remained a non-significant factor in our spatial panel fixed models. Second, the associations of social conditions and housing vacancy/tenure with mortality are mostly consistent across models, reconfirming the fundamental-cause argument (Link & Phelan, 1995). Third, though Pickett and Wilkinson (2015) concluded that the causality between inequality and health received strong support, our analysis did not confirm this. Our findings challenge the belief that inequality adversely affects mortality and highlight the potential bias resulting from ignoring the spatiotemporal structure. We suggest that, at least, the causality between inequality and mortality in U.S. counties warrants more research.

Our findings above carry some policy implications. First, the absolute measures of one's resources (e.g., poverty and unemployment) appear to play a larger role than inequality. This suggests that policies targeting vulnerable populations and that provide or improve access to necessary services might alleviate part of the burden related to the lack of resources. For example, female-headed families could receive services related to affordable daycare or flexible working hours, which may in turn minimize the family-work conflicts and promote health for these women. Second, housing vacancy and vacant housing are associated with mortality. Policies that promote access to affordable housing and home ownership as well as lead to investments in community infrastructure and re-development (e.g., community gardens) may help reduce area-level mortality.

It should be noted that we implemented a series of sensitivity analysis with three-year average mortality rates (i.e., 1988–1990, 1998–2000, and 2008–2010) and single year mortality rates for two time periods to examine if using different dependent variables alters the conclusions. Due to the space constraint, we did not present all of the results but they are available upon request. Two major findings can be drawn from the sensitivity analysis models. One is that the inequality-mortality relationship was non-significant in most models and no positive association was observed, regardless of the time span used in this analysis. The other is that the findings presented in this study are the most conservative estimates as using only two time periods yielded more significant and negative association between inequality and mortality. The sensitivity analysis results further strengthen the argument that the relationship of inequality with mortality should be either null or negative, in light of the temporal trends since 1990s.

This study is subject to several limitations. First, only three time points were considered and the fluctuation/variation in mortality and inequality, as well as other sociodemographic variables, *within* each decade cannot be captured by our analysis. Second, our spatial panel models are static (Millo, 2014) and do not account for potential spatiotemporal interactions; we are unable to estimate the lagged effects of the independent variables on mortality. While such dynamic spatial panel models have been proposed (Elhorst, 2012), there remains a lack of user-friendly software programs (Millo, 2014). Third, this study focused only on income inequality and we agree with Pickett and Wilkinson (2015) that future research should attempt to explore other types of inequality, such as wealth. Fourth, as a county-level study, our findings cannot be generalized to other geographic levels and changing county boundaries, while minimal in the U.S. context, may change findings (Fotheringham & Wong, 1991). Finally, our analysis are age and sex standardized and we focuses on the entire population. As such, our analysis may downplays the relationships observed for certain age groups (e.g., 50–65) that have been found to suffer more from inequality (Case & Deaton, 2015; Chetty et al., 2016).

In light of the limitations, we propose several future research directions. First, the analysis by different age groups and cause-of-death should be considered in order to fully understand the heterogeneous relationship between inequality and mortality. Second, the migration history of the deceased should help to examine the role of human migration (particularly selective migration) in confounding the inequality-mortality relationship. Third, beyond the direct association between inequality and mortality, more attention should be paid to the

mechanisms through which inequality affects mortality. One explanation for a non-significant inequality-mortality relationship is that some independent variables may fully mediate their association, but little is known about what the mechanisms are.

In sum, this study made three contributions to the literature: (a) Using the spatial panel modeling approach, this study found no association between inequality and mortality in U.S. counties and suggested that without considering the temporal trends in mortality and inequality, researchers may obtain biased results. (b) Our findings indicated that the causality between inequality and mortality in U.S. counties remains inconclusive and warrants more effort to clarify. (c) The multivariate analytic results reflected the descriptive spatial and temporal trends in mortality and inequality between 1990 and 2010, underscoring the importance of the spatiotemporal structure in exploring the inequality-mortality relationship at the county level.

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Appendix A

Spatial distributions of mortality and inequality using the same cutting thresholds

- We fill the gap that the spatiotemporal structure is overlooked in the literature.
- The spatial panel modeling did not support the inequality-mortality relationship.
- Our findings suggest that temporal trends should be considered in future research.

Figure 1.
Spatial distributions of mortality and income inequality from 1990 to 2010

Spatial Panel Fixed Effects on Mortality (Positive) 1990-2010

Spatial Panel Fixed Effects on Mortality (Negative) 1990-2010

Figure 2.
County fixed effects drawn from Model 8 in Table 4 (only significant effects are shown)

Table 1Descriptive statistics of the county-level variables by years (N=3,105)[#]

Variables	1990	2000	2010
Age-sex standardized mortality (per 1,000 population)	9.225 (1.260)	8.919 (1.368)	8.170 (1.399)
Income inequality (Gini Coefficient)	0.423 (0.038)	0.434 (0.038)	0.431 (0.037)
Population Structure			
Proportion of Black	0.086 (0.144)	0.087 (0.145)	0.089 (0.147)
Proportion of Hispanics	0.044 (0.111)	0.062 (0.121)	0.079 (0.129)
Social Conditions			
Proportion of housing units without any vehicle	0.087 (0.046)	0.075 (0.039)	0.063 (0.037)
Poverty	0.167 (0.079)	0.142 (0.065)	0.155 (0.064)
Unemployment	0.066 (0.031)	0.058 (0.027)	0.079 (0.034)
Proportion of Population receiving public assistance	0.085 (0.045)	0.085 (0.042)	0.023 (0.015)
Proportion of Female-headed families	0.182 (0.075)	0.208 (0.074)	0.258 (0.091)
Proportion of population with at least bachelor degree	0.135 (0.066)	0.165 (0.078)	0.190 (0.086)
Housing vacancy/tenure			
Proportion of owner-occupied housing units	0.618 (0.092)	0.635 (0.086)	0.607 (0.090)
Proportion of vacant housing units	0.147 (0.104)	0.141 (0.095)	0.171 (0.101)

[#]Standard deviation in parenthesis

Table 2

Cross-sectional OLS modeling results for 1990, 2000, and 2010[†]

Variables	Model 1: 1990		Model 2: 2000		Model 3: 2010	
	β	S.E.	β	S.E.	β	S.E.
Income inequality (Gini Coefficient)	0.639	0.663	1.575	0.721	3.734	0.618
Population Structure						
Proportion of Black	0.448	0.200	*	0.670	0.521	0.179
Proportion of Hispanics	-1.736	0.154	***	-2.042	-2.160	0.137
Social Conditions						
Proportion of housing units without any vehicle	2.173	0.532	***	-3.519	-1.597	0.598
Poverty	-0.388	0.471		0.890	6.247	0.475
Unemployment	6.338	0.768	***	2.984	3.370	0.671
Proportion of Population receiving public assistance	3.120	0.819	***	7.633	0.701	1.329
Proportion of Female-headed families	6.343	0.475	***	5.636	2.686	0.336
Proportion of population with at least bachelor degree	-4.132	0.329	***	2.984	-5.901	0.263
Housing vacancy/tenure						
Proportion of owner-occupied housing units	-0.458	0.326		-1.523	-0.164	0.367
Proportion of vacant housing units	1.564	0.267	***	3.238	2.110	0.299
Intercept	6.534	0.288	***	5.483	4.309	0.296
AIC	7776.72		8454.40		8315.28	

Note:

[†] All the variance inflation factor (VIF) values among the independent variables are well-below 10 and the VIF of inequality is consistently lower than 2.5 across models.

* p < .05;

** p < .01;

*** p < .001

Table 3

Spatial panel modeling with random effects, spatial lag effect, and spatially and serially correlated errors

Variables	Model 4		Model 5		Model 6	
	β	S.E.	β	S.E.	β	S.E.
Income inequality (Gini Coefficient)	0.672	0.374	0.672	0.374	0.649	0.374
Population Structure						
Proportion of Black	0.905	0.104	***	0.905	0.104	***
Proportion of Hispanics	-2.019	0.086	***	-2.019	0.086	***
Social Conditions						
Proportion of housing units without any vehicle	0.193	0.351	0.193	0.351	0.183	0.351
Poverty	0.567	0.264	*	0.567	0.264	*
Unemployment	2.423	0.426	***	2.423	0.426	***
Proportion of Population receiving public assistance	8.655	0.294	***	8.655	0.294	***
Proportion of Female-headed families	2.510	0.202	***	2.510	0.202	***
Proportion of population with at least bachelor degree	-6.009	0.162	***	-6.009	0.162	***
Housing vacancy/tenure						
Proportion of owner-occupied housing units	-2.720	0.191	***	-2.720	0.191	***
Proportion of vacant housing units	3.357	0.161	***	3.357	0.161	***
Intercept	5.019	0.172	***	5.020	0.172	***
Random Effect Variance (ϕ)	--	--	--	0.000	0.000	*
Serially Correlated Errors (ψ)	0.050	0.013	***	0.050	0.013	***
Spatially Correlated Errors (ρ)	0.043	0.029		0.043	0.037	
Spatial Lag Effect (λ)	0.225	0.019	***	0.225	0.022	***
AIC	24903.94		24905.94		24914.46	

Note:

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 4
Spatial panel modeling with time period fixed effects, space fixed effect, and spatial lag effect

Variables	Model 7		Model 8		Model 9	
	β	S.E.	β	S.E.	β	S.E.
Income inequality (Gini Coefficient)	-0.487	0.324	-1.317	0.323	***	-0.125 0.361
Population Structure						
Proportion of Black	-0.931	0.144	***	-0.632 0.423	-0.160	0.135
Proportion of Hispanics	-1.775	0.152	***	-3.448 0.28	***	-2.026 0.128
Social Conditions						***
Proportion of housing units without any vehicle	1.437	0.374	***	0.142 0.518	0.821	0.393 *
Poverty	1.601	0.272	***	-0.401 0.284	1.802	0.292 ***
Unemployment	5.961	0.435	***	-1.317 0.368	5.922	0.465 ***
Proportion of Population receiving public assistance	4.433	0.444	***	3.965 0.271	4.235	0.466 ***
Proportion of Female-headed families	3.120	0.200	***	-0.873 0.185	3.894	0.221 ***
Proportion of population with at least bachelor degree	-4.146	0.164	***	-8.068 0.283	-4.837	0.173 ***
Housing vacancy/tenure						
Proportion of owner-occupied housing units	-1.899	0.182	***	-2.931 0.377	-1.946	0.199 ***
Proportion of vacant housing units	2.489	0.161	***	3.039 0.369	2.809	0.171 ***
Spatially Correlated Errors (ρ)	0.873	0.007	***	0.295 0.015	0.581	0.011 ***
Spatial Lag Effect (λ)	-0.590	0.021	***	-- --	--	-- --
Time Period Fixed Effects:						
1990	0.531	0.136	***	-- --	0.279	0.152 +
2000	0.256	0.141	+	-- --	0.178	0.158
2010	-0.787	0.143	***	-- --	-0.457	0.16 **

Note:

+ $p < .1$;

* $p < .05$;

** $p < .01$;

*** $p < .001$