Spatial Covariance Structures and the Income Elasticity of Life Expectancy: Theory and Evidence

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August 2026

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Building on recent advances in modeling spatial dependence, we demonstrate that accounting for spatial correlation modifies the estimand by transforming the estimated relationship between life expectancy and income from a localized partial effect into a system-wide equilibrium comparative static characterized by endogenous uncertainty. Upon detecting significant spatial dependence in data, we use machine learning methods—Adaptive Least Absolute Shrinkage and Selection Operator, Bayesian Information Criterion, and Cross Validation—to maximize explanatory power conditional on a parsimonious set of controls. Under a Generalized Least Squares framework incorporating spatial covariance structures induced by Lévy–Brownian motion, we find that the income elasticity of life expectancy declines by about 30% and the confidence interval contracts substantially, with the lower bound decreasing by nearly 40% and the upper bound by more than 20%, relative to robust Ordinary Least Squares estimates. Our findings suggest that spatial dependence governs both the estimated results and their uncertainties, underscoring the necessity of regionally coordinated policy responses due to the evident interconnections of health and income outcomes across geographic areas.

JEL Classification Code(s): R10, D91, J17, I12, O15.

Keywords: Spatial dependence, Lévy-Brownian motion, Machine learning. Life expectancy, Preston curve.

"Everything is related to everything else, but near things are more related than distant things" – Tobler (1970)

1. Introduction

Observed associations linking life expectancy to income have, since Preston (1975), been consistently documented in cross-country comparisons. At the turn of the twenty-first century, Deaton (2003) reignited interest in this relationship by reporting a correlation of 0.84 between the log of GDP per capita and life expectancy. Building on this evidence, Cutler, Deaton, and Lleras-Meraz (2006) argued that if the diseases disproportionately affecting poor populations are genuinely "diseases of poverty," then economic growth may generate substantial health improvements as a byproduct, potentially complementing or even outweighing the effects of direct health interventions. Yet, despite the extensive literature on cross-country differences, studies examining within-country (intranational)

variation—where individuals or regions with lower incomes tend to experience shorter life expectancy within the same national institutional and policy environment—remain comparatively sparse. One plausible explanation for this relative paucity is the presence of spatial dependence in subnational data, whereby economic and health outcomes in one geographic area are systematically related to outcomes in neighboring areas. Such dependence complicates conventional intranational assessments of the Preston curve because observations cannot be treated as statistically independent.

We show how spatial dependence can fundamentally alter the economic interpretation of the estimated income–life expectancy relationship. Once spatial correlation is recognized, the estimand shifts from a localized partial effect—interpreted as the association between income and life expectancy within an individual region—to a system-wide equilibrium comparative static that incorporates interregional linkages and endogenous uncertainty. We first detect and characterize significant spatial dependence and then employ machine-learning-based model selection, using Adaptive Least Absolute Shrinkage and Selection Operator (Adaptive LASSO), Bayesian Information Criterion (BIC), and Cross Validation (CV), to identify a parsimonious set of controls while maximizing explanatory power. We subsequently estimate the relationship within a Generalized Least Squares (GLS) framework that incorporates spatial covariance structures induced by Lévy–Brownian motion.

We infer that accounting for spatial dependence materially changes both the magnitude and precision of the estimated income elasticity of life expectancy. Relative to robust Ordinary Least Squares estimates, a GLS specification reduces the estimated elasticity by approximately 30%, while substantially narrowing its confidence interval: the lower bound

decreases by nearly 40% and the upper bound by more than 20%. These results indicate that spatial dependence governs not only the estimated relationship itself but also the uncertainty surrounding that relationship. More broadly, the findings suggest that health and income outcomes are geographically interconnected, implying that policies aimed at improving population health cannot be evaluated solely through localized interventions. Instead, effective policy responses may require regional coordination that accounts explicitly for the spatial transmission and interdependence of economic and health conditions.

With this backdrop, our study contributes to the rapidly growing literature on the Preston curve by presenting new evidence from granular, county-level data within the United States, and by leveraging recent developments in econometric modeling of spatial correlation. The remainder of the paper proceeds as follows. The next section places our contribution in the context of the relevant literature. Section 3 constructs an equilibrium dependence framework to derive nontrivial implications of spatial correlation for estimating any relationship between life expectancy and income. Section 4 describes the data and estimation strategy employed in this study and presents our empirical findings. We conclude in Section 5.

2. Context

Preston (1975) was among the earliest to systematically examine the relationship between life expectancy and per capita GDP. He identified a positive association between the two variables and showed that successive increases in per capita income produced less-than-proportional gains in life expectancy in the 1900s, 1930s, and 1960s. However, the

relationship described by the Preston curve has not remained stable over time. For example, Kakwani (1993) developed an index of life expectancy and demonstrated that its correlation with per capita income differed between the 1970s and 1980s. These temporal shifts suggest that variations in life expectancy cannot be attributed solely to changes in per capita income. Subsequent research has further explored the extent to which income growth explains improvements in longevity. Wilkinson (2007) noted that, although cross-sectional analyses reveal a strong relationship between per capita income and life expectancy at birth, increases in income account for only 10–25 percent of observed improvements in life expectancy over time. Mackenbach and Looman (2013) replicated the Preston curve for the period 1900–2008 and confirmed Preston's findings for the pre-1960 era, while also suggesting that per capita income explained a larger share of life expectancy gains from 1960 onward. Similarly, Dalgaard and Strulik (2014) calibrated a life-cycle model for the year 2000 incorporating physiological constraints on households, concluding that the influence of per capita income on life expectancy largely operates through improved access to modern health care.

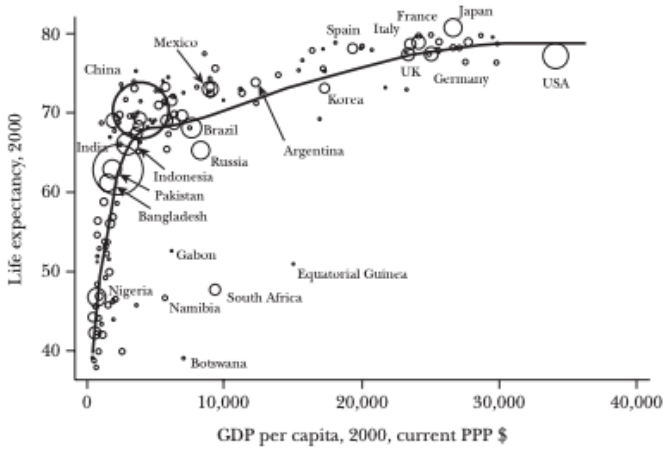


Figure 1. Life Expectancy and Per Capita GDP

Note: Areas of circles are proportional to countries' population size.
Source: Reproduced from Deaton (2003, Figure 1).

Relatively recently, de la Escosura (2023) conducted a comprehensive review and empirical replication, estimating statistical associations between the Kakwani life expectancy index and the natural logarithm of real GDP per capita. The results confirm persistent outward shifts in the life expectancy–income relationship over time. In particular, pronounced shifts occurred between 1913 and 1950 and again between 1970 and 2015, whereas more moderate movements were observed during 1870–1913 and 1950–1970. Efforts to isolate the contribution of per capita income to life expectancy improvements at each cross-section suggest that modern economic growth accounted for more than 60 percent of the increase in the Kakwani life expectancy index during 1870–1913 and 1970–2015. In contrast, during the first half of the twentieth century—especially when compared with the postwar "Golden Age" (1950–1970)—economic growth contributed substantially less, explaining only about one quarter of the gains in life expectancy. More recent evidence highlights persistent distributional dimensions of the income–health relationship. Chakrabarti (2026) finds that (a) every 10-percentage-point increase in the proportional income gap between the Caucasian and African American populations is associated with nearly a one-percentage-point increase in the proportional gap in their life expectancy; and (b) the elasticity of life expectancy with respect to income is roughly two percentage points higher among populations residing in Republican-leaning counties than among those in Democratic-leaning counties.

In hindsight, the Preston curve has been estimated using cross-sectional or repeated cross-sectional comparisons across spatial units, with the coefficient on income interpreted as a local partial effect of income on health. This interpretation is coherent only when health outcomes are effectively "local"—that is, when variations in income or health in one area

do not systematically influence neighboring areas and when the stochastic environment exhibits weak spatial dependence. Empirical evidence of spatial clustering in both income and health, along with conceptual considerations related to diffusion processes, shared health infrastructure, and regional public goods, suggest that the income–health relationship is instead embedded within a spatial equilibrium. In such contexts, the economically meaningful quantity is not a local derivative but a system-wide comparative static that incorporates spatial spillovers. This motivates replacing the conventional reduced-form Preston regression with an equilibrium framework that explicitly allows for income spillovers and strong spatial dependence in the stochastic environment, modeled as Lévy–Brownian or "spatial unit root" processes.

Our primary contribution lies in developing a unified theoretical foundation for estimating the Preston curve under these conditions. The framework generates endogenous equilibrium relationships without postulating parametric correlation structures, instead accommodating general Lévy–Brownian stochastic environments that formalize strong, low-frequency spatial dependence. The resulting theory implies three findings not derivable from standard Preston-curve regressions: (a) equilibrium marginal effects are inherently non-local; (b) conventional reduced-form regressions identify an incorrect estimand; and (c) spatial dependence endogenously amplifies estimation uncertainty. These results are particularly salient for subnational analyses—such as those using county-level U.S. data—where increasing the density of observations within a fixed geographic boundary invalidates the assumption that each unit constitutes an independent replicate. A distinctive aspect of this analysis is its reliance on fixed domain (infill) asymptotics. In many spatial settings, including those defined over the contiguous United States, the

relevant geographic domain is fixed, even as measurement becomes denser or spatial resolution improves. Under fixed domain asymptotics, spatial dependence does not dissipate as in increasing-domain frameworks; low-frequency components of the spatial process remain dominant, potentially violating standard central limit assumptions. Consequently, the fixed-domain perspective provides an appropriate basis for evaluating whether Preston-curve-type regressions identify economically meaningful quantities in the presence of strong spatial dependence.

3. Theory

In this section, we draw on Banerjee and Chakrabarti (2026) to construct a theoretical framework for spatial regression of the Preston Curve relationship. Our approach, taking a cue from Müller and Watson (2024), departs from traditional spatial econometric specifications e.g. Spatial Durbin Model which typically rely on rigid parametric covariance structures like the Matérn or Simultaneous Autoregressive models. Instead of assuming a predefined covariance matrix we characterize spatial dependence through a class of "spatial unit root" processes. This is achieved via low-frequency asymptotics and functional limit theory, offering several distinct advantages that include the following.

a. Spatial dependence is modeled through stochastic-process limits—specifically Lévy–Brownian motion—rather than a fixed, finite-sample covariance matrix.
b. The model implicitly defines a covariance class characterized by a singularity at frequency zero. This represents the spatial analogue to unit root behavior in time-series analysis, where long-run persistence dominates the variance.
c. The covariance structure is not imposed a priori; rather, it is induced by the scaling and limiting behavior of the underlying spatial unit root process.

Let observations be indexed by $i = 1, \ldots, n$, each associated with a spatial coordinate $s_i \in \mathbb{R}^d$; $y_i$denote a health outcome (for example, premature mortality or life expectancy); and $x_i$denote an income measure (for example, GDP per capita or median household income). The classical Preston curve is represented by the regression relationship

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

where β is interpreted as the marginal effect of income on health and $\varepsilon_i$is an idiosyncratic error term. Empirical extensions of this specification often include nonlinear transformations of income, additional socioeconomic covariates, or panel fixed effects. Implicit in such a formulation is the assumption that spatial units are independent, or that any cross-unit dependence can be treated as a nuisance captured by the error term. The estimand of interest is therefore a local partial effect: the change in health in unit $i$associated with a change in income in the same unit, holding outcomes in all other units fixed. Now, consider the equilibrium relationship

$$y = f(x) + \varepsilon \tag{1}$$

where $y \in \mathbb{R}^n$is the outcome vector, $x \in \mathbb{R}^n$is a vector of covariates, and $\varepsilon$is a zero-mean disturbance. Assume $\varepsilon$is generated by a Lévy–Brownian stochastic process indexed by space, so that

$$\mathrm{Var}(\varepsilon) = \Sigma, \quad \Sigma_{ij} = \sigma^2 K\big(\| s_i - s_j \|\big) \tag{2}$$

where $K(\cdot)$is a positive definite kernel associated with Brownian motion or a Lévy process. Examples include the Brownian motion kernel, fractional Brownian motion kernels, integrated white noise kernels, etc. Such covariance structures imply long-range

dependence and dense covariance matrices. Approximating $f(x)$locally by $X\beta$, the GLS estimator becomes

$$\hat{\beta}_{GLS} = (X^{\top}\Sigma^{-1}X)^{-1}X^{\top}\Sigma^{-1}y \tag{3}$$

This estimator coincides with the Müller and Watson (2018) estimator when Σ is treated as a low-frequency covariance operator and inference is based on long-run asymptotics.

Proposition I. Suppose $y = f(x) + \varepsilon$ and $\mathrm{Var}(\varepsilon) = \Sigma$, where Σis dense and positive definite. Then the population GLS estimand satisfies

$$\beta^{*} = (E[X^{\top}\Sigma^{-1}X])^{-1}E[X^{\top}\Sigma^{-1}f(x)] \tag{4}$$

and depends on the entire distribution of x. In particular, for scalar x,

$$\beta^{*} = \sum_{j} w_j\, f'(x_j), w_j \propto \text{ entries of } \Sigma^{-1} \tag{5}$$

Proof. The GLS estimator converges in probability to its population analogue under standard regularity conditions (Hayashi (2011)). Taking expectations of (3) under the true model yields (4). Since Σ is generated by a Lévy–Brownian kernel, Σ^{-1} is dense (Williams and Rasmussen (2006)). Therefore, the inner product $X^{\top}\Sigma^{-1}f(x)$ aggregates information globally across all locations, implying (5).

It may be noted that, while GLS consistency is standard, the interpretation of β^{*} as a *non-local equilibrium marginal effect* in spatial health–income relationships is new.

Proposition II. Suppose that the true model is given by equations (1)–(2). However, the researcher instead estimates the model

$$y_i = f(x_i) + u_i, \mathrm{Var}(u) = \sigma^2 I \tag{6}$$

Under this specification, it follows in general that

$$E[u_i \mid x_i] \neq 0 \tag{7}$$

even when $x$is strictly exogenous.

Proof. Under the true model, $u = \varepsilon$. Consider

$$E[u \mid x] = E[\varepsilon \mid x]$$

Because $x$and $\varepsilon$are both functions of spatial location and are generated by correlated stochastic processes, their joint distribution does not factorize. Formally, for any i,

$$\mathrm{Cov}(x_i, \varepsilon_i) = \sum_j \mathrm{Cov}(x_i, \varepsilon_j) \neq 0 \tag{8}$$

whenever $\mathrm{Cov}(x_i, x_j) \neq 0$and $\Sigma_{ij} \neq 0$for some $j \neq i$. By the law of iterated expectations,

$$E[\varepsilon_i \mid x_i] = E[E[\varepsilon_i \mid x] \mid x_i] \neq 0 \tag{9}$$

except in knife-edge cases where spatial dependence vanishes. This result can be interpreted as a spatial analogue of omitted-variable bias under correlated regressors (Wooldridge (2010)) but arising from equilibrium dependence rather than omitted covariates.

Proposition III. Let $y = f(x) + \varepsilon$with $\mathrm{Var}(\varepsilon) = \Sigma$. Then

$$\mathrm{Var}(\hat{\beta}_{GLS}) = (X^\top \Sigma^{-1} X)^{-1} \tag{10}$$

Any estimator imposing $\mathrm{Var}(\varepsilon) = \sigma^2 I$ understates uncertainty whenever Σ exhibits long-range dependence.

Proof. From classical GLS theory (Aitken (1935); Greene (2018)),

$$\mathrm{Var}(\hat{\beta}_{GLS}) = (X^\top \Sigma^{-1} X)^{-1} \tag{11}$$

If $\Sigma \neq \sigma^2 I$, then by the matrix inequality for positive definite matrices,

$$(X^\top X)^{-1} \prec (X^\top \Sigma^{-1} X)^{-1} \tag{12}$$

whenever Σ has eigenvalues diverging from σ^2. Thus, iid-based standard errors are downward biased.

Proposition IV. Let Σ be the covariance matrix generated by Brownian motion on [0,1], with

$$\Sigma_{ij} = \sigma^2 \min(s_i, s_j) \tag{13}$$

Then Σ admits the eigen-decomposition

$$\Sigma\, \phi_k = \lambda_k\, \phi_k$$

with eigenvalues

$$\lambda_k = \frac{\sigma^2}{\left(k - \frac{1}{2}\right)^2 \pi^2} \qquad k = 1,2,\ldots,n \tag{14}$$

and $\lambda_k \to 0$ as $k \to \infty$, while the total variance diverges as $n \to \infty$.

Proof. This follows from the Karhunen–Loève expansion of Brownian motion. Specifically, Brownian motion on $[0, 1]$has the representation (Adler and Taylor (2007)):

$$B(t) = \sum_k Z_k \sqrt{\lambda_k}\, \phi_k(t)$$

where $Z_k$are i.i.d. $N(0,1)$, $\phi_k(t) = \sqrt{2}\sin((k - \frac{1}{2})\pi t)$, and $\lambda_k$is given by (14). Discretizing this operator yields the matrix Σ with eigenvalues converging to (14) as $n \to \infty$ (Grenander (1958)). In effect, variance concentrates in low-frequency modes, exactly the regime targeted by Müller–Watson inference.

In sum, with infill (fixed-domain) asymptotics, the spatial domain remains fixed while the sampling density increases i.e. that additional observations are collected within the same geographic region rather than expanding the study area. In this setting, spatial dependence plays a critical role in determining how much new information each observation contributes. When observations are spatially correlated, measurements taken at nearby locations tend to be similar, so adding more points in close proximity does not increase the amount of independent information proportionally. Consequently, the effective sample size—the number of observations that contribute independent information—can be substantially smaller than the nominal sample size. In other words, increasing sampling density in a fixed spatial domain may yield diminishing returns in terms of independent statistical information. In what follows, while conventional econometric analyses rely on rigid parametric covariance structures to model the correlation structure among nearby observations to address issues arising from spatial dependence, we rely on Lévy–Brownian GLS by allowing equilibrium dependence to arise from continuous-space stochastic processes.

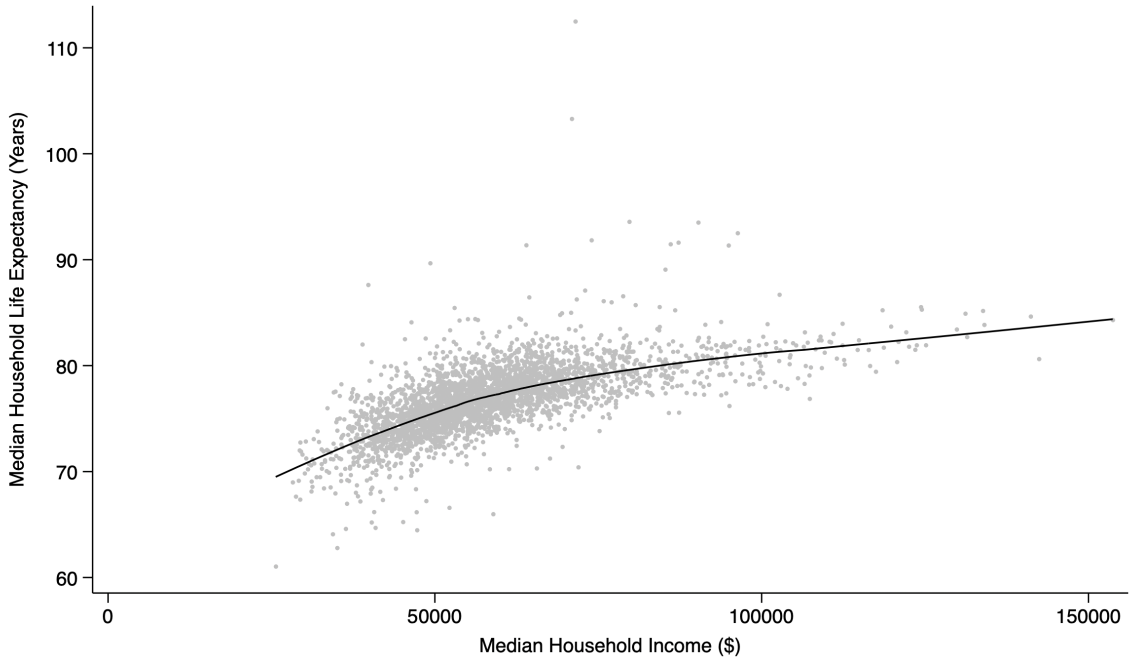
4. Evidence

We match and merge multiple data sets extracted from Population Level Analysis and Community Estimates (PLACES) for the year 2021: as an initiative of the Centers for Disease Control and Prevention, in partnership with the Robert Wood Johnson Foundation, county level data across all 50 states and the District of Columbia of the US are publicly available from PLACES. Figure 2 presents a visual exposition of the relationship between life expectancy and income of median households across US counties. We pin our estimation to variants of the following specification:

$$\log(Life\ Expectancy)_c = \alpha_s + \beta \log(Income)_c + \Gamma Z + \epsilon_c \quad (15)$$

where life expectancy and income of the median household are measured, respectively, by $(Life\ Expectancy)_c$ and $(Income)_c$ for each county c; α_s captures state-specific fixed effects due to any unobserved heterogeneity between states; β, the scalar parameter of interest, measures the income elasticity of life expectancy; Γ is a vector of parameters corresponding to controls included in vector Z; and ϵ_c are errors. For the most parsimonious selection of controls, we combine machine learning approaches of Adaptive Least Absolute Shrinkage Selection Operator, Bayesian Information Criterion, and Cross-Validation to harness the optimum explanatory power conditional on data.

Figure 2. Life Expectancy and Income of Median Households across US Counties (2021)



Our benchmark results from robust Ordinary Least Squares (OLS) estimation of equation (15) are summarized in table 1. The point elasticity of life expectancy with respect to income is positive (0.038) and statistically significant with a lower bound of 0.032 and

upper bound of 0.044 based on a 95% confidence interval. However, any inference based on the results reported in table 1 may be spurious since observations geographically close to each other tend to be correlated.

Table 1. Robust OLS Estimation

Dependent Variable = log (Life Expectancy of Median Household)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	*t*-statistic	Lower Bound	Upper Bound
log (Median Household Income)	0.0352029	7.91	0.0264731	0.0439327
Motor Vehicle Crash Deaths	-0.0004695	-0.29	-0.0036286	0.0026896
Percent of Population Aged 65 Years or More	0.0469006	18.49	0.0419278	0.0518735
Preventable Hospital Stays	-0.0076782	-4.73	-0.0108598	-0.0044966
Children in Poverty	-0.0026594	-1.22	-0.0069421	0.0016233
Injury Deaths	-0.0106372	-3.67	-0.0163265	-0.0049480
Low Birthweight	-0.0628572	-26.42	-0.0675232	-0.0581913
Unemployment Rate	-0.0006375	-3.87	-0.0009602	-0.0003147
Percent of Adults with Bachelor's Degree	0.0001671	4.61	0.0000960	0.0002383
Constant	1.797423	73.08	1.7491940	1.8456520
Number of Observations = 2,629				
R-squared = 0.8095				

Figure 4. Spatial Distribution of Life Expectancy across US Counties

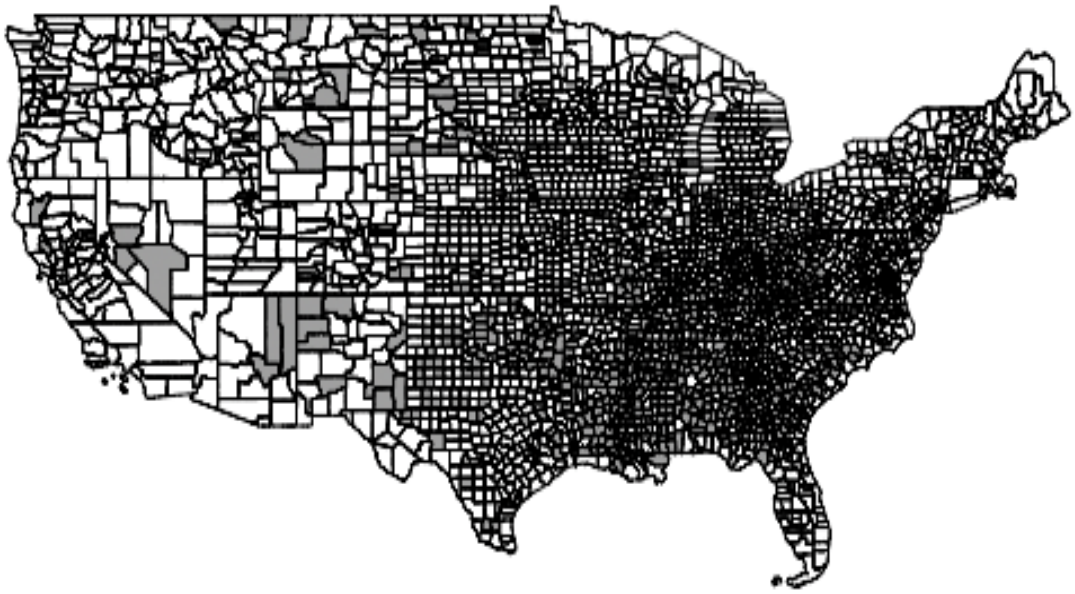


Figure 4, where relatively dark shades on the map inclusive of the contiguous states of the US reflect lower life expectancy of the median household, illustrates the presence of

potential spatial dependence in the data. Our tests for spatial correlation, following Müller and Watson (2022, 2024), discriminate between spatial $I(1)$ and $I(0)$ processes by exploiting variance-covariance structures implied by the canonical spatial $I(1)$ and local-to-unity (LTU) models:

Spatial $I(1)$: $\log(Life\ Expectancy)_c = L(s_c), E[L(s)L(r)] = \frac{1}{2}(|s| + |r| - |s - r|)$

LTU: $\log(Life\ Expectancy)_c = O_c(s_c), E[O_c(s)O_c(r)] = \frac{1}{2d}e^{-d|s-r|}$

where s and r denote spatial locations; $|r| = r'r$ and $|s| = s's$; $L(\cdot)$ is Levy-Brownian motion (LBM); and O_c is a spatial generalization of the Ornstein-Uhlenbeck process with mean-reversion parameter $d > 0$. Accordingly, the null hypotheses are:

A. H_0: $\log(Life\ Expectancy)$ is $I(0)$

B. H_0: $\log(Life\ Expectancy)$ is $I(1)$

Table 2. Robust Estimation after GLS-LBM Transformation

Dependent Variable = log (Life Expectancy of Median Household)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	t-statistic	Lower Bound	Upper Bound
log (Median Household Income)	0.025268	5.52	0.0162979	0.0342382
Motor Vehicle Crash Deaths	0.0000934	0.06	-0.0032340	0.0034208
Percent of Population Aged 65 Years or More	0.0390738	13.66	0.0334632	0.0446845
Preventable Hospital Stays	-0.0080999	-5.33	-0.0110772	-0.0051225
Children in Poverty	-0.0015319	-0.66	-0.0060572	0.0029935
Injury Deaths	-0.0071146	-2.89	-0.0119444	-0.0022847
Low Birthweight	-0.0572591	-22.35	-0.0622832	-0.0522349
Unemployment Rate	-0.0007819	-3.73	-0.0011931	-0.0003707
Percent of Adults with Bachelor's Degree	0.00016	4.75	0.0000940	0.0002260
Constant	1.76E-18	0.00	-0.0041542	0.0041542
Number of Observations = 2,629				
R-squared = 0.6084				

The tests for A and B return p-values of 0.0089 and 0.0790, respectively: in effect, we reject A at 1% level of significance and cannot reject B at 5% level of significance. To address such spatial dependence in data, Müller and Watson (2024) have designed a

Generalized Least Squares (GLS) transformation based on a spatial covariance matrix induced by LBM. This GLS-LBM transformation provides explicit robustness and has several desirable properties including, in the context of our model, though not limited to the removal of any restriction on the number of regressors but for the requirement that $(\log Income_c)'\epsilon_c$ is covariance stationary and weakly dependent. This transformation essentially subtracts a weighted mean, with weights quickly decaying with distance, of all surrounding observations for each variable included in the regression: table 2 reports the results. The revised point elasticity of life expectancy with respect to income are 0.025, with a lower bound of 0.016 and upper bound of 0.034 for a 95% confidence interval: while the point estimate of the income elasticity of life expectancy drops by nearly 30%, compared to robust Ordinary Least Squares estimation, its lower bound shrinks by nearly 40% and the upper bound by more than 20%.

5. Conclusion

Debates over the association between life expectancy and income have garnered substantial attention and contestation. Although cross-country evidence frequently appears most persuasive in supporting a link between life expectancy and income, a fundamental caveat arises from the regression framework itself: observations are drawn from a single population, and countries may differ in ways that call into question their suitability for inclusion in a common regression. Additionally, despite credible data sources, inferences from cross-country analyses must be interpreted with caution, as data quality and reliability may be sensitive to reporting inaccuracies that vary across countries. Against this backdrop, and in light of the relative sparsity of robust intranational studies, we offer new evidence on the income–life expectancy relationship using PLACES data and recent

advances in econometric methods for spatial correlation. Analytically, although the spatial multiplier is well established in spatial econometrics, we reinterpret the Preston curve slope as an equilibrium comparative-static outcome rather than as a local partial effect. This reinterpretation is novel within the Preston curve literature, where income coefficients are typically treated as local marginal effects even when substantial spatial dependence is present. We emphasize that neglecting spatial interaction does more than introduce ordinary econometric bias; it alters the estimand itself. The non-spatial Preston curve targets a counterfactual in which neighboring outcomes are held fixed, a scenario that is incompatible with spatial equilibrium behavior. This distinction is notably absent from existing Preston-curve analyses. Moreover, we demonstrate that ignoring spatial dependence understates not only spillover effects but also the true uncertainty surrounding income–health relationships and related policy counterfactuals. Compared with robust ordinary least squares estimation, generalized least squares–linear mixed model (GLS-LBM) transformations dampen the point estimate of the income–life expectancy relationship by approximately 30%; the corresponding 95% confidence interval bounds for income elasticities shrink by about 40% on the lower end and by more than 20% on the upper end in the presence of pronounced spatial dependence detected in the data. Our findings underscore that spatial dependence influences both outcomes and uncertainties, emphasizing the importance of regional coordination in policy efforts due to the evident interconnectedness of health and income across geographic areas. The fact that accounting for spatial spillovers reduces the estimated impact of income on health suggests that income growth alone may be insufficient for health improvements without complementary investments in areas like public health, education, or the environment. Ignoring spatial

dependence can underestimate spillover effects and the true uncertainty around causal estimates, pointing to the need for evaluation frameworks that incorporate these complexities. Above all, investing in detailed analysis of intranational spatial data—such as local health and socioeconomic databases—will enable more accurate modeling of regional dynamics, leading to more effective and nuanced policy interventions.

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