Life Expectancy and Income:
Spatial Correlation on US Rural-Urban Continuum

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February 2026

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In the light of most recent advances in econometric modeling of spatial correlation (Müller and Watson (2024)), we present new evidence on Preston curves for populations residing in Metro and Non-Metro US counties, We provide a novel equilibrium interpretation of Preston curves under spatial dependence by demonstrating that accounting for spatial correlation alters the estimand itself, transforming any relationship between life expectancy and income from a local partial effect into a system-wide equilibrium comparative static with endogenous uncertainty. 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. Robust estimation, using Generalized Least Squares transformation with spatial covariance matrices based on Levy-Brownian motion, reveals that typically any increase in life expectancy associated with every percentage point increment in income is proportionally about twice for the residents of Metro areas than those of Non-Metro areas in the US where significant spatial dependence is detected from data.

JEL Classification Code(s): R10, D91, F1, J17, I12, O15.

Keywords: Life expectancy, Preston curve, Machine learning, Spatial correlation, Levy-Brownian motion.

1. Introduction

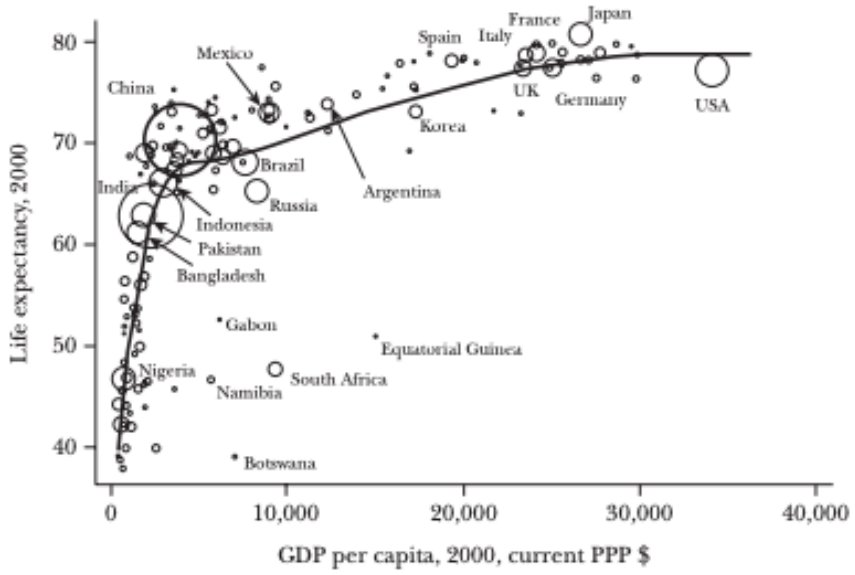
The most notable relationship between life expectancy and income has typically been borne by cross-country data since Preston (1975) identified a plausible association between life expectancy at birth and real per capita GDP from cross-country data. This association, popularly known as the "Preston curve" in the relevant studies that followed, has been replicated in a wide range of settings (de la Escosura (2023) and Chakrabarti (2025a)). In the light of most recent advances in econometric modeling of spatial correlation (Müller and Watson (2024)), upon detecting spatial correlation in data on US counties, we contribute to this vast and growing literature by presenting new evidence on any role that location plays in the relationship between life expectancy and income. In the next section, we review the relevant literature on the Preston curve. In section 3, we lay out a

methodological framework of equilibrium dependence to derive non-trivial implications of spatial correlation for estimating any relationship between life expectancy and income. With this backdrop, in section 4, we describe the data and estimation used in this paper and present our findings. We conclude in the final section.

2. The Preston Curve

Preston (1975) was the earliest to investigate any link between life expectancy and per capita GD: he identified a positive association between the two and reported that successive increases in per capita income resulted in less than proportional increases in life expectancy in 1900s, 1930s, and 1960s.

Figure 1. The Preston Curve: Life Expectancy and Per Capita GDP



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

At the dawn of this millennium, Deaton (2003) drew renewed attention toward the Preston curve that fit well with data from 2000 as illustrated in figure 1: the observed correlation between the log of GDP per capita and life expectancy was 0.84 when countries

were weighted by population (and only slightly lower if they are not weighted). The relationship appears to be nearly linear: a doubling of GDP per capita is associated with an increase in life expectancy of roughly five years. However, the Preston curve has shifted over time. For instance, Kakwani (1993) had developed an index of life expectancy to demonstrate that its correlation with per capita income had varied between the 1970s and 1980s. Such temporal shifts signal that differences in life expectancy are attributable to factors other than per capita income. Wilkinson (2007) remarked that, despite strong evidence on cross-sectional relationships between per-capita income and life expectancy at birth, increases in income explains only 10-25 percent of the improvement in life expectancy over time. Mackenbach and Looman (2013) replicated the Preston curve for 1900–2008: the authors' findings confirm Preston's observation for the pre-1960 period and suggest that per capita income explained most of the life expectancy gains from 1960 onwards. Dalgaard and Strulik (2014) calibrated a life cycle model for the year 2000, where households are subject to physiological, and concluded that the impact of per-capita income on life expectancy has largely been due to access to modern health care. Jetter et al. (2019) confirmed the existence of a non-linear relationship between per capita income and life expectancy, from a large country sample over two centuries, and that economic growth has been the main driver of long-run gains in life expectancy while the access to medical innovations was largely restricted to higher income countries. In a comprehensive review and replications, de la Escosura (2023) estimated statistical associations between the Kakwani index of life expectancy and the natural logarithm of real per capita GDP. This study confirms the existence of sustained outward shifts in the life expectancy-per capita income relationship over time. Strong outward shifts between 1913 and 1950 and between

1970 and 2015 contrast with moderate movements during 1870–1913 and 1950–1970: attempts to 'factor out' the contribution of per-capita income to life expectancy gains at each cross-section led to the conclusion that modern economic growth contributed above 60 per cent of the increase in the Kakwani index of life expectancy over 1870–1913 and during 1970–2015. However, in sharp contrast with the Golden Age (1950–1970), the contribution of economic growth was substantially lower during the first of half of the twentieth century when it provided only a quarter of the gains in life expectancy. Chakrabarti (2025b, 2025c) observed that a) every 10 percentage point expansion in the proportional difference between the income of the Caucasian and African American population is associated with an increment in the proportional difference between their life expectancy by nearly a percentage point; and b) the elasticity of life expectancy with respect to income is about a couple of percentage points higher for populations residing in Republican counties than those in Democratic counties. With this backdrop, to the best of our knowledge, this is the first study that quantifies any role that location plays in the relationship between life expectancy and income when spatial dependence is detected in data.

3. Methodological Framework

Let observations be indexed by i = 1,…,n, each associated with a spatial coordinate $s_i \in \mathbb{R}^d$. Let y_i denote a health outcome (for example, premature mortality or life expectancy) and let 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 ε_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 ε is a zero-mean disturbance. Assume ε is generated by a Lévy–Brownian stochastic process indexed by space, so that

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

where $K(\cdot)$ is a positive definite kernel associated with Brownian motion or a Lévy process. Examples include 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 boils down to

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

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 asymptotes.

Proposition I (Non-local equilibrium marginal effects under GLS): Suppose $y = f(x) + \varepsilon$ with $\mathrm{Var}(\varepsilon) = \Sigma$, where Σ is dense and positive definite. Then the population GLS estimand satisfies

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

and depends on the entire distribution of x.

In particular, for scalar x,

$$\beta^* = \sum_j w_j f'(x_j),\ w_j \text{ proportional to entries of } \Sigma^{-1} \tag{5}$$

Proof. The GLS estimator converges in probability to its population analogue under standard regularity conditions (see Hayashi, 2000, *Econometrics*, Theorem 3.3). Taking expectations of (3) under the true model yields (4). Since Σ is generated by a Lévy–Brownian kernel, Σ^{-1} is dense (Rasmussen and Williams (2006)). Therefore, the inner product $X^T \Sigma^{-1} f(x)$ 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 (Equilibrium misspecification under iid regression): Suppose the true model is (1)–(2), but the researcher estimates

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

Then, generically,

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

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 ε are both functions of spatial location and 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 is a spatial analogue of omitted-variable bias under correlated regressors (Wooldridge (2010)) but applied to equilibrium dependence rather than missing covariates.

Proposition III (Variance amplification under Lévy–Brownian dependence): Let $y = f(x) + \varepsilon$ with $\mathrm{Var}(\varepsilon) = \Sigma$. Then

$$\mathrm{Var}(\hat{\beta}_GLS) = (X^T \Sigma^{-1} X)^{-1} \tag{10}$$

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)),

$$\mathrm{Var}(\hat{\beta}_GLS) = (X^T \Sigma^{-1} X)^{-1} \tag{11}$$

If $\Sigma \neq \sigma^2 I$, then by the matrix inequality for positive definite matrices (Bhatia (1997)),

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

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

Proposition IV (Eigenvalue growth under Brownian covariance): 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

$$\Sigma \varphi_k = \lambda_k \varphi_k$$

with eigenvalues

$$\lambda_k = \sigma^2 / ((k - 1/2)^2 \pi^2), \qquad k = 1,2,\dots n \tag{14}$$

and $\lambda_k \to 0$ as $k \to \infty$, while 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)):

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

where Z_k are iid N(0,1), $\varphi_k(t) = \sqrt{2} \sin((k - 1/2)\pi t)$, and λ_k is given by (14).

Discretizing this operator yields the matrix Σ with eigenvalues converging to (14) as $n \to \infty$ (Grenander and Szegö (1958)). In effect, variance concentrates in low-frequency modes, exactly the regime targeted by Müller–Watson inference.

Corollary (SAR-induced covariance): Consider the SAR model

$$y = \rho W y + \varepsilon, \qquad \varepsilon \sim (0, \sigma^2 I) \tag{15}$$

Then

$$\mathrm{Var}(y) = \sigma^2 (I - \rho W)^{-1} (I - \rho W)^{-T} \tag{16}$$

This corresponds to (2) with Σ constrained to the SAR-implied form.

Proof. Solve (15) for y and apply $\mathrm{Var}(A\varepsilon) = A\,\mathrm{Var}(\varepsilon)\,A^T$ (Greene (2018)).

SAR models impose a parametric approximation to the covariance operator Σ. Lévy–Brownian GLS relaxes this restriction, allowing equilibrium dependence to arise from continuous-space stochastic processes.

4. Data, Estimation, and Findings

All data used in this paper are downloaded from Population Level Analysis and Community Estimates (PLACES), American Community Survey (ACS), National Center for Health Statistics (NCHS), and Economic Research Service (ERS) of the United States Department of Agriculture (USDA). According to the Centers for Disease Control and Prevention (CDC), PLACES is an expansion of the 500 Cities Project. Launched by the CDC, in partnership with the Robert Wood Johnson Foundation, the 500 Cities Project was expanded to provide data that spans up to 72,337 census tracts; 32,409 ZIP Code Tabulation Areas (ZCTA); 28,484 Census Designated Places (CDP); and 3,143 counties hosting more than 332 million people across the 50 states and District of Columbia of the United States of America. The ACS reports earnings for each household. Life expectancy is measured, based on mortality files from the NCHS, by the average number of years a person can expect to live. We match and merge these publicly available data sets by Rural-Urban Continuum Codes (Table 1), distinguishing US metropolitan (Metro) counties by the population size of their metro area and nonmetropolitan (Non-Metro) counties by their degree of urbanization and adjacency to a metro area, provided by the ERS of the USDA.

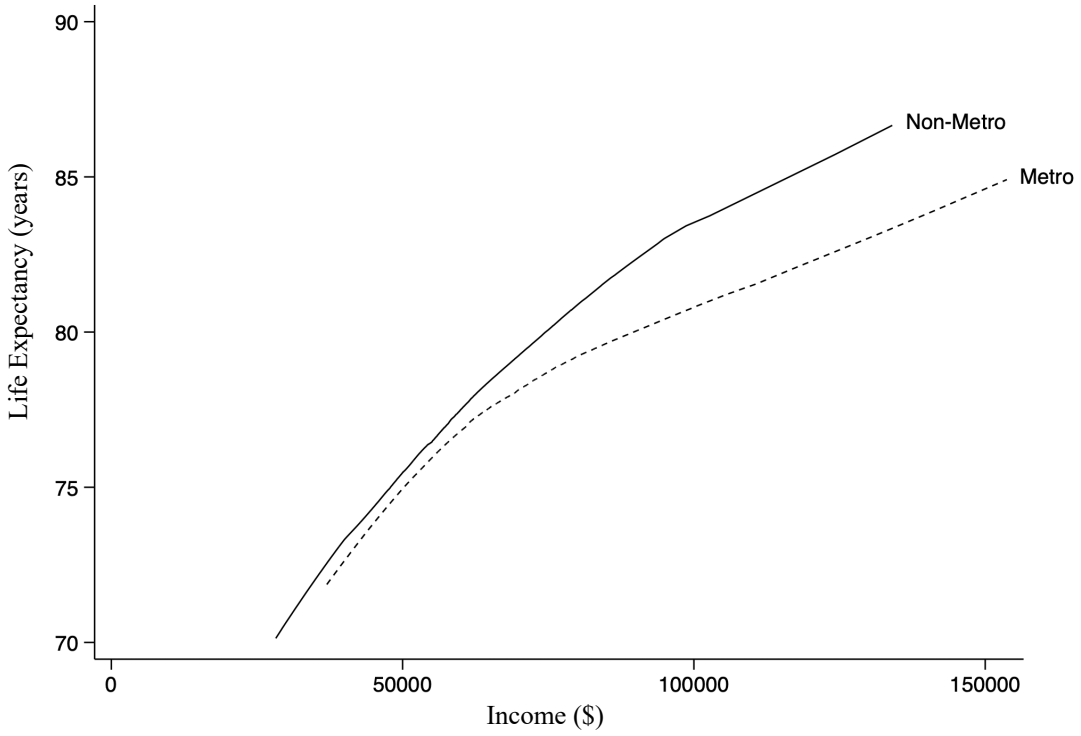
Figure 2 plots Preston curves, using non-parametric locally weighted scatterplot smoothing, for the median households from Metro and Non-Metro US counties.

Table 1. US Rural-Urban Continuum Codes

Code	Description
Metro counties:	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Nonmetro counties:	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 5,000 to 20,000, adjacent to a metro area
7	Urban population of 5,000 to 20,000, not adjacent to a metro area
8	Urban population of fewer than 5,000, adjacent to a metro area
9	Urban population of fewer than 5,000, not adjacent to a metro area

Source: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

Figure 2. Median Household Income and Life Expectancy:
Counties in Metro and Non-Metro Areas, US (2020)



For estimation, we use variants of the following specification:

$$\log(Life\ Expectancy)_{ij} = \alpha_i + \alpha_s + \beta \log(Income)_{ij} + \Gamma_i Z_i + \epsilon_{ij}$$

where $i = m, n$ indexes Metro and Non-Metro areas, respectively; j indexes US counties; life expectancy and income of the median household are measured, respectively, by $(Life\ Expectancy)_{ij}$ and $(Income)_{ij}$; 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_i is a vector of parameters corresponding to controls included in vector Z_i; and ϵ_{ij} are errors. For the most parsimonious selection of controls, we combine machine learning approaches of Adaptive Least Absolute Shrinkage Selection Operator, Cross-Validation, and Bayesian Information Criterion (ref. figures 3 and 4, respectively, where λ is a tuning parameter balancing any tradeoff between bias and variance in coefficients) harnessing optimum explanatory power conditional on data: our benchmark results from robust Ordinary Least Squares (OLS) estimation of equation (1) are summarized in tables 2 and 3.

Figure 3. Bayesian Information Criterion (BIC) Plot: Counties in Metro Areas

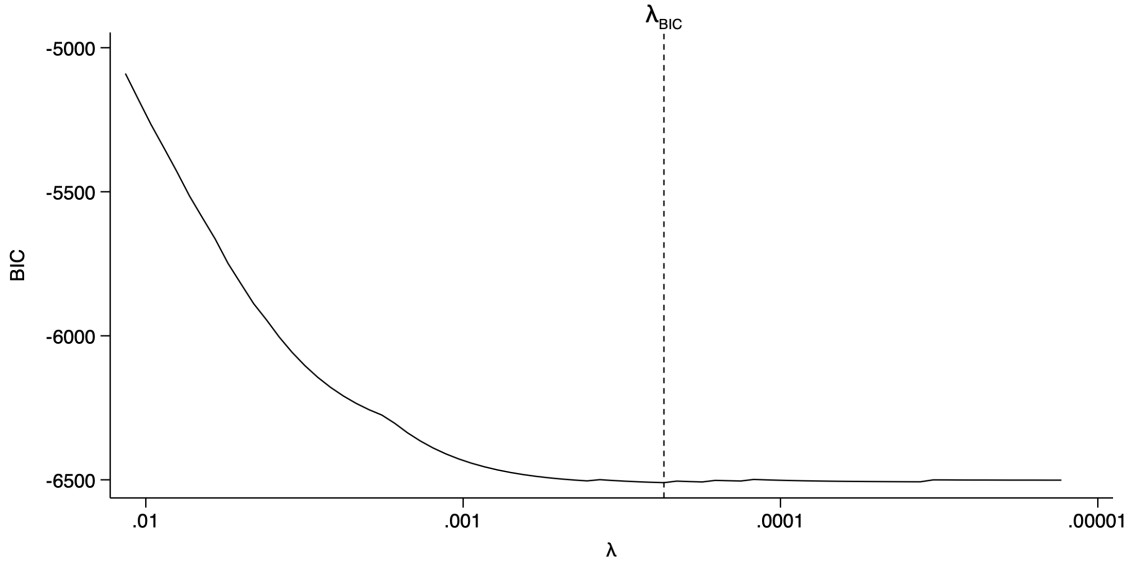


Figure 4. Bayesian Information Criterion (BIC) Plot: Counties in Non-Metro Areas

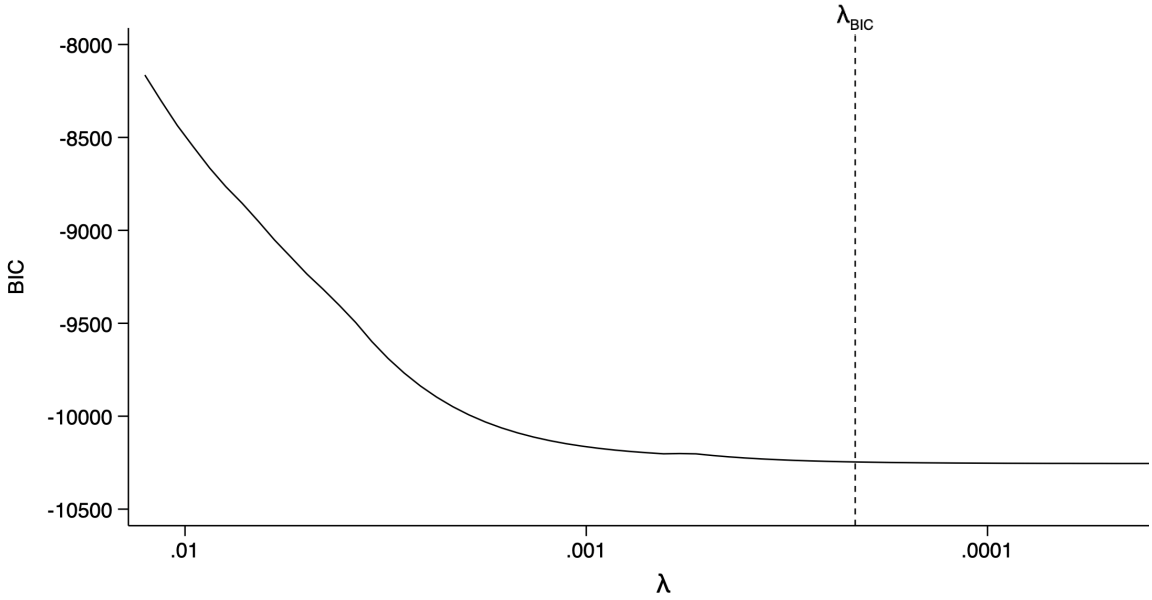


Table 2. Robust OLS Estimation: Metro Areas

Dependent Variable = log(Life Expectancy)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	*t*-statistic	Lower Bound	Upper Bound
log(Income)	0.0347216	11.3	0.0286940	0.0407491
Motor Vehicle Crash Deaths	-0.001988	-0.95	-0.0060897	0.0021138
Percent Population Aged 65 Years or Older	0.0351657	10.51	0.0286012	0.0417303
Preventable Hospital Stays	-0.00226	-1.08	-0.0063845	0.0018645
Injury Deaths	-0.0555084	-18.74	-0.0613200	-0.0496967
Low Birthweight	-0.0305938	-7.44	-0.0386609	-0.0225267
Unemployment Rate	0.0000389	0.18	-0.0003899	0.0004677
Percent of Adults with Bachelor's Degree	0.0003094	9.07	0.0002425	0.0003764
Constant	1.805289	92.55	1.7670110	1.8435670
Number of Observations = 1084				
R-squared = 0.8530				
Root MSE = 0.0060				

Table 3. Robust OLS Estimation: Non-Metro Areas

Dependent Variable = log(Life Expectancy)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	*t*-statistic	Lower Bound	Upper Bound
log(Income)	0.0219562	3.82	0.0106762	0.0332362
Motor Vehicle Crash Deaths	0.0013035	0.63	-0.0027638	0.0053707
Percent Population Aged 65 Years or Older	0.0521516	15.11	0.0453805	0.0589228
Preventable Hospital Stays	-0.0065756	-4.51	-0.0094350	-0.0037162
Flu Vaccinations	-0.0054042	-2.21	-0.0102026	-0.0006059
Children in Poverty	-0.0305201	-7.98	-0.0380261	-0.0230142
Injury Deaths	-0.0676242	-19.56	-0.0744048	-0.0608437
Low Birthweight	-0.0159963	-4.42	-0.0230993	-0.0088933
Unemployment Rate	-0.0002063	-1	-0.0006115	0.0001990
Percent of Adults with Bachelor's Degree	0.0002061	4.33	0.0001127	0.0002996
Constant	1.918725	61.24	1.8572680	1.9801820
Number of Observations = 1545				
R-squared = 0.7973				
Root MSE = 0.00791				

The point elasticities of life expectancy with respect to income are statistically significant for the residents of Metro and Non-Metro areas. However, any inference based on the results reported in tables 1 and 2 may be spurious since observations geographically close to each other tend to be correlated.

Figure 5. Spatial Distribution of Life Expectancy across US Counties

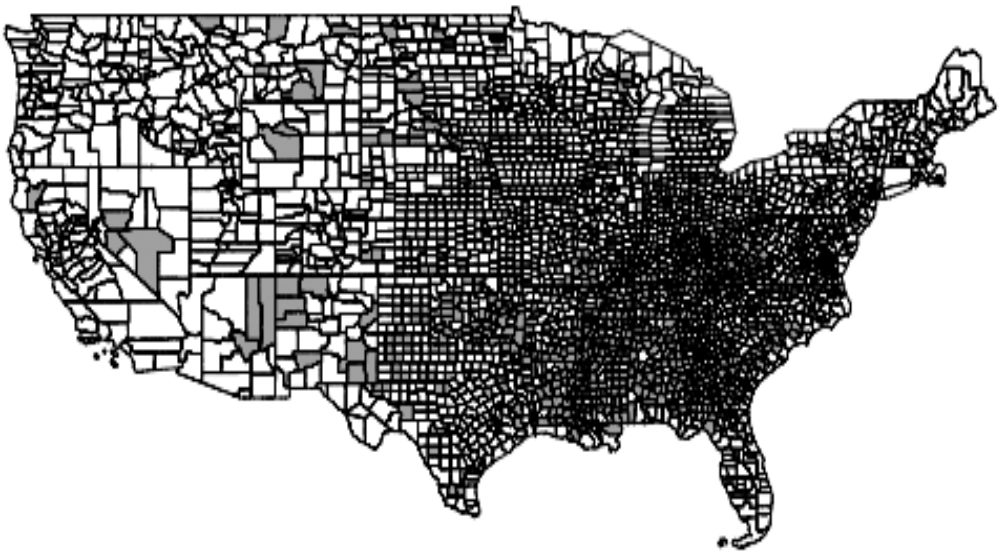


Figure 5, where relatively dark shades on the map inclusive of the contiguous states of the US reflect lower life expectancy of the median household, illustrates the possibility of potential spatial dependence in the data. Our tests for spatial correlation, following Müller and Watson (2022, 2024), discriminate 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 $I(1)$: $\log(Life\ Expectancy)_{ij} = L(s_j), E[L(s)L(r)] = \frac{1}{2}(|s| + |r| - |s - r|)$

LTU: $\log(Life\ Expectancy)_{ij} = O_j(s_j), E[O_j(s)O_j(r)] = \frac{1}{2d}e^{-d|s-r|}$

where s and r denote spatial locations; $|r| = r'r$ and $|s| = s's$; $L(\cdot)$ is Levy-Brownian

motion (LBM); and O_j is a spatial generalization of the Ornstein-Uhlenbeck process with mean-reversion parameter $d > 0$. Accordingly, the null hypotheses are:

A. H_0: $\log(Life\ Expectancy)_{ij}$ is $I(0)$

B. H_0: $\log(Life\ Expectancy)_{ij}$ is $I(1)$

The tests for A and B return p-values of i) 0.0178 and 0.095, respectively, for counties belonging to Metro areas; and ii) 0.0015 and 0.1707, respectively, for counties belonging to Non-Metro areas. Since A is rejected and B cannot be rejected 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.

The 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 $\log(Life\ Expectancy)_{ij}{}'\epsilon_{ij}$ 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 4. Robust Estimation after GLS-LBM Transformation: Metro Areas

Dependent Variable = log(Life Expectancy)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	t-statistic	Lower Bound	Upper Bound
log(Income)	0.0234725	5.91	0.0156854	0.0312596
Motor Vehicle Crash Deaths	0.0004188	0.19	-0.0039206	0.0047582
Percent Population Aged 65 Years or Older	0.0271795	8.07	0.0205737	0.0337853
Preventable Hospital Stays	-0.001872	-0.8	-0.0064816	0.0027376
Injury Deaths	-0.0548873	-17.28	-0.0611216	-0.0486531
Low Birthweight	-0.027956	-6.27	-0.0367096	-0.0192025
Unemployment Rate	-0.0005736	-1.77	-0.0012101	0.0000629
Percent of Adults with Bachelor's Degree	0.0002883	8.8	0.0002240	0.0003526
Constant	1.46E-18	0	-0.0047502	0.0047502
Number of Observations = 1084				
R-squared = 0.7688				
Root MSE = 0.0797				

Table 5. Robust Estimation after GLS-LBM Transformation: Non-Metro Areas

Dependent Variable = log(Life Expectancy)				
			95% Confidence Interval	
Explanatory Variables	Coefficient	*t*-statistic	Lower Bound	Upper Bound
log(Income)	0.0118486	1.75	-0.0014555	0.0251527
Motor Vehicle Crash Deaths	0.0009127	0.4	-0.0035647	0.0053901
Percent Population Aged 65 Years or Older	0.0518868	12.98	0.0440473	0.0597264
Preventable Hospital Stays	-0.0056368	-3.5	-0.0087928	-0.0024808
Flu Vaccinations	-0.0028511	-1.1	-0.0079504	0.0022483
Children in Poverty	-0.0293297	-7.46	-0.0370397	-0.0216197
Injury Deaths	-0.0611243	-18.03	-0.0677739	-0.0544747
Low Birthweight	-0.0128336	-3.4	-0.0202330	-0.0054343
Unemployment Rate	-0.0003139	-1.2	-0.0008263	0.0001985
Percent of Adults with Bachelor's Degree	0.000155	3.28	0.0000623	0.0002477
Constant	-1.56E-18	0	-0.0055065	0.0055065
Number of Observations = 1545				
R-squared = 0.5257				
Root MSE = 0.11034				

Tables 4 and 5 summarize our final findings. As a result of robust estimation following Generalized Least Squares transformation based on spatial covariance matrices induced by Levy-Brownian motion in the face of significant spatial dependence detected in data, the revised point elasticities of life expectancy with respect to income remain positive and significant but have shrunk to 0.012 for the residents of Non-Metro areas and 0.022 for those of Metro areas. In comparison, on average, increase in life expectancy associated with every percentage point increment in income is proportionally about twice for the residents of Metro areas than those of Non-Metro areas in the US.

5. Conclusion

While mounting evidence of positive associations between income and life expectancy has given rise to the widespread view that the “diseases of poor” are the “diseases of poverty” (Cutler (2006)), to the best of our knowledge, this is the first study that quantifies any role that location plays in the relationship between life expectancy and income when spatial dependence is detected in data. Analytically, while the spatial multiplier is well known in spatial econometrics, we reframe the Preston curve slope as an equilibrium

comparative static rather than a local partial effect. In the Preston curve literature, this reinterpretation is novel where in previous work income coefficients are typically treated as local marginal effects even in the presence of strong spatial dependence. We also clarify that ignoring spatial interaction does not merely introduce bias in the usual econometric sense; it changes the estimand itself. The non-spatial Preston curve targets a counterfactual in which neighboring outcomes are held fixed, a scenario incompatible with spatial equilibrium behavior. This distinction is conspicuously absent from existing literature on the Preston curve. We also show that ignoring spatial dependence understates not only spillovers but also the true uncertainty surrounding income–health relationships and related policy counterfactuals. Finally, consistent with most recent advances in econometric analyses of spatial correlation (Müller and Watson (2024)), we infer with reasonable confidence that increase in life expectancy associated with every percentage point increment in income is proportionally about twice for the residents of Metro areas than those of Non-Metro areas in the US.

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