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

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We contribute to the literature on life expectancy and income, by presenting new evidence from granular data on populations residing in Metro and Non-Metro US counties, in the light of most recent advances in econometric modeling of spatial correlation (Müller and Watson (2024). 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.

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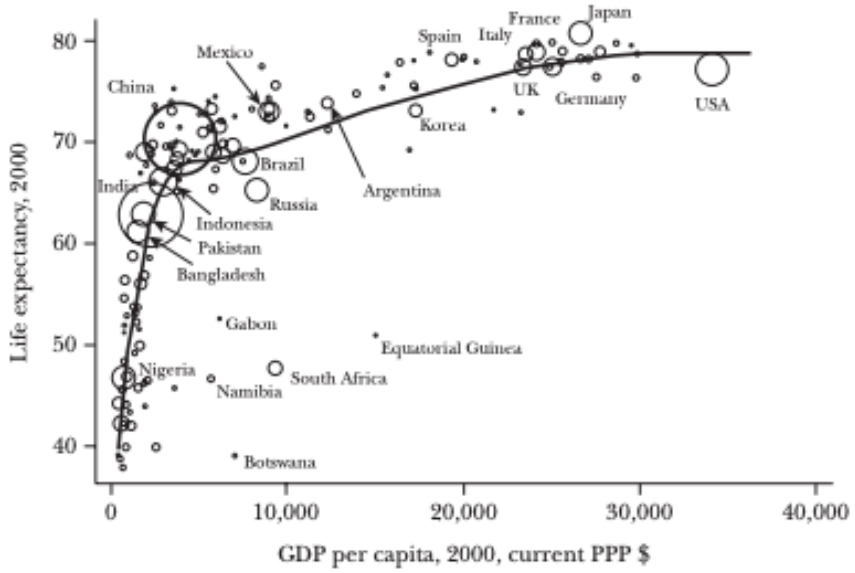
1. Introduction

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 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. Spatial Correlation and the Preston Curve

Let i = 1, …, N index spatial units such as countries, regions, or counties. 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. If we relax the independence assumption by allowing health outcomes to be interdependent across space, let W denote an N × N spatial weights matrix, where element w_{ij} measures the strength of interaction between units i and j. The matrix W is assumed to be row-standardized with zeros on the diagonal, following standard practice in spatial econometrics. Then

$$y = \rho W y + X \beta + \varepsilon$$

where y is an N × 1 vector of health outcomes, X is a matrix of covariates including income, β is a conformable parameter vector, ρ is the spatial autoregressive parameter, and ε is an error vector with mean zero and variance σ^2 times the identity matrix. Solving for y yields the reduced-form representation,

$$y = (I - \rho W)^{-1} X \beta + (I - \rho W)^{-1} \varepsilon$$

where I denotes the N × N identity matrix. Existence and uniqueness of this solution require that the spectral radius of ρW is strictly less than one. For row-standardized W, this condition reduces to $|\rho| < 1$.

This model admits a natural equilibrium interpretation. Suppose each spatial unit's health outcome is a linear best response to neighboring outcomes and local income. Under this interpretation, the regression coefficients summarize equilibrium outcomes rather than

primitive behavioral responses. To allow income spillovers in addition to outcome spillovers, suppose

$$y = \rho W y + X\beta + WX\theta + \varepsilon$$

where *WX* contains spatial lags of the covariates and θ captures spillover effects of income and other regressors.

Theorem I (Equilibrium marginal effects are non-local) In the spatial autoregressive model, the marginal effect of income on health is not equal to the coefficient β. Instead, it is given by the equilibrium multiplier $(I - \rho W)^{-1}\beta$. Consequently, a change in income in one unit affects health outcomes in all spatial units.

More generally, assume that health outcome, y, determined as the unique solution to the spatial equilibrium system,

$$Y = \rho W y + f(x),\ \rho \geq 0 \qquad (1)$$

We impose the standard stability condition, as follows.

Assumption (Equilibrium stability): $\rho(W)<1$, where $\rho(\cdot)$ denotes the spectral radius.

Under A1, equation (1) has the unique solution:

$$y = (I - \rho W) - 1 f(x) \qquad (2)$$

Suppose that both equations (1) and (2) hold. Then the marginal effect of income on a health outcome (such as life expectancy) is given by,

$$\partial y/\partial x = (I - \rho W) - 1Df(x) \quad (3)$$

where $Df(x) = diag(f'(x1), \ldots, f'(xn))$.

In particular, for each unit i,

$$\partial y_i \,/\, \partial x_i \;=\; \sum_{j=1}^{n} [(I \;-\; \rho W)^{-1}]_{ij}\, f'(x_j),$$

which depends on the entire income distribution x, not solely on x_i.

Proof.

From the reduced-form solution $y \;=\; (I \;-\; \rho W)^{-1}\, X\beta \;+\; (I \;-\; \rho W)^{-1}\, \varepsilon$, the derivative of y with respect to income is

$$\partial y \,/\, \partial x \;=\; (I \;-\; \rho W)^{-1}\, \beta.$$

Because the inverse matrix $(I - \rho W)^{-1}$ is generally dense whenever ρ is nonzero, the effect of income propagates through the entire spatial system. The average equilibrium marginal effect corresponds to the average row sum of this multiplier applied to β.

For the more general formulation,

Differentiate equation (2) with respect to x to obtain

$$\partial y \,/\, \partial x \;=\; (I \;-\; \rho W)^{-1}\, \partial f(x) \,/\, \partial x$$

Because the function f(x) enters elementwise, its Jacobian with respect to x is given by

$$\partial f(x) \,/\, \partial x \;=\; Df(x)$$

Pre-multiplication by $(I - \rho W)^{-1}$ yields equation (3), completing the proof.

While spatial multipliers are well known in spatial econometrics, this theorem reframes the Preston curve slope as an equilibrium comparative static rather than a local partial derivative. We propose this new reinterpretation, which has not been explicitly developed in the Preston curve literature, where income coefficients are typically treated as local effects even when spatial dependence is present.

Our next result considers equilibrium misspecification when spatial adjustments are not used.

Theorem II (Equilibrium misspecification under non-spatial regression) If the true data-generating process follows a spatial equilibrium with $\rho \neq 0$, then a non-spatial regression of health on income converges to a parameter that does not correspond to any equilibrium marginal effect.

Mathematically (and more generally), suppose the true model is given by equations (1)–(2), but the researcher estimates the reduced-form Preston curve in equation (3). Then the regression error

$$u_i := y_i - f(x_i)$$

Satisfies, $E[u_i \mid x_i] \neq 0$, generically, even if income x is exogenous.

Proof.

When the true model is $y = \rho Wy + X\beta + \varepsilon$, a non-spatial regression omits the endogenous feedback term ρWy. This term is absorbed into the regression error and is generally

correlated with income when covariates exhibit spatial correlation. As a result, the estimator converges to a pseudo-true parameter reflecting a mis-specified conditional expectation rather than the equilibrium derivative derived in Theorem 1. This discrepancy persists even under income exogeneity and as sample size grows.

To prove the more general statement, note that, From equation (2),

$$y = f(x) + \rho W y = f(x) + \rho W (I - \rho W)^{-1} f(x).$$

Therefore, the regression error from the reduced-form Preston curve is given by

$$u = \rho W (I - \rho W)^{-1} f(x).$$

spatially correlated—a weak and empirically relevant condition—then conditioning on x_i does not eliminate dependence on neighboring incomes. As a result, $E[u_i \mid x_i] \neq 0$, which establishes equilibrium misspecification of the reduced-form regression.

This result clarifies that ignoring spatial interaction changes the estimand itself rather than merely introducing bias or inefficiency. The standard Preston curve regression implicitly conditions on a counterfactual in which neighboring outcomes remain fixed, a condition incompatible with spatial equilibrium behavior.

Our next result combines estimation precision and equilibrium.

Theorem III (Endogenous amplification of uncertainty) Under spatial equilibrium, the variance of health outcomes is amplified by spatial interaction, implying that uncertainty in estimated income effects is itself an equilibrium outcome.

A more generalized mathematical form of our previous results can be derived as follows. Let the outcome vector y satisfy the spatial equilibrium equation

$$y = \rho W y + \varepsilon$$

where ε is a zero-mean random vector with variance–covariance matrix Var(ε) = Σ, and the spatial parameter ρ satisfies the stability condition $|\rho| < 1 / \lambda_{max}(W)$. Then the variance–covariance matrix of y is given by

$$Var(y) = (I - \rho W)^{-1} \Sigma (I - \rho W)^{-T}$$

Moreover, ignoring spatial interaction (i.e. imposing $\rho = 0$) understates uncertainty whenever $\rho \neq 0$.

Proof.

Assuming ε has variance $\sigma^2 I$, the variance of y is

$$Var(y) = \sigma^2 (I - \rho W)^{-1} (I - \rho W')^{-1}$$

As the magnitude of ρ increases, the eigenvalues of $(I - \rho W)^{-1}$ grow, amplifying the variance of both outcomes and estimated marginal effects. Thus, spatial dependence endogenously increases uncertainty through equilibrium feedback.

Expanding on the above framework, the proof for the more general variance equation is given below.

Rearranging the equilibrium equation yields, $(I - \rho W)\, y = \varepsilon$.

Under the stated stability condition, the matrix $(I - \rho W)$ is invertible, and the unique equilibrium solution is, $y = (I - \rho W)^{-1} \varepsilon$.

Using the standard result for linear transformations of random vectors, we obtain,

$$Var(y) = Var(\,(I - \rho W)^{-1} \varepsilon\,) = (I - \rho W)^{-1} Var(\varepsilon)\,(\,(I - \rho W)^{-1}\,)^{\mathrm{T}}$$
$$= (I - \rho W)^{-1} \Sigma\, (I - \rho W)^{-\mathrm{T}}.$$

This establishes the stated variance expression.

To see why ignoring spatial interaction understates uncertainty, note that setting $\rho = 0$ implies $Var(y) = \Sigma$. When $\rho \neq 0$, the variance matrix is pre-multiplied and post-multiplied by the spatial multiplier $(I - \rho W)^{-1}$, which expands variability through spatial feedback. In particular, for any unit i, the marginal variance $Var(y_i)$ incorporates not only the local shock variance Σ_{ii}, but also weighted contributions from shocks in all other units transmitted through the spatial network.

Since $(I - \rho W)^{-1}$ has strictly positive off-diagonal elements whenever $\rho \neq 0$ and W contains at least one nonzero neighbor link, $Var(y) - \Sigma$ is positive semidefinite. Consequently, treating outcomes as spatially independent necessarily understates uncertainty in the presence of spatial equilibrium feedback. This completes the proof of the more general statement for theorem 3.

Although the variance structure of SAR models has been algebraically studied before, interpreting variance inflation as an equilibrium phenomenon is our novel contribution in

the Preston curve context. Ignoring spatial interaction therefore understates both spillovers and policy-relevant uncertainty.

Together, these results establish that spatially adjusted models recover a fundamentally different economic object: the equilibrium marginal effect of income on health. This framework provides the theoretical basis for the simulation studies and empirical analyses that follow, which assess the ability of spatial and non-spatial estimators to recover equilibrium effects under controlled and observed data-generating 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

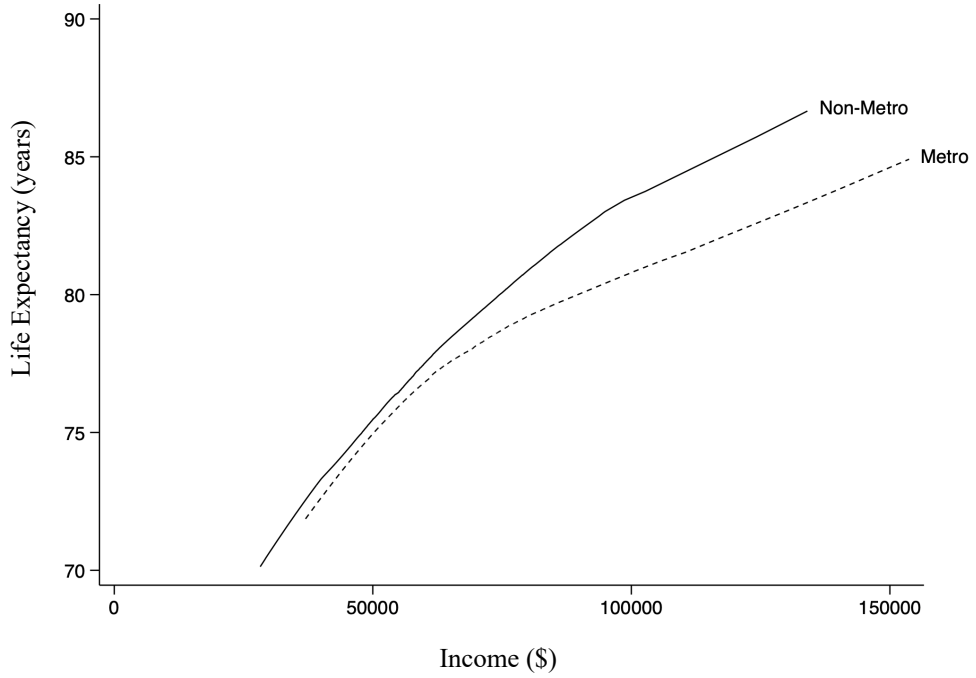
degree of urbanization and adjacency to a metro area, provided by the ERS of the USDA. Figure 2 plots Preston curves, using non-parametric locally weighted scatterplot smoothing, for the median households from Metro and Non-Metro US counties.

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

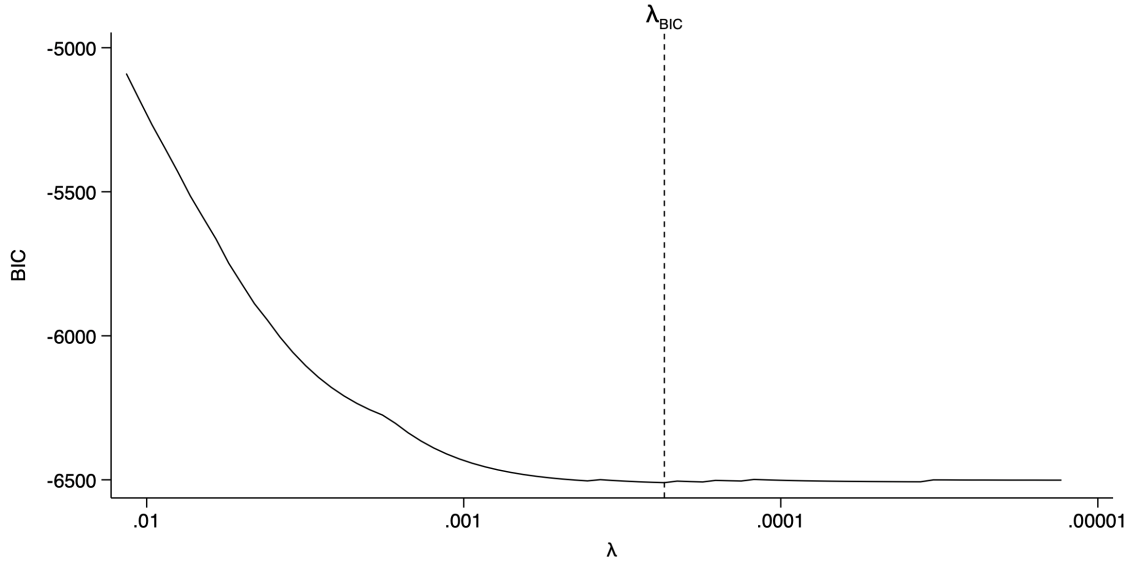


Figure 4. Bayesian Information Criterion (BIC) Plot: Counties in Non-Metro Areas

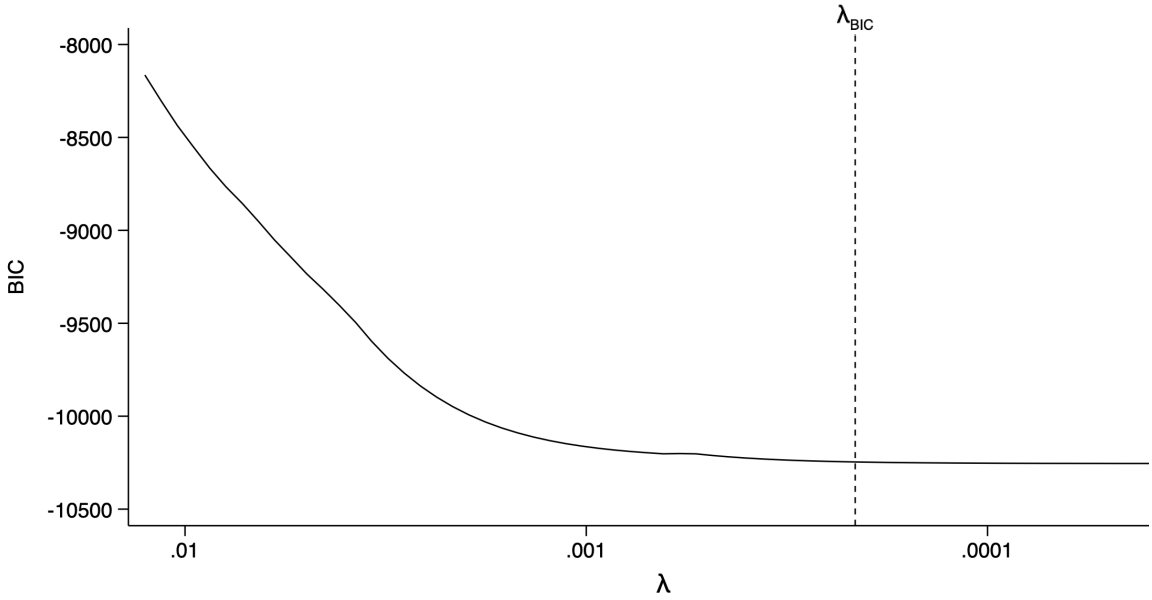


Table 2. Robust OLS Estimation: Metro Areas

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

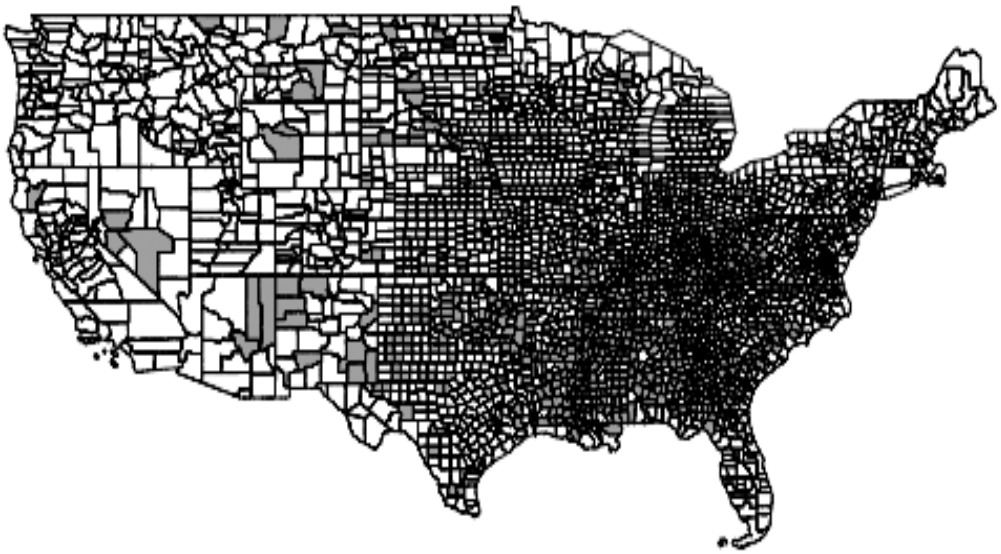


Figure 5, where relatively dark shades on the map inclusive of the contiguous states of the US reflect lower life expectancy of the median household, illustrates the possibility of potential spatial dependence in the data. Our tests for spatial correlation, following Müller and Watson (2022, 2024), discriminate 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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