Quantifying and explaining variation in life expectancy at census tract, county, and state levels in the United States

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Studies on geographic inequalities in life expectancy in the United States have exclusively focused on single-level analyses of aggregated data at state or county level. This study develops a multilevel perspective to understanding variation in life expectancy by simultaneously modeling the geographic variation at the levels of census tracts (CTs), counties, and states. We analyzed data from 65,662 CTs, nested within 3,020 counties and 48 states (plus District of Columbia). The dependent variable was age-specific life expectancy observed in each of the CTs. We also considered the following CT-level socioeconomic and demographic characteristics as independent variables: population density; proportions of population who are black, who are single parents, who are below the federal poverty line, and who are aged 25 or older who have a bachelor's degree or higher; and median household income. Of the total geographic variation in life expectancy at birth, 70.4% of the variation was attributed to CTs, followed by 19.0% for states and 10.7% for counties. The relative importance of CTs was greater for life expectancy at older ages (70.4 to 96.8%). The CT-level independent variables explained 5 to 76.6% of between-state variation, 11.1 to 58.6% of between-county variation, and 0.7 to 44.9% of between-CT variation in life expectancy across different age groups. Our findings indicate that population inequalities in longevity in the United States are primarily a local phenomenon. There is a need for greater precision and targeting of local geographies in public policy discourse aimed at reducing health inequalities in the United States.

life expectancy | inequalities | geography | multilevel | United States

During much of the 20th century, longevity has increased in the United States primarily due to socioeconomic advances and progress in basic public health, including vaccine developments and sanitation improvements (1). However, not everybody in the United States has equally benefited, as this trend has been accompanied by increasing gaps in longevity by place of residence (2), race/ethnicity (3–5), and socioeconomic groups (6–8). A child born in 2014 in the United States can be expected to live, on average, 79.1 y. However, this United States-wide average masks substantial geographic differences: in 2014, there was a 20.1-y gap between the lowest and the highest life expectancy (LE) at birth (LE0) across all counties (2).

Meanwhile, studies monitoring geographic inequalities in LE in the United States as a whole have exclusively focused on single-level analyses of aggregated data at regional, state, or county level. Chang et al. (9) explored the differences among US regions in LE and reported that the Northeast had the highest values and the South had the lowest. An analysis of the state-specific life tables for 1999 to 2001 showed that Hawaii (80.23 y) had the highest LE0 and Mississippi had the lowest (73.88 y) (10). Most studies have focused on counties when analyzing geographic inequalities in LE in the United States. Exploring data from 2007, Kulkarni et al. (11) identified that the difference between counties with the highest and the lowest LE was 15.2 y for men and 12.5 y for women. Wang et al. (12) and Dwyer-Lindgren et al. (2) also used counties as the unit of analysis and reported not only the great magnitude of inequalities between counties but also their increase in-between the 1980s and the early 21st century.

The implicit recognition that counties matter most for understanding inequalities in longevity in the United States results from a problematic inference based on single-level studies of counties. The sensitivity of geographic patterns to the choice of areal units has been well recognized, both in terms of the arbitrariness of any single aggregate level [also known as the "modifiable areal unit problem" (13)] and in terms of the need to consider multiple relevant units as outlined in the classic paper "geographical variances" by Moellering and Tobler (14). To truly examine which geographic scales matter the most for inequalities in longevity in the United States, multiple levels that are thought to influence longevity must be simultaneously considered (15). For instance, states and counties are important because legislation, policies, and programs that provide health care, economic assistance, and social services are administered and implemented at both levels (15). A multilevel study partitioning variation in

Significance

Current knowledge on which geographic scale matters the most for inequalities in longevity in the United States is largely confined to counties, which have been the smallest unit at which national data on life expectancy were available. Making the inference that "counties make a difference" simply because "counties differ" is potentially problematic. In this systematic investigation of ascertaining the relative importance of three geographic scales: states, counties, and census tracts (CTs), we find that more than three-fourths of the total variation in life expectancy is attributable to CTs. This indicates that population inequalities in longevity are primarily a local phenomenon, and there is a need for greater precision and targeting of local geographies in public policy discourse.

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LE demonstrated that prior county-level studies have overestimated the importance of the county level by omitting states (15). Further expansion of such multilevel perspective with inclusion of data at smaller levels like census tracts (CTs) can more accurately partition the geographic variation in longevity at relevant levels. By analyzing CTs as a geographic unit, it becomes possible to better understand intraurban disparities and better design local public policies.

Furthermore, simply because prior studies have found that "counties differ" does not automatically mean "counties make a difference." The observed significant variation at the county level from prior single-level studies is likely an artifact resulting from a conflation of "contextual effects" of counties and "compositional effects" of local areas (16). Here, composition refers to the geographic clustering of CTs with high or low LE as well as those with certain socioeconomic and demographic makeup. The contextual effect for each state and county can be better estimated after explicitly accounting for these compositional characteristics (16). More generally, expanding the levels of analysis to include areas in which people reside can potentially illuminate alternative public policy solutions to understand and address the persistent problems of social inequalities across multiple contexts (17). While counties have been the smallest geographic unit at which national data on LE were available in the United States, the recently released CT data enables an analysis to simultaneously assess multiple geographic levels and to effectively control for local compositional effects.

Given the identified gaps in current literature, we systematically investigate the relative importance of three geographic scales for longevity in the United States: states, counties, and CTs. By partitioning variations in age-specific LEs to these geographic levels, we establish evidence to identify at which geographic scale action lies to improve equity in longevity. Then, we further explore the extent to which established socioeconomic and demographic characteristics at the CT level account for the variation in longevity at each of the three levels.

Results

For LE0, the difference between the extreme CTs was 41.2 y, and there was a 13.1-y gap between the 5th and the 95th percentile (Fig. 1*A*). The lowest value of LE0 was observed in a CT in Adair County, Oklahoma (56.3 y), and the highest one in Chatham County, North Carolina (97.5 y). Considerable variation was also observed when analyzing LE in the 65 to 74 age group (LE65-74), with the figures ranging from 7.2 to 37.1 y across CTs. The lowest values were observed in the south-eastern and central-eastern parts of the country (Fig. 2*A*). For the main interpretation of our results, we focus on LE0 and LE65-74 for illustrating patterns in the early and later ages, but large variation in LE was consistently observed across CTs for all 11 age groups as presented in *SI Appendix*, Fig. S1.

Partitioning Variation in LE across Multiple Geographic Levels. CTs accounted for the majority of the total variation in LE across all ages (Table 1). CTs accounted for 70.4% (var_{CT} = 11.4 [SE: 0.06]) of the variation in LE0, followed by 19% for states (var_{state} = 3.1 [SE: 0.65]) and 10.7% for counties (var_{county} = 1.7 [SE: 0.07]). A similar pattern was observed across all age-groups, with the relative importance of CTs being greater for LE at older ages (70.4 to 96.8%). The proportion of variance in LE attributable to states and counties ranged from 2 to 19% and 1 to 11%, respectively.

The importance of simultaneously considering all three geographic levels in the analysis of LE was highlighted when models with different multilevel specifications were assessed. We ran sensitivity analyses with two-level models (CTs and states [omitting counties]; CTs and counties [omitting states]) (*SI Appendix*, Tables S1 and S2, respectively). Compared to our main results from the three-level models, the proportion of variation attributable to each geographic unit was substantially different from the two-level models. In the two-level model that ignored states, the between-CT variation in LE0 was 19.4 percentage points higher than what was found in the three-level model. Similarly, when counties were omitted, the between-CT variation was 12.1 percentage points higher than what was found in the main analysis.

Mapping the Unique Multilevel Geographies. To effectively visualize the value of partitioning the variance of LE into three unique geographic levels, we adapted statistical regression maps of residuals unique to CTs, counties, and states. In the statistical maps

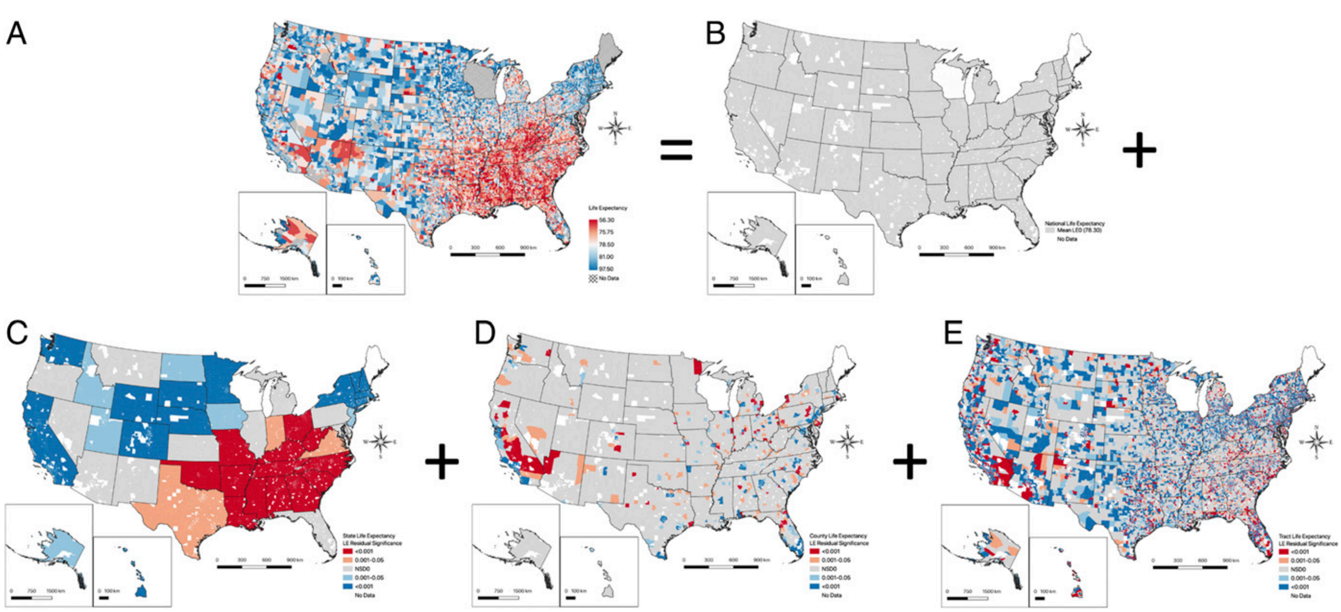

Fig. 1. Statistical regression maps for life expectancy at birth (LE0). The equation shows (*A*) observed census tract (CT) LE0 as the sum of (*B*) national LE0, (*C*) state-specific residual in LE0, (*D*) county-specific residual in LE0, and (*E*) CT-specific residual in LE0. United States, 2010 to 2015.

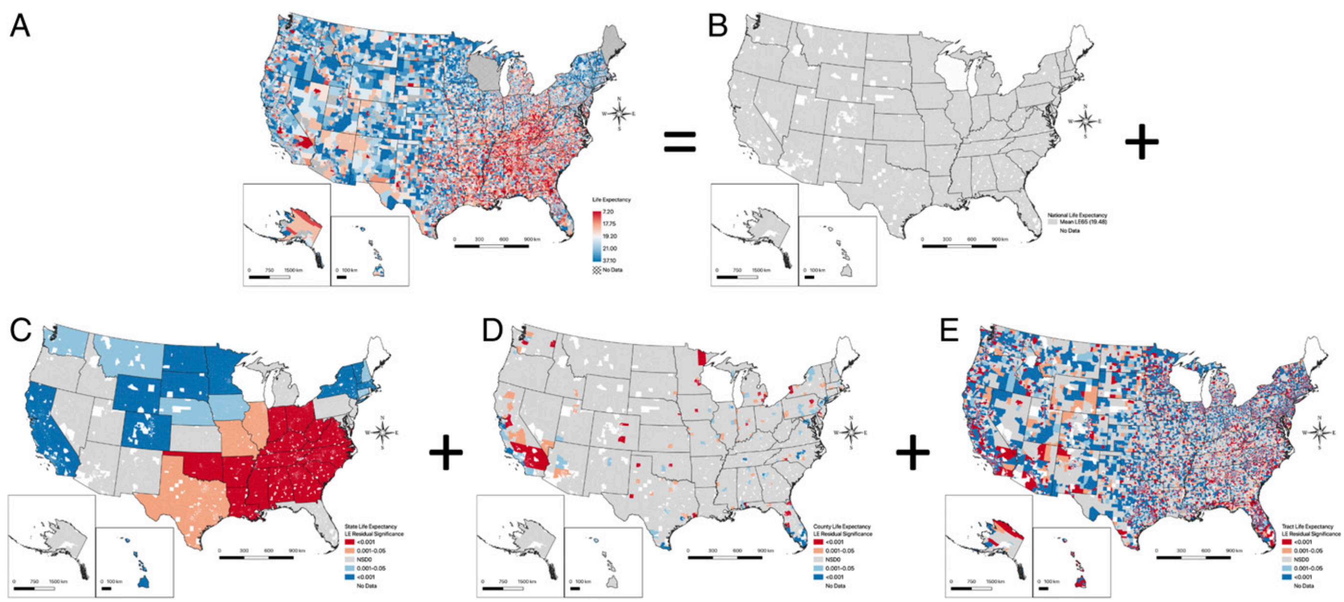

Fig. 2. Statistical regression maps for life expectancy at 65 to 74 y of age (LE65-74). The equation shows (*A*) observed census tract (CT) LE65-74 as the sum of (*B*) national LE65-74, (*C*) state-specific residual in LE65-74, (*D*) county-specific residual in LE65-74, and (*E*) CT-specific residual in LE65-74. United States, 2010 to 2015.

for LE0 (Fig. 1) and LE65-74 (Fig. 2), the observed variation in LE across CTs (*A*) is modeled as a function of US-wide average that applies to all CTs (*B*) and the sum of residual differences that are unique to each state (*C*), county (*D*), and CT (*E*).

For instance, disaggregation of LE0 for the CT with the highest value (97.5 y) by different geographies indicate that this CT is located within a state (North Carolina) that has a lower LE0 by 1.1 y than the overall national average (78.3 y) and within a county (Chatam) that has a higher LE0 by 3.2 y than the overall state average in which it is nested. The remaining difference of 17.2 y is attributed to the CT effect. Hence, for this particular CT, the LE0 of 97.5 is represented as the overall national average (visualized as map 1*B*) + state-specific residual (map 1*C*) + county-specific residual (map 1*D*) + CT-specific residual (map 1*E*), which is equivalent to 78.3 y + (−1.1 y) + (3.2 y) + (17.2 y).

Similarly, Fig. 2 illustrates that the CT effects trump state and county effects for LE65-74. Compared to the overall national average LE65-74 of 19.5 y (visualized as map 2*B*), the CT with the lowest LE65-74 (7.2 y) is located within a state that has a lower LE65-74 by 1.2 y (map 2*C*) than the overall national average, and within a county that has a lower LE65-74 by 0.7 y (map 2*D*) than the overall state average in which it is nested. The remaining difference of 10.4 y (map 2*E*) is attributed to the CT effect. Hence, for this particular CT, the LE65-74 of 7.2 y is the sum of 19.5 y + (−1.2 y) + (−0.7 y) + (−10.4 y).

Explaining Variation in LE across Multiple Geographic Levels. CT-level socioeconomic and demographic variables explained more than 70% of the between-state variance, 50% of the between-county variance, and 30% of the between-CT variance for LE at all age groups up to 55 to 64 y (Table 2). In the older groups, the variance explained was smaller but still relevant, with the exception of the 85 and older age group. When each of the CT-level socioeconomic and demographic variables were independently considered, income and education explained the largest proportion of variation in LE (*SI Appendix*, Fig. S2). In most age groups, income and education together accounted for more than 80% of what the full model explained of the between-state and between-county variance.

Table 1. Variance estimates (SEs) in life expectancy by ages, and the proportion of variance attributable to state, county, and census tract: United States, 2010 to 2015

	State		County		Census tract		Total	
Age	Var (SE)	% VPC	Var (SE)	% VPC	Var (SE)	% VPC	Var (SE)	% VPC
Under 1	3.09 (0.648)	18.97	1.74 (0.073)	10.69	11.45 (0.064)	70.37	16.27 (0.785)	100.00
1–4	2.82 (0.593)	18.55	1.61 (0.069)	10.59	10.77 (0.060)	70.86	15.21 (0.722)	100.00
5–14	2.76 (0.580)	18.36	1.58 (0.068)	10.51	10.69 (0.060)	71.12	15.03 (0.708)	100.00
15–24	2.71 (0.569)	18.22	1.56 (0.067)	10.48	10.61 (0.060)	71.30	14.88 (0.696)	100.00
25–34	2.60 (0.545)	18.06	1.47 (0.064)	10.21	10.33 (0.058)	71.74	14.4 (0.667)	100.00
35–44	2.35 (0.493)	17.38	1.31 (0.058)	9.69	9.86 (0.055)	72.93	13.52 (0.606)	100.00
45–54	1.98 (0.416)	16.60	1.07 (0.049)	8.97	8.88 (0.050)	74.43	11.93 (0.515)	100.00
55–64	1.39 (0.293)	14.78	0.74 (0.036)	7.86	7.28 (0.041)	77.36	9.41 (0.370)	100.00
65–74	0.77 (0.163)	11.15	0.41 (0.023)	5.93	5.73 (0.032)	82.92	6.91 (0.218)	100.00
75–84	0.36 (0.079)	5.89	0.16 (0.013)	2.61	5.60 (0.031)	91.50	6.12 (0.123)	100.00
85 and older	0.20 (0.046)	2.21	0.09 (0.012)	1.00	8.73 (0.048)	96.78	9.02 (0.106)	100.00

Var, variance; VPC, variance partitioning coefficient. All estimates from null three-level model.

Table 3 shows the regression coefficients for the association between LE and each independent variable. We observed a positive association between LE and the CT median income (except for the median income in the two oldest age groups) as well as the proportion of people with a college degree. A negative association was observed for the other independent variables. A larger proportion of black people, single parents, and population density was each associated with lower LE.

Discussion

Our study has three salient findings. First, of the total geographic variation in LE, the unit of CTs accounted for the substantial majority (70.4 to 96.8%), followed by states (2.2 to 19.0%) and counties showing the least amount of variability (1.0 to 10.7%). Second, CT-level socioeconomic and demographic variables were highly associated with LE, and education and income in particular explained much of the variation at all three levels of states, counties, and CTs. Finally, the patterns related to the overwhelming importance of CTs was observed across all age-specific LEs.

Our multilevel assessment of the relative importance of states, counties, and CTs indicate that prior studies that have emphasized counties as the primary driver of variability in longevity in the United States need to be reassessed. What had appeared to be a significant county variation in prior studies was probably an artifact resulting from the failure to partition variation in longevity by other relevant units like states and CTs. Our sensitivity analyses omitting counties and states one at a time provides a rough estimation of the extent to which the choice of relevant geographic scales in multilevel modeling matters. Furthermore, the mapping of residuals at each level visually reinforces the lack of variation at county level when state and CT levels are simultaneously accounted for.

A few prior studies had focused on disparities in LE across CTs within certain states, although they had not employed a multilevel perspective. Talbot et al. (18) analyzed data from 2,751 CTs in New York state and found that LE was 8.5 y lower in the CTs with the highest proportion of poor (≥25%) and African Americans (≥50%). When analyzing LE data among local communities in Chicago, Hunt et al. (19) reported a difference of 14.9 y between the areas with the highest and lowest values. Dwyer-Lindgren et al. (20) analyzed data from neighborhoods in King County, Washington, and found that although the county's LE was in the 95th percentile among all counties in the United States, marked inequalities were found across the CTs. Among men, the values varied from 68.4 to 86.7 y and among women from 73.6 to 88.4 y. These findings reinforce the relevance of analyses that decompose the estimates to smaller local areas and suggest that CT-level data can potentially expand scientific knowledge about the impact of local context on health with remarkable policy relevance (21).

Adjusting for CT-level socioeconomic and demographic variables explained a large proportion of variation in longevity at state and county levels, indicating the strong compositional effect of CTs. Poorer socioeconomic status at the local level may affect residents' health outcomes via greater exposure to fast-food outlets and problems related to aesthetic and safety perceptions (22), lesser green spaces (23–26), more exposure to air pollution (27), increased risk of engaging in harmful behaviors like smoking (28), and reduced ability to acquire knowledge about, locate, or obtain access to health-promoting resources (19). With regard to the racial composition of CTs, predominantly black neighborhoods have a higher proportion of fast-food restaurants, lower availability of healthy foods (29) and physical activity-related facilities (30), and the residents are more likely to perceive the area as less safe and less pleasant for physical activity (31).

We observed a strong positive association between median income and LE across all ages, except for the two oldest age groups. This may be due to survivor effect, with those living in the poorest areas who survive into older age being more robust, on average, than those from wealthier areas. Alternatively, it could reflect a tendency for nursing homes to be located further away from the poorest areas. A larger proportion of variance at state and county levels remained unexplained for LE at older ages. The unexplained variation may reflect a mix of true contextual effect that is unique at its own level and some residual compositional effects that remain to be further explained when a more comprehensive set of CT-level data become available (16).

Evidence of subnational geographic inequalities in LE has been reported for other high-income (32, 33) and low- and middle-income countries (34). However, the high magnitude of variation observed in the United States is noteworthy. Differences in social policies may help to explain such difference. The United States has the highest relative poverty rate and the highest concentration of income and wealth among the top 10%

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Table 2. Variance estimates (SEs) in life expectancy by ages, and the percent explained in variation by adjusting for census tract socioeconomic and demographic variables: United States, 2010 to 2015

	State		County		Census tract		Total
Age	Var (SE)*	% Var explained†	Var (SE)*	% Var explained†	Var (SE)*	% Var explained†	Var (SE)*
Under 1	0.72 (0.156)	76.62	0.72 (0.037)	58.62	6.31 (0.036)	44.89	7.75
1–4	0.67 (0.144)	76.24	0.68 (0.036)	57.76	6.02 (0.034)	44.10	7.37
5–14	0.65 (0.142)	76.45	0.67 (0.036)	57.59	6.01 (0.034)	43.78	7.33
15–24	0.64 (0.139)	76.38	0.67 (0.036)	57.05	5.99 (0.034)	43.54	7.3
25–34	0.62 (0.134)	76.15	0.63 (0.034)	57.14	5.87 (0.033)	43.18	7.12
35–44	0.56 (0.121)	76.17	0.56 (0.031)	57.25	5.70 (0.032)	42.19	6.82
45–54	0.49 (0.106)	75.25	0.46 (0.027)	57.01	5.45 (0.031)	38.63	6.4
55–64	0.39 (0.085)	71.94	0.34 (0.021)	54.05	5.09 (0.028)	30.08	5.82
65–74	0.30 (0.066)	61.04	0.22 (0.016)	46.34	4.83 (0.027)	15.71	5.35
75–84	0.23 (0.052)	36.11	0.12 (0.011)	25.00	5.42 (0.030)	3.21	5.77
85 and older	0.19 (0.044)	5.00	0.08 (0.011)	11.11	8.67 (0.048)	0.69	8.94

Var, variance.

*Variance from three-level models adjusted for CT socioeconomic and demographic variables: percentage of black people, percentage of people with college degree, median income, percentage of poor people, population density, and percentage of single parents.

†Percent of variance explained when compared to the null model.

Table 3. Regression coefficient of life expectancy according to census tract socioeconomic and demographic variables: United States, 2010 to 2015

	β Coefficient* ($CI_{95\%}$) (mean differences in life expectancy, y)					
Age	% Black people	% College degree	Median income	% Poor people	Populational density	% Single parents
Under 1	−1.919 (−2.012;−1.826)	3.384 (3.292;3.476)	2.548 (2.432;2.664)	−0.946 (−1.047; −0.846)	−0.436 (−0.053; −0.337)	−1.024 (−1.112; −0.937)
1–4	−1.754 (−1.845;−1.662)	3.303 (3.213;3.394)	2.424 (2.310;2.537)	−0.934 (−1.032; −0.836)	−0.460 (−0.556; −0.363)	−0.981 (−1.066;v0.896)
5–14	−1.742 (−1.833;−1.651)	3.269 (3.179;3.359)	2.399 (2.286;2.512)	−0.937 (−1.035; −0.838)	−0.484 (−0.581; −0.388)	−0.980 (−1.066; −0.895)
15–24	−1.719 (−1.810;−1.628)	3.245 (3.155;3.335)	2.376 (2.263;2.489)	−0.945 (−1.043; −0.847)	−0.521 (−0.618; −0.425)	−0.972 (−1.057; −0.887)
25–34	−1.684 (−1.774;−1.594)	3.161 (3.072;3.250)	2.324 (2.212;2.436)	−0.979 (−1.076; −0.882)	−0.617 (−0.712; −0.521)	−0.927 (−1.011; −0.843)
35–44	−1.658 (−1.746;−1.570)	3.000 (2.911;3.087)	2.196 (2.086;2.306)	−0.997 (−1.093; −0.901)	−0.780 (−0.874; −0.686)	−0.902 (−0.985; −0.819)
45–54	−1.577 (−1.663;−1.491)	2.795 (2.710;2.881)	1.840 (1.732;1.948)	−0.940 (−1.033; −0.846)	−0.856 (−0.947; −0.765)	−0.786 (−0.868; −0.705)
55–64	−1.388 (−1.471;−1.306)	2.467 (2.385;2.550)	1.140 (1.036;1.243)	−0.774 (−0.865; −0.684)	−0.813 (−0.900; −0.726)	−0.591 (−0.669; −0.513)
65–74	−1.015 (−1.094;−0.936)	1.862 (1.783;1.942)	0.296 (0.196;0.397)	−0.526 (−0.614; −0.439)	−0.678 (−0.762; −0.595)	−0.364 (−0.440; −0.288)
75–84	−0.562 (−0.643;−0.480)	1.007 (0.923;1.090)	−0.431 (−0.536; −0.326)	−0.316 (−0.408; −0.224)	−0.498 (−0.583; −0.413)	−0.173 (−0.253; −0.092)
85 and older	−0.266 (−0.366;−0.166)	0.363 (0.258;0.467)	−0.758 (−0.889; −0.627)	−0.251 (−0.367; −0.135)	−0.404 (−0.506; −0.302)	−0.056 (−0.157;0.045)

*Coefficient comparing the fifth quintile of the distribution of each variable to the first quintile (reference category).

of households across the Organization for Economic Cooperation and Development countries (35). Also, the United States has weaker employment protection laws, no federal program for housing assistance (36), and a high proportion of people who feel financially insecure (35). These are characteristics of the nation as a whole, but nonetheless illustrate the weakness of public policies that seek to promote equity. Another important aspect is that in the United States millions of people lack access to health care. Stone et al. (37) found remarkable geographic inequalities in health insurance coverage, and their multivariate analysis suggested that county's poverty and unemployment rates are associated with lower coverage. More studies on global comparison of the different magnitudes of subnational inequalities in LE may shed some light on the exact mechanisms.

This study has four limitations. First, the use of six CT-level variables may not be adequate to fully capture all of the relevant compositional effects. For instance, the microclustering of people into elderly facilities (i.e., many deaths occur among those whose residence location is listed as a nursing home or other elderly care facility) may have inflated the variation at the CT level, but we were not able to adjust for this. Moreover, we did not have data on individual-level behavioral and biological variables in our models, which could help better understand the factors that explain variation in LE and in exploring mediation and more complex analytical models. Second, it is also important to note that CT boundaries are arbitrarily drawn and the individuals may be more influenced by an adjacent CT or by their workplace CT. Third, in regard to LE estimates, Arias et al. (38) highlighted the lack of CT-level intercensal population estimates based on decennial census counts. Sample data had to be used to estimate population size, and additional error could have been introduced into the estimates. The authors, in some cases of missing deaths, calculated a predicted value based on the CT's combination of socioeconomic and demographic characteristics, which may have affected the associations we estimated. The exclusion of two states and some CTs constitutes an additional limitation for describing the population of the United States. Finally, limitations on the quality of the data available in smaller geographical units should be considered when interpreting the results due to small sample sizes and high variability.

Despite these data-related limitations, the present findings demonstrate that population inequalities in longevity in the United States is primarily a local phenomenon. Geographic clustering of CTs with high or low LE as well as those with certain socioeconomic and demographic makeup should not be conflated with, and interpreted as, the contextual effect of counties. There is a need for greater precision and targeting of local geographies in public policy discourse aimed at reducing health inequalities in the United States. Identification of local communities with greater needs can guide more equitable resource allocation, and assessment of good local practices and community experiences can be replicated in other areas.

Materials and Methods

Geographical Units. All of the analyses were carried out taking into account of the hierarchical structure of the data. LE was calculated for US CTs, which are nested within counties that are nested within states. We analyzed data from 65,662 CTs from 3,020 counties and 48 states and the District of Columbia. In the United States, states are the primary legal subdivision of the country. There are currently 50 states, and each one holds executive, legislative, and judicial authority over its territory. Counties are the primary legal divisions of most states. The structure and powers of a county government vary across the states, but most of them are functioning governmental units. Usually, within a county, there are several CTs, which is a geographic region that, in the United States, typically contains 1,200 to 8,000 people, with an optimum size of 4,000 people.

Estimation of LE. LE data were obtained from the US Small-Area Life Expectancy Estimates Project, conducted by the National Center for Health Statistics (39). To calculate the US CT abridged life tables, a few steps were followed. First, death records for each year of the period 2010 to 2015, as informed by the National Vital Statistics System, were obtained, and the residential address information for every death was geocoded to identify the corresponding CT code. Data were not available for Maine and Wisconsin. CTs with 6-y total population size smaller than 5,000 ($n = 4,703$), the minimum population size necessary for reliable estimates, were excluded from the study (38). Second, population data from the 2010 decennial census and from the 2011 to 2015 American Community Survey (ACS) were used to estimate the number of residents living in each CT. Finally, considering the existence of missing age-specific death counts, the small population, and the low death count in some CTs, demographic techniques and statistical modeling strategies were carried out to check the quality of the estimates (14). In addition, considering that the population estimates were based on sample data, the methods to calculate the abridged life tables were adjusted. LE was calculated for 11 age groups: 0, 1 to 4, 5 to 14, 15 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74, 75 to 84, and 85 and over. More details on the calculation of the LE are provided elsewhere (38).

Socioeconomic and Demographic Variables. To explain the variability observed in the outcomes, we included six socioeconomic and demographic variables in the analysis that were available at the CT level: 1) population density (number of residents per square mile), calculated by dividing the total population according to the 2000 Decennial Census by land area in square miles as registered in the 2010 Census Gazetteer Files; 2) proportion of black people in the CT according to the 2010 Census; 3) proportion of single parents, defined as the proportion of households with a female head (and no husband present) or a male head (and no wife present) with their own children under 18 y old present (2006 to 2010 ACS data estimate); 4) proportion of residents below the federal poverty line, measured in the 2006 to 2010 period using the ACS data; 5) proportion of people aged 25 or older who have a bachelor's degree, master's degree, professional school degree, or doctorate degree, for which 2006 to 2010 ACS data were used to obtain the estimate for 2010; and 6) median household income, obtained for 2016 from the 2012 to 2016 ACS. These data are available on the Opportunity Insights database (38).

Statistical Analysis. We fitted multilevel linear models with random effects for state, county, and CTs, and LE of each age group as the outcome. First, the null model was calculated to quantify the total amount of variation at each level (i.e., var_{state}, var_{county}, var_{CT}). The proportion of variance attributed to each level z was computed as follows: $var_z/(var_{state} + var_{county} + var_{CT})$. Then we included the CT variables to the three-level linear model and compared the final variance estimates obtained in the full model with the variance estimates from the null model to compute the percent explained. In the fully adjusted model, the β coefficients with respective confidence intervals (95% CIs) were reported. In order to visualize the geography of LE by CTs, counties, and states, we mapped the LE values for each age group. We also mapped the residuals of LE at birth (LE0) and LE at 65 to 74 (LE65-74) at different levels as estimated from the three-level model. CTs, counties, and states with residuals within the 95% coverage bounds of the average LE were classified as "average" (denoted with gray). Geographic units with residuals that deviated statistically significantly below the average were colored in red, and those that deviated above the average were denoted with blue. All of the analyses were carried out using MLwiN 3.0 and Stata 15. The maps were created using QGIS 3.10.1.

Data Availability. CT LE data can be downloaded from the National Center for Health Statistics US Small-Area Life Expectancy Estimates Project (available at https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html). Census tract socioeconomic and demographic variables can be downloaded from the Opportunity Insights database (https://opportunityinsights.org/). Codes used to run multilevel analyses in Stata 15 and those used to create the maps in QGIS 3.10.1 are available as Datasets S1 and S2.

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SOCIAL SCIENCES

1. D. Cutler, G. Miller, The role of public health improvements in health advances: The twentieth-century United States. *Demography* **42**, 1–22 (2005).
2. L. Dwyer-Lindgren *et al*., Inequalities in life expectancy among US counties, 1980 to 2014: Temporal trends and key drivers. *JAMA Intern. Med.* **177**, 1003–1011 (2017).
3. M. R. Cullen, C. Cummins, V. R. Fuchs, Geographic and racial variation in premature mortality in the U.S.: Analyzing the disparities. *PLoS One* **7**, e32930 (2012).
4. S. Harper, R. F. MacLehose, J. S. Kaufman, Trends in the black-white life expectancy gap among US states, 1990–2009. *Health Aff. (Millwood)* **33**, 1375–1382 (2014).
5. N. Krieger *et al*., 50-year trends in US socioeconomic inequalities in health: US-born black and white Americans, 1959–2008. *Int. J. Epidemiol.* **43**, 1294–1313 (2014).
6. W. C. Hadden, P. D. Rockswold, Increasing differential mortality by educational attainment in adults in the United States. *Int. J. Health Serv.* **38**, 47–61 (2008).
7. R. Chetty *et al*., The association between income and life expectancy in the United States, 2001–2014. *JAMA* **315**, 1750–1766 (2016).
8. I. Sasson, Trends in life expectancy and lifespan variation by educational attainment: United States, 1990–2010. *Demography* **53**, 269–293 (2016).
9. M. H. Chang *et al*., Differences in healthy life expectancy for the US population by sex, race/ethnicity and geographic region: 2008. *J. Public Health (Oxf.)* **37**, 470–479 (2015).
10. R. Wei, R. N. Anderson, L. R. Curtin, E. Arias, U.S. decennial life tables for 1999–2001: State life tables. *Natl. Vital Stat. Rep.* **60**, 1–66 (2012).
11. S. C. Kulkarni, A. Levin-Rector, M. Ezzati, C. J. Murray, Falling behind: Life expectancy in US counties from 2000 to 2007 in an international context. *Popul. Health Metr.* **9**, 16 (2011).
12. H. Wang, A. E. Schumacher, C. E. Levitz, A. H. Mokdad, C. J. Murray, Left behind: Widening disparities for males and females in US county life expectancy, 1985–2010. *Popul. Health Metr.* **11**, 8 (2013).
13. S. Openshaw, *The Modifiable Areal Unit Problem*, (Geo Abstracts, University of East Anglia, 1984).
14. H. Moellering, W. Tobler, Geographical variances. *Geogr. Anal.* **4**, 34–50 (1972).
15. R. Kim, S. V. Subramanian, What's wrong with understanding variation using a single-geographic scale? A multilevel geographic assessment of life expectancy in the United States. *Procedia Environ. Sci.* **36**, 4–11 (2016).
16. K. Jones, What's hiding behind statistical maps. *Bull. Soc. Univ. Cartogr.* **24**, 13–30 (1991).
17. N. Krieger, J. T. Chen, P. D. Waterman, D. H. Rehkopf, S. V. Subramanian, Race/ethnicity, gender, and monitoring socioeconomic gradients in health: A comparison of area-based socioeconomic measures—the public health disparities geocoding project. *Am. J. Public Health* **93**, 1655–1671 (2003).
18. T. O. Talbot, D. H. Done, G. D. Babcock, Calculating census tract-based life expectancy in New York state: A generalizable approach. *Popul. Health Metr.* **16**, 1 (2018).
19. B. R. Hunt, G. Tran, S. Whitman, Life expectancy varies in local communities in Chicago: Racial and spatial disparities and correlates. *J. Racial Ethn. Health Disparities* **2**, 425–433 (2015).
20. L. Dwyer-Lindgren *et al*., Variation in life expectancy and mortality by cause among neighbourhoods in king county, WA, USA, 1990–2014: A census tract-level analysis for the global burden of disease study 2015. *Lancet Public Health* **2**, e400–e410 (2017).
21. N. Krieger, A century of census tracts: Health and the body politic (1906–2006). *J. Urban Health* **83**, 355–361 (2006).
22. G. S. Lovasi, M. A. Hutson, M. Guerra, K. M. Neckerman, Built environments and obesity in disadvantaged populations. *Epidemiol. Rev.* **31**, 7–20 (2009).
23. T. Astell-Burt, X. Feng, S. Mavoa, H. M. Badland, B. Giles-Corti, Do low-income neighbourhoods have the least green space? A cross-sectional study of Australia's most populous cities. *BMC Public Health* **14**, 292 (2014).
24. S. A. Schüle, K. M. A. Gabriel, G. Bolte, Relationship between neighbourhood socioeconomic position and neighbourhood public green space availability: An environmental inequality analysis in a large German city applying generalized linear models. *Int. J. Hyg. Environ. Health* **220**, 711–718 (2017).
25. R. McCormick, Does access to green space impact the mental well-being of children: A systematic review. *J. Pediatr. Nurs.* **37**, 3–7 (2017).
26. P. J. Villeneuve, M. Jerrett, J. G. Su, S. Weichenthal, D. P. Sandler, Association of residential greenness with obesity and physical activity in a US cohort of women. *Environ. Res.* **160**, 372–384 (2018).
27. A. Hajat *et al*., Air pollution and individual and neighborhood socioeconomic status: Evidence from the multi-ethnic study of atherosclerosis (MESA). *Environ. Health Perspect.* **121**, 1325–1333 (2013).
28. G. D. Datta *et al*., Individual, neighborhood, and state-level predictors of smoking among US black women: A multilevel analysis. *Soc. Sci. Med.* **63**, 1034–1044 (2006).
29. N. I. Larson, M. T. Story, M. C. Nelson, Neighborhood environments: Disparities in access to healthy foods in the U.S. *Am. J. Prev. Med.* **36**, 74–81 (2009).

30. L. M. Powell, S. Slater, F. J. Chaloupka, D. Harper, Availability of physical activity-related facilities and neighborhood demographic and socioeconomic characteristics: A national study. *Am. J. Public Health* **96**, 1676–1680 (2006).
31. S. E. Boslaugh, D. A. Luke, R. C. Brownson, K. S. Naleid, M. W. Kreuter, Perceptions of neighborhood environment for physical activity: Is it "who you are" or "where you live"? *J. Urban Health* **81**, 671–681 (2004).
32. D. Dorling, R. Mitchell, M. Shaw, S. Orford, G. D. Smith, The Ghost of Christmas Past: Health effects of poverty in London in 1896 and 1991. *BMJ* **321**, 1547–1551 (2000).
33. S. Nomura *et al*., Population health and regional variations of disease burden in Japan, 1990–2015: A systematic subnational analysis for the global burden of disease study 2015. *Lancet* **390**, 1521–1538 (2017).
34. A. F. Boing, S. V. Subramanian, A. C. Boing, Reducing socioeconomic inequalities in life expectancy among municipalities: The Brazilian experience. *Int. J. Public Health* **64**, 713–720 (2019).
35. OECD, *Society at a Glance 2019: OECD Social Indicators*, (OECD Publishing, Paris, 2019).
36. M. Avendano, I. Kawachi, Why do Americans have shorter life expectancy and worse health than do people in other high-income countries? *Annu. Rev. Public Health* **35**, 307–325 (2014).
37. L. C. Stone, B. Boursaw, S. P. Bettez, T. Larzelere Marley, H. Waitzkin, Place as a predictor of health insurance coverage: A multivariate analysis of counties in the United States. *Health Place* **34**, 207–214 (2015).
38. E. Arias, L. A. Escobedo, J. Kennedy, C. Fu, J. Cisewski, U.S. small-area life expectancy estimates project: Methodology and results summary. *Vital Health Stat. 2* **34**, 1–40 (2018).
39. National Center for Health Statistics, U.S. small-area life expectancy estimates project (USALEEP): Life expectancy estimates file for 2010–2015. https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html Accessed 2 December 2018.