**Heterogeneity in Disparities in Life Expectancy across US Metropolitan Areas**

Alina S. Schnake-Mahl1, Pricila Mullachery1, Jonathan Purtle?,

Ran Li1, Ana V. Diez Roux1,2, Usama Bilal1,2,

1. Urban Health Collaborative, Drexel Dornsife School of Public Health, Philadelphia, PA, USA
2. Department of Epidemiology and Biostatistics, Drexel Dornsife School of Public Health, Philadelphia, PA, USA

**Corresponding Author:**

Alina Schnake-Mahl, ScD MPH

Urban Health Collaborative

Drexel Dornsife School of Public Health

3600 Market St, Room 730, Philadelphia, PA, 19104

Phone: +1-267-359-6378

Email: alinasmahl@drexel.edu

Target journal: Health and Place (2nd AJPH)

**WC**: 2841

**Abstract**

Life expectancy in the US has declined since 2014, but we lack a characterization of disparities within and across metropolitan areas of the country. Using census tract-level life expectancy data from the 2010-2015 US Small-area Life Expectancy Estimates Project, we calculate nine measures of disparities in life expectancy within and across 359 Metropolitan Statistical Areas of the US. Cities in the South and Midwest had the widest life expectancy disparities, mostly driven by differences in life expectancy in areas of lower income. Cities in the West showed the narrowest disparities within MSAs, but also had the highest overall levels of life expectancy. We found that larger cities had significantly wider disparities. Compositional and contextual factors likely help explain variation in life expectancy disparities within and across cities. Further investment in local-level health-promoting social policies may reduce disparities in life expectancy.

**Highlights**

* Life expectancy in the US has declined since 2014.
* We described disparities in life expectancy within and between metropolitan areas of the US.
* Cities in the South and Midwest had the widest life expectancy disparities, mostly driven by differences in life expectancy in areas of lower income.
* Cities in the West showed the narrowest disparities within MSAs, but also had the highest overall levels of life expectancy.
* Larger cities had wider disparities in life expectancy.

**Keywords**: social inequalities; health disparities; urban health; life expectancy; US

**Introduction**

Life expectancy in the United States has declined since 2014(Kochanek et al., 2017), and disparities in mortality between non-Hispanic whites and Non-Hispanic Blacks have continued increasing(Bilal and Diez-Roux, 2018). These racial life expectancy disparities, as well as inequities by socioeconomic status and geography(Bosworth, 2018; Harper et al., 2014), are a persistent feature of the American epidemiologic map [Wami, 2021 #4219]. Even in the years of overall increasing life expectancy (1969 to 2013), the average improvements(Kim, 2016), obscured substantial heterogeneity in life expectancy between states(Boscoe, 2015; Wei et al., 2008) and counties(Ezzati et al., 2008; Kulkarni et al., 2011). These unequal, and unjust, short life spans are produced by the inequitable distribution of resources due to income inequality, systemic racism, environmental injustice, differential access to health care, and state and local policies (Montez et al., 2020; Woolf and Braveman, 2011). The COVID-19 pandemic has aggravated these patterns, by causing further declines in life expectancy, with larger decreases for racial and ethnic minorities (Arias et al., 2021; Woolf et al., 2021).

The environments where we live, work and play are important for our health(Braveman and Egerter, 2013), as decades of place-based health effects have shown(Diez Roux and Mair, 2010). Studies have found disparities in life expectancy, when measured at the region, state, county, or neighborhood level, or when measuring multiple levels of geography simultaneously[Kim, 2016 #3942;Boing, 2020 #3943;Trias-Llimós, 2020 #4220;[Bilal, 2019 #4222; Bilal, 2021 #4221]. For example, a study by Woolf et al, found that in 2016 Hawaii (81.7 years) had the longest life expectancy at birth of any state, and Mississippi (74.7 years) the shortest [Woolf, 2019 #4223]. Arguing for census tracts as the geography accounting for the greatest amount of variation in LE, Boing et all, found a 13.1-year difference in life expectancy between the 5th and 95th percentile U.S. census tracts(Boing et al., 2020). Chetty et al has found that between 1994 and 2014 there was a 14.6-year (95%CI 14.4 to 14.8 years) gap for men and 10.1 years (95% CI 9.9 to 10.3) between the richest and poorest 1% of individuals(Chetty et al., 2016). Chetty et al also found that life expectancy among low-income individuals was positively associated with local area proportion of immigrants (*r* = 0.72, *P* < .001), college graduates (*r* = 0.42, *P* < .001), and government expenditures (*r* = 0.57, *P* < .001)(Chetty et al., 2016).

Prior work has documented differences in life expectancy by neighborhood within specific cities, for example by quantifying the differences in expected years of life between neighborhoods: two miles and 8 years separate the Upper West Side and East Harlem in NYC; in Chicago the life expectancy gap in neighboring Hyde Park and Washington Park is 13 years(Tavernise and Sun, 2015). However, research has not previously characterized disparities in life expectancy for all metropolitan areas across the US, nor provided comparisons in inequities between US regions. The primary objective of this study was to estimate disparities in life expectancy within metropolitan areas in the US from 2010-2015 using publicly available data. Quantifying the various measures of life expectancy disparities improves our understanding of place effects on health, and lends itself to further research identifying policies, practices, and population characteristics that impact these disparities.

**Methods**

Study Setting

We used data on all census tracts in the US with life expectancy data and that belonged to a core-based statistical area (CBSA) of the metropolitan type, usually called Metropolitan Statistical Areas (MSAs). We included all MSAs in the 48 contiguous US states, except MSAs with a census tract in Wisconsin and Maine, since life expectancy data was unavailable for census tracts in these two states. We use the term city and MSAs interchangeably throughout the article.

Outcome

We obtained Life expectancy data for 2010-2015 from the US Small-area Life Expectancy Estimates Project (USALEEP)(Arias et al., 2018). The project calculated abridged period life tables for 88.8% of all U.S. census tracts using a combination of geocoding, ACS and census data linkage, and standard demographic techniques and statistical modeling. Further details are available elsewhere(Arias et al., 2018).

Predictors

We obtained median household income (MHI) data at the census tract and MSA level from the American Community Survey 2011-2015 5-year estimates (Table S1901). We operationalized MHI as MSA-level household-weighted ventiles that represent 1/20th (5%) of the number of households in each city, similar to the approach by Chetty et al [Chetty, 2016 #3944]. We also obtained MSA-level total population size from the 2011-2015 ACS. Last, we categorized MSAs according to the census region where most of the MSA population resides.

Statistical Analysis

For each MSA, we computed several measures of absolute disparity and of income-related disparities. Different disparity measures can often lead to different interpretations of the same data, and selection between carry with them several value-laden decisions(Harper et al., 2010). To provide a more comprehensive picture of these disparities, we computed a total of 8 measures of disparity, but focused on two: absolute differences and relative ratio differences. A full list of computed measures can be found in **Appendix Table 1**.

We selected absolute and relative ratio differences because, for our data, inferences did not differ substantially by measure, and absolute differences and relative ratio differences are most intuitive and easy to understand. We measured these as the difference or ratio between the 90th and 10th population-weighted percentiles of life expectancy for each city. We also calculated the coefficient of variation (CV) for each census region.

We present our results in two different ways: overall (all MSAs) and restricted to MSAs with >1 million people. The appendix and interactive dashboard (link) display results for different population cutoffs. Last, we explored whether MSA-level population size and MHI were predictive of the magnitude of disparities. For this, we ran an MSA-level linear regression model with the P90-P10 difference (absolute) as the outcome and population (log transformed) and MHI (log transformed) as predictors.

All analyses were conducted in R v4.0.2. All code and data are available here: xx. A dashboard with interactive results is available here: https://drexel-uhc.shinyapps.io/LE\_Income\_Inequalities\_City\_dev/.

**Results**

We included data from 73,056 census tracts and 359 MSAs in four census regions. **Table 1** shows the measures of disparities in life expectancy for MSAs with >1 million people, sorted by the rank across absolute and relative differences. **Appendix Figure 2** shows the correlation between life expectancy disparity indicators. Within absolute and relative measures of inequality, all measures were highly correlated with each other (rho> 0.80 in all cases). Absolute to income-related disparities showed moderate correlations (rho ranging from 0.57 to 0.77). Among MSAs with >1 million people, the metro area with the widest overall disparities were Memphis (TN), Louisville (KY), and Detroit (MI) where there was an absolute gap of 10.7 years (70.8 to 81.5 years, 71.3 to 82 years, and 71.6 to years, respectively) and a relative ratio of 1.15, or a 15% longer life expectancy in the 90th versus 10th percentile census tracts (**Table 1**). The city with the narrowest overall disparities was San Jose (CA), where there was an absolute gap of 6.6 years (79.6 to 86.2 years) and a relative ratio of 1.08, or an 8% longer life expectancy in the 90th versus 10th percentile census tracts (Table 1). The interactive dashboard includes the full list of MSAs, and all measures of disparities. All the top 10 ranked cities were in the South (5) and Midwest (6). While rank differed slightly by absolute or relative disparity, the top and bottom 10 MSAs were the same using both metrics.

**Figure 1** shows the distribution of absolute and relative disparity within census regions and between cities. Across both measures, the region with the largest disparities was the Midwest, followed by the South, then the Northeast, and finally the West. While disparities were largest in the Midwest, the coefficient of variation was smallest in the Midwest for absolute differences (16.9), indicating limited variation in disparities between MSAs despite large disparities within MSAs.

**Figure 2** shows the spatial distribution of absolute differences across the U.S. Darker red blocks indicate higher ranked cities, or cities with greater levels of within city disparities. The maps did not differ substantively between measures, so we only display absolute differences (see **Appendix Figure 1** for relative differences). MSAs with the widest disparities clustered in the South and Midwest. Very few of the highest ranked cities were in the West. The interactive dashboard allows readers to explore specific geographies and disparity measure rankings.

**Figure 3** shows life expectancy plotted against decile of median household income, for the MSA’s with more than 1 million people. Across all regions, life expectancy increased with higher median household income. The Midwest had the greatest disparity in life expectancy by income within cities but had limited variation in life expectancy between cities. For example, in Cincinnati (OH), life expectancy varied by more than 10 years between the lowest and highest decile census tracts. The West showed the narrowest disparities within cities, but also had the highest overall levels of life expectancy. Both the South and Northeast showed wide between city variation in life expectancy at the lower levels of income levels. In other words, differences in life expectancy between cities were narrowest for the highest income levels and widest for the lowest income levels. For example, in the Northeast life expectancy differed by as much as 6.6 years (between 78.0 and 71.4 years) at the lowest income decile, while at the highest income decile life expectancy only differed by 3.0 years (between 84.4 and 81.4 years).

Table 2 shows the results of the analysis predicting life expectancy disparities by MSA-level total population and median household income. We found that larger cities had wider disparities as compared to smaller cities, while disparities did not vary by MSA-level income. After adjusting for both variables, we found that a 10% increase in population size or median household income was associated with a 0.03-year (95% CI 0.01 to 0.04%) and -0.06-year (95% CI -0.15 to -0.04%) change in the life expectancy disparity.

**Discussion**

Our study has four major findings. First, measures of disparities in life expectancy were highly correlated with each other. Second, metropolitan areas in the Midwest had the widest life expectancy disparities while those in the West had the narrowest. Third, life expectancy monotonically increased with median household income, though median household income at the MSA-level was not predictive of the magnitude of these life expectancy disparities, while larger MSAs had wider disparities. Fourth, disparities in life expectancy between MSAs were larger at low-income levels, particularly in the South and Northeast, whereas they did not vary as much in the Midwest, and generally there were narrow between MSA disparities in the Midwest at all income levels.

We saw substantially larger life expectancy disparities in MSAs in the Midwest and South than Northeast and West coast; among the largest MSAs, all of the MSAs with the widest disparities were located in the Midwest and South. Our findings suggest that larger cities have larger life expectancy gaps, but higher MSA-level MHI does not predict larger disparities. However, population size and MHI are only two potential predictors of LE disparities. As proposed by Cummins et al. (Cummins et al., 2007), both contextual and compositional factors, along with their reciprocal relationships (e.g., areas with higher income families receiving more infrastructure investments, leading to more high income families moving in) may be drivers of health. We offer a few potential mechanisms regarding context, composition, and their reciprocal relationships, that may be behind our observed patterns.

Karas Montez et al argue that state policies, a contextual factor, contribute to decreasing life-expectancy and increasing between state differences in life expectancy from 1970-2014, and in particular that states that implemented more conservative policies were more likely to experience declining LE (Montez et al., 2020). While more progressive states have enacted social policies that benefit life expectancy, such as expanding Medicaid (Miller et al., 2019), or increasing the minimum wage [Van Dyke, 2018 #4227], more conservative states have deregulated industry(Montez et al., 2020), enacted policies limiting union power[Eisenberg-Guyor, 2020 #4228], and preempted (prohibited) local government from enacting health-promoting legislation such as paid sick leave, state minimum wage laws (Wolf et al., 2021), all of which benefit health, and likely help explain state level disparities in mortality. States enacting more conservative policies are overwhelmingly located in the South and Midwest. For example, all of the states that have not yet expanded Medicaid are located in the South and Midwest (Kaiser Family Foundation (KFF), 2021).

The Midwest experienced limited variation between MSAs, which may be explained by high rates of preemption of city-level policies, limiting between city variation. More generally, these policies, when enacted (or preempted from being enacted) at the local- level, likely help explain between MSA disparities. For example, we found wider life expectancy gaps at low income levels, similar to the findings of Chetty et al(Chetty et al., 2016). Chetty examined associations between life expectancy for the bottom income quartile and various factors, and found the strongest associations between local fraction of immigrants, median home values, population density, fraction of college graduates, and local government expenditures (Chetty et al., 2016), pointing to both contextual and compositional factors as potential predictors of heterogeneity in life expectancy among low-income populations. Local expenditures per capita is one measure of policy investment, but further research is needed specifically examining impacts of local-level policy on life expectancy levels and disparities, in particular impacts of policies targeting low-income populations. Other contextual factors such as aspects of the local environment, for example exposure to pollutants [Di, 2017 #4231] or levels of violent crime [Redelings, 2010 #4229; Sharkey, 2019 #4230] may play an additional role in producing LE variation.

Compositional differences may also explain LE differences within and between cities and regions. Differences in populations with various sociodemographic, behavioral, and social factors by census tract, and between cities may impact life expectancy and disparities in life expectancy [Chetty, 2016 #3944]. For example, there is a dose response relationship between education and life expectancy [Rostron, 2010 #4232], so area with higher proportions of individuals with advanced education may experience longer lives. Boing et al have found that greatest amount of variation in census tract life expectancy is explained by census tract-level income and education (nearly 80% of model explained variation). They also found significant associations between % Black and % single parents and lower life expectancy(Boing et al., 2020). While associations between % Black and life expectancy are compositional in nature, they are reflections of systemic racism [Bailey, 2017 #3876], a contextual factor.

And finally, the reciprocal relationship between context and composition, in which context shapes composition, and composition shapes context, likely helps explains our findings (Cummins et al., 2007). For example, economic decline and changing economic opportunities may create the context for both changing composition (declining middle class) and changing behaviors (greater substance dependence), which both may impact life expectancy(Case and Deaton, 2015). Deaths of despair, which disproportionately impact midlife adults and therefore greatly impact life expectancy, have been found to be higher in areas of higher economic insecurity[Knapp, 2019 #4224]. In highly educated areas residents may push for policies to further invest in education, which may further elevate educational levels in the area.

Limitations

We leverage a newly available detailed census tract-level dataset to explore local-level variation in life expectancy between 2010-2015. The methodology employed by the NCHS improves upon prior approaches to calculating life tables, namely challenges due to small population sizes and missing age-specific death counts. However, because of lack of census population counts during the 2010-2015 period, the methodology uses population estimates from census-tract level ACS data, which introduce additional error into the life table estimates(Arias et al., 2018). Moreover, as with other model-based small area estimates [[Zhang, 2015 #4225], we lack the ability to estimate the impact of policies on census tract life expectancy. Measures of disparities can differ substantially in magnitude, direction, and rate of change, producing drastically different insights about whether and how a disparity has changed over time (Harper et al., 2010; Harper and Lynch, 2005). However, we found consistent patterns of disparities across measures. Our dataset only allowed a single life expectancy estimate, aggregated across a five-year period, so we could not measure changes in disparities. Our analysis uses only one city definition (core based statistical areas, specifically metropolitan statistical areas). There are numerous alternative definitions and measures of cities(Diez Roux, 2021), including census designated places, commuting zones, combined statistical areas, or even just counties. These definitions have implications, as they may include or exclude suburbs and exurbs. Given geographic differences in contextual (e.g. access to care (Schnake-Mahl and Sommers, 2017)) and compositional factors (e.g. racial/ethnic demographics and income levels (Parker et al., 2018)) between suburban and urban areas, life expectancy disparities likely differ by city definition.

Conclusion

In this study of census-tract level life expectancy estimates within and across cities, we found wide variation in the magnitude of disparities in life expectancy, both absolute and income-related. Cities in the South and Midwest had the largest disparities, mostly driven by large differences between cities in life expectancy in low-income areas. Differences in local context and composition, and their reciprocal relationships, may be behind these disparities. Further political and economic investment in social policies at the local level may help to reduce inequities in life expectancy.

**Acknowledgements**

USALEEP?

**Author contributions**

UB conceived this study. RL supported data compilation and cleaning efforts and created the interactive dashboard. ASM and UB conducted the statistical analyses. ASM drafted the first version of the manuscript with support from UB and PHM. All authors participated in the interpretation of results and approved the final version of the manuscript.

**Conflicts of interest:** None declared.

**Funding:** This study was supported by the Office of the Director of the National Institutes of Health under award number DP5OD26429, and by a Pilot Award from the Urban Health Collaborative. The funding agencies had no involvement in the study design; in the data collection, analyses or interpretation of data; in the writing of this work; or in the decision to submit the manuscript for publication.

**References**

Arias, E., Escobedo, L.A., Kennedy, J., Fu, C., Cisewski, J.A., 2018. US small-area life expectancy estimates project: methodology and results summary.

Arias, E., Tejada-Vera, B., Ahmad, F., Kochanek, K.D., 2021. Provisional Life Expectancy Estimates for 2020, in: Stystem, N.V.S. (Ed.), Vital Statistics Rapid Release. U.S. Department of Health and Human Services , Centers for Disease Control and Prevention, National Center for Health Statistic.

Bilal, U., Diez-Roux, A.V., 2018. Troubling trends in health disparities. New England Journal of Medicine 378, 1557-1558.

Boing, A.F., Boing, A.C., Cordes, J., Kim, R., Subramanian, S., 2020. Quantifying and explaining variation in life expectancy at census tract, county, and state levels in the United States. Proceedings of the National Academy of Sciences 117, 17688-17694.

Boscoe, F.P., 2015. Persistent and extreme outliers in causes of death by state, 1999–2013. PeerJ 3, e1336.

Bosworth, B., 2018. Increasing disparities in mortality by socioeconomic status. Annu Rev Public Health 39, 237-251.

Braveman, P., Egerter, S., 2013. Overcoming obstacles to health in 2013 and beyond. Robert Wood Johnson Foundation Commission to Build a Healthier America. Retrieved September 1, 2015.

Case, A., Deaton, A., 2015. Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. Proceedings of the National Academy of Sciences 112, 15078-15083.

Chetty, R., et al., 2016. The association between income and life expectancy in the United States, 2001-2014. JAMA 315, 1750-1766.

Cummins, S., Curtis, S., Diez-Roux, A.V., Macintyre, S., 2007. Understanding and representing ‘place’in health research: a relational approach. Social Science & Medicine 65, 1825-1838.

Diez Roux, A.V., 2021. What is Urban Health? Defining the Geographic and Substantive Scope, in: Lovasi, G.S., Diez Roux, A.V., Kolker, J. (Eds.), Urban Public Health. Oxford University Press, New York.

Diez Roux, A.V., Mair, C., 2010. Neighborhoods and health. Annals of the New York Academy of Sciences 1186, 125-145.

Dockery, D.W., et al., 1993. An association between air pollution and mortality in six US cities. New England Journal of Medicine 329, 1753-1759.

Ezzati, M., Friedman, A.B., Kulkarni, S.C., Murray, C.J., 2008. The reversal of fortunes: trends in county mortality and cross-county mortality disparities in the United States. PLoS Med 5, e66.

Harper, S., et al., 2010. Implicit value judgments in the measurement of health inequalities. The Milbank Quarterly 88, 4-29.

Harper, S., Lynch, J., 2005. Methods for measuring cancer disparities: using data relevant to healthy people 2010 cancer-related objectives.

Harper, S., MacLehose, R.F., Kaufman, J.S., 2014. Trends in the black-white life expectancy gap among US states, 1990–2009. Health affairs 33, 1375-1382.

Kaiser Family Foundation (KFF), 2021. Status of state medicaid expansion decisions. Kaiser Family Foundation.

Kim, D., 2016. The associations between US state and local social spending, income inequality, and individual all-cause and cause-specific mortality: the National Longitudinal Mortality Study. Prev Med 84, 62-68.

Kim, R., Subramanian, S., 2016. What's wrong with understanding variation using a single-geographic scale? A multilevel geographic assessment of life expectancy in the United States. Procedia Environmental Sciences 36, 4-11.

Kochanek, K.D., Murphy, S., Xu, J., Arias, E., 2017. Mortality in the United States, 2016. NCHS Data Brief, 1-8.

Kulkarni, S.C., Levin-Rector, A., Ezzati, M., Murray, C.J., 2011. Falling behind: life expectancy in US counties from 2000 to 2007 in an international context. Popul Health Metr 9, 16.

Miller, S., Johnson, N., Wherry, L.R., 2019. Medicaid and mortality: new evidence from linked survey and administrative data. National Bureau of Economic Research.

Montez, J.K., et al., 2020. US state policies, politics, and life expectancy. The Milbank Quarterly 98, 668-699.

Parker, K., et al., 2018. What unites and divides urban, suburban and rural communities. Pew Research Center.

Schnake-Mahl, A.S., Sommers, B.D., 2017. Health Care In The Suburbs: An Analysis Of Suburban Poverty And Health Care Access. Health affairs 36, 1777-1785.

Tavernise, S., Sun, A., 2015. Same city, but very different life spans. New York Times.

Wei, R., Anderson, R.N., Curtin, L.R., Arias, E., 2008. US decennial life tables for 1999–2001, State Life Tables.

Wolf, D.A., Monnat, S.M., Montez, J.K., 2021. Effects of US state preemption laws on infant mortality. Prev Med 145, 106417.

Woolf, S.H., Braveman, P., 2011. Where health disparities begin: the role of social and economic determinants—and why current policies may make matters worse. Health affairs 30, 1852-1859.

Woolf, S.H., Masters, R.K., Aron, L.Y., 2021. Effect of the covid-19 pandemic in 2020 on life expectancy across populations in the USA and other high income countries: simulations of provisional mortality data. BMJ 373, n1343.

1. Kochanek KD, Murphy S, Xu J, et al. Mortality in the United States, 2016. *NCHS Data Brief* 2017(293):1-8.

2. Bilal U, Diez-Roux AV. Troubling trends in health disparities. *New England Journal of Medicine* 2018;378(16):1557-1558.

3. Harper S, MacLehose RF, Kaufman JS. Trends in the black-white life expectancy gap among US states, 1990–2009. *Health affairs* 2014;33(8):1375-1382.

4. Bosworth B. Increasing disparities in mortality by socioeconomic status. *Annual review of public health* 2018;39:237-251.

5. Kim D. The associations between US state and local social spending, income inequality, and individual all-cause and cause-specific mortality: the National Longitudinal Mortality Study. *Preventive medicine* 2016;84:62-68.

6. Wei R, Anderson RN, Curtin LR, et al. US decennial life tables for 1999–2001, State Life Tables. 2008.

7. Boscoe FP. Persistent and extreme outliers in causes of death by state, 1999–2013. *PeerJ* 2015;3:e1336.

8. Kulkarni SC, Levin-Rector A, Ezzati M, et al. Falling behind: life expectancy in US counties from 2000 to 2007 in an international context. *Population health metrics* 2011;9(1):16.

9. Ezzati M, Friedman AB, Kulkarni SC, et al. The reversal of fortunes: trends in county mortality and cross-county mortality disparities in the United States. *PLoS Med* 2008;5(4):e66.

10. Montez JK, Beckfield J, Cooney JK, et al. US state policies, politics, and life expectancy. *The Milbank Quarterly* 2020;98(3):668-699.

11. Woolf SH, Braveman P. Where health disparities begin: the role of social and economic determinants—and why current policies may make matters worse. *Health affairs* 2011;30(10):1852-1859.

12. Woolf SH, Masters RK, Aron LY. Effect of the covid-19 pandemic in 2020 on life expectancy across populations in the USA and other high income countries: simulations of provisional mortality data. *Bmj* 2021;373:n1343.

13. Arias E, Tejada-Vera B, Ahmad F, et al. Provisional Life Expectancy Estimates for 2020. In: Stystem NVS, ed. *Vital Statistics Rapid Release*: U.S. Department of Health and Human Services , Centers for Disease Control and Prevention, National Center for Health Statistic, 2021.

14. Braveman P, Egerter S. Overcoming obstacles to health in 2013 and beyond. Robert Wood Johnson Foundation Commission to Build a Healthier America. *Retrieved September* 2013;1:2015.

15. Diez Roux AV, Mair C. Neighborhoods and health. *Annals of the New York Academy of Sciences* 2010;1186:125-145.

16. Kim R, Subramanian S. What's wrong with understanding variation using a single-geographic scale? A multilevel geographic assessment of life expectancy in the United States. *Procedia Environmental Sciences* 2016;36:4-11.

17. Boing AF, Boing AC, Cordes J, et al. Quantifying and explaining variation in life expectancy at census tract, county, and state levels in the United States. *Proceedings of the National Academy of Sciences* 2020;117(30):17688-17694.

18. Chetty R, Stepner M, Abraham S, et al. The association between income and life expectancy in the United States, 2001-2014. *Jama* 2016;315(16):1750-1766.

19. Tavernise S, Sun A. Same city, but very different life spans. *New York Times* 2015.

20. Arias E, Escobedo LA, Kennedy J, et al. US small-area life expectancy estimates project: methodology and results summary. 2018.

21. Harper S, King NB, Meersman SC, et al. Implicit value judgments in the measurement of health inequalities. *The Milbank Quarterly* 2010;88(1):4-29.

22. Cummins S, Curtis S, Diez-Roux AV, et al. Understanding and representing ‘place’in health research: a relational approach. *Social science & medicine* 2007;65(9):1825-1838.

23. Miller S, Johnson N, Wherry LR. Medicaid and mortality: new evidence from linked survey and administrative data. National Bureau of Economic Research, 2019.

24. Wolf DA, Monnat SM, Montez JK. Effects of US state preemption laws on infant mortality. *Preventive Medicine* 2021;145:106417.

25. Kaiser Family Foundation (KFF). Status of state medicaid expansion decisions. Kaiser Family Foundation, 2021.

26. Dockery DW, Pope CA, Xu X, et al. An association between air pollution and mortality in six US cities. *New England journal of medicine* 1993;329(24):1753-1759.

27. Case A, Deaton A. Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. *Proceedings of the National Academy of Sciences* 2015;112(49):15078-15083.

28. Harper S, Lynch J. Methods for measuring cancer disparities: using data relevant to healthy people 2010 cancer-related objectives. 2005.

29. Diez Roux AV. What is Urban Health? Defining the Geographic and Substantive Scope. In: Lovasi GS, Diez Roux AV, Kolker J, eds. *Urban Public Health*. New York: Oxford University Press, 2021.

30. Schnake-Mahl AS, Sommers BD. Health Care In The Suburbs: An Analysis Of Suburban Poverty And Health Care Access. *Health Affairs* 2017;36(10):1777-1785.

31. Parker K, Horowitz JM, Brown A, et al. What unites and divides urban, suburban and rural communities. *Pew Research Center* 2018.

**Table 1: Absolute and Relative in life expectancy in US MSAs >1 million people**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Absolute Disparity** | | | | **Relative Disparity** | | | |
| **Name** | **Region** | **Rank** | **Abs Dif** | **Name** | **Region** | **Rank** | **Rel Dif** |
| Louisville/Jefferson County, KY-IN | South | 1 | 10.7 | Memphis, TN-MS-AR | South | 1 | 1.15 |
| Memphis, TN-MS-AR | South | 2 | 10.7 | Louisville/Jefferson County, KY-IN | South | 2 | 1.15 |
| Detroit-Warren-Dearborn, MI | Midwest | 3 | 10.7 | Detroit-Warren-Dearborn, MI | Midwest | 3 | 1.15 |
| Baltimore-Columbia-Towson, MD | South | 4 | 10.3 | Birmingham-Hoover, AL | South | 4 | 1.15 |
| Birmingham-Hoover, AL | South | 5 | 10.3 | Baltimore-Columbia-Towson, MD | South | 5 | 1.14 |
| Cincinnati, OH-KY-IN | Midwest | 6 | 10.2 | Cincinnati, OH-KY-IN | Midwest | 6 | 1.14 |
| Cleveland-Elyria, OH | Midwest | 7 | 10 | Cleveland-Elyria, OH | Midwest | 7 | 1.14 |
| Nashville-Davidson—Murfreesboro—Franklin, TN | South | 8 | 10 | Nashville-Davidson—Murfreesboro—Franklin, TN | South | 8 | 1.14 |
| Indianapolis-Carmel-Anderson, IN | Midwest | 9 | 9.9 | Indianapolis-Carmel-Anderson, IN | Midwest | 9 | 1.14 |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | Northeast | 10 | 9.9 | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | Northeast | 10 | 1.14 |
| Miami-Fort Lauderdale-West Palm Beach, FL | South | 11 | 9.7 | Columbus, OH | Midwest | 11 | 1.13 |
| Columbus, OH | Midwest | 12 | 9.7 | Jacksonville, FL | South | 12 | 1.13 |
| Jacksonville, FL | South | 13 | 9.5 | St. Louis, MO-IL | Midwest | 13 | 1.13 |
| St. Louis, MO-IL | Midwest | 14 | 9.5 | Miami-Fort Lauderdale-West Palm Beach, FL | South | 14 | 1.13 |
| Richmond, VA | South | 15 | 9.4 | Richmond, VA | South | 15 | 1.13 |
| Charlotte-Concord-Gastonia, NC-SC | South | 16 | 9.2 | Oklahoma City, OK | South | 16 | 1.13 |
| Kansas City, MO-KS | Midwest | 17 | 9.2 | New Orleans-Metairie, LA | South | 17 | 1.13 |
| Oklahoma City, OK | South | 18 | 9.2 | Charlotte-Concord-Gastonia, NC-SC | South | 18 | 1.13 |
| Rochester, NY | Northeast | 19 | 9.2 | Kansas City, MO-KS | Midwest | 19 | 1.13 |
| New Orleans-Metairie, LA | South | 20 | 9.1 | Buffalo-Cheektowaga-Niagara Falls, NY | Northeast | 20 | 1.12 |
| Buffalo-Cheektowaga-Niagara Falls, NY | Northeast | 21 | 9 | Rochester, NY | Northeast | 21 | 1.12 |
| Tampa-St. Petersburg-Clearwater, FL | South | 22 | 8.8 | Tampa-St. Petersburg-Clearwater, FL | South | 22 | 1.12 |
| San Francisco-Oakland-Hayward, CA | West | 23 | 8.7 | Virginia Beach-Norfolk-Newport News, VA-NC | South | 23 | 1.12 |
| New York-Newark-Jersey City, NY-NJ-PA | Northeast | 24 | 8.7 | Pittsburgh, PA | Northeast | 24 | 1.12 |
| Virginia Beach-Norfolk-Newport News, VA-NC | South | 25 | 8.6 | New York-Newark-Jersey City, NY-NJ-PA | Northeast | 25 | 1.11 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | South | 26 | 8.6 | San Francisco-Oakland-Hayward, CA | West | 26 | 1.11 |
| Pittsburgh, PA | Northeast | 27 | 8.5 | Atlanta-Sandy Springs-Roswell, GA | South | 27 | 1.11 |
| Denver-Aurora-Lakewood, CO | West | 28 | 8.4 | Washington-Arlington-Alexandria, DC-VA-MD-WV | South | 28 | 1.11 |
| Seattle-Tacoma-Bellevue, WA | West | 29 | 8.3 | Denver-Aurora-Lakewood, CO | West | 29 | 1.11 |
| Atlanta-Sandy Springs-Roswell, GA | South | 30 | 8.3 | Orlando-Kissimmee-Sanford, FL | South | 30 | 1.11 |
| Orlando-Kissimmee-Sanford, FL | South | 31 | 8.2 | Seattle-Tacoma-Bellevue, WA | West | 31 | 1.11 |
| Sacramento—Roseville—Arden-Arcade, CA | West | 32 | 8.1 | Sacramento—Roseville—Arden-Arcade, CA | West | 32 | 1.11 |
| Los Angeles-Long Beach-Anaheim, CA | West | 33 | 8 | Riverside-San Bernardino-Ontario, CA | West | 33 | 1.11 |
| Riverside-San Bernardino-Ontario, CA | West | 34 | 8 | Houston-The Woodlands-Sugar Land, TX | South | 34 | 1.11 |
| Houston-The Woodlands-Sugar Land, TX | South | 35 | 7.9 | Los Angeles-Long Beach-Anaheim, CA | West | 35 | 1.1 |
| Raleigh, NC | South | 36 | 7.7 | Las Vegas-Henderson-Paradise, NV | West | 36 | 1.1 |
| Las Vegas-Henderson-Paradise, NV | West | 37 | 7.6 | San Antonio-New Braunfels, TX | South | 37 | 1.1 |
| San Antonio-New Braunfels, TX | South | 38 | 7.6 | Raleigh, NC | South | 38 | 1.1 |
| Boston-Cambridge-Newton, MA-NH | Northeast | 39 | 7.5 | Dallas-Fort Worth-Arlington, TX | South | 39 | 1.1 |
| Dallas-Fort Worth-Arlington, TX | South | 40 | 7.4 | Salt Lake City, UT | West | 40 | 1.1 |
| Hartford-West Hartford-East Hartford, CT | Northeast | 41 | 7.4 | Hartford-West Hartford-East Hartford, CT | Northeast | 41 | 1.1 |
| Salt Lake City, UT | West | 42 | 7.4 | Boston-Cambridge-Newton, MA-NH | Northeast | 42 | 1.1 |
| Phoenix-Mesa-Scottsdale, AZ | West | 43 | 7.3 | Phoenix-Mesa-Scottsdale, AZ | West | 43 | 1.1 |
| San Diego-Carlsbad, CA | West | 44 | 7.3 | Austin-Round Rock, TX | South | 44 | 1.09 |
| Austin-Round Rock, TX | South | 45 | 7.2 | San Diego-Carlsbad, CA | West | 45 | 1.09 |
| Providence-Warwick, RI-MA | Northeast | 46 | 7.1 | Providence-Warwick, RI-MA | Northeast | 46 | 1.09 |
| Portland-Vancouver-Hillsboro, OR-WA | West | 47 | 6.8 | Portland-Vancouver-Hillsboro, OR-WA | West | 47 | 1.09 |
| San Jose-Sunnyvale-Santa Clara, CA | West | 48 | 6.6 | San Jose-Sunnyvale-Santa Clara, CA | West | 48 | 1.08 |

Footnote**:** Absolute disparity was calculated as the difference between the 90th and 10th population-weighted percentiles of life expectancy for each city. Relative disparity was calculated as the ratio between the 90th and 10th population-weighted percentiles of life expectancy for each city.

**Table 2: Association between MSA Population and Median Household Income and Life Expectancy Disparities**

|  |  |  |  |
| --- | --- | --- | --- |
| **Predictor** | **Model 1**  **Beta (95% CI)** | **Model 2**  **Beta (95% CI)** | **Model 3**  **Beta (95% CI)** |
| Population Sizea | 0.26(0.11, 0.40) | - | 0.29(0.13, 0.46) |
| Median Household Incomea | - | 0.21(-0.75, 1.16) | -0.60(-1.6, 0.44) |

**Footnote: a**Log of population and Median Household Income. Coefficients are interpreted as xx…

**Figure 1: Total and Income-Based Life Expectancy Inequality Indicators in US MSAs.**

Diagram

Description automatically generated with medium confidenceCoefficient of Variation: Absolute disparities: Midwest (16.9), South (18.51), Northeast (18.28), West (18.5); Relative Disparity: Midwest (1.95), South (1.93), Northeast (1.82), West (1.79);\* Note: point size is proportional to MSA population.

**Figure 2: Spatial distribution of absolute disparity in life expectancy by MSA in the US.**

Map

Description automatically generated

Footnote: Rank indicates the widest (1) to narrowest (499) disparities.

**Figure 3: Life expectancy by median household income decile for each US MSA > 1million people by region**



**Appendix**

**Appendix Table 1 Disparity Measures: Type, name, and calculation**

|  |  |  |
| --- | --- | --- |
| **Measure Type** | **Measure Name** | **Calculation** |
| Absolute Disparities | Absolute/Relative Ratios differences | Difference/Ratio between 90th and 10th population-weighted percentiles of life expectancy for each city |
| Coefficient of variation (CV) | Standard deviation of life expectancy/mean, all weighted population |
| Gini Coefficient | Calculated using the reldist package in R[Handcock, 2016 #4218] |
| Mean log deviation | Calculated using the dineq package in R [Schulenberg, 2018 #4217] |
| Income-related Disparities | Top-bottom gaps/ratios | Differences/ratios between the population-weighted average life expectancy in census tracts in the top and bottom deciles of income |
| Slope index of inequality | For each city run separate linear model with life expectancy at the census tract level as the outcome, and income decile as a continuous (ordinal) variable. SII is the regression coefficient for each income decile and represents the average change in life expectancy per 1-decile increase in income. |
| Relative index of inequality (RII) | Divided the SII over the average LE at the city level. |

**Appendix Figure 2: Spatial distribution of absolute disparity in life expectancy by MSA in the US.**

**Map

Description automatically generated**

**Appendix Figure 2: Correlation between life expectancy disparity indicators**

Diagram

Description automatically generated

Footnote: \*\*\* (p<0.001)