

Supplementary Notes

Variable Definitions and Meaning

Measures of neighborhood effects were taken from a diverse range of datasets. The sources and definitions of these variables are detailed below.

Ten variables were taken from the 2015-2019 American Community Survey (ACS) 5-year estimate data ¹. *No Plumbing* is the "The percentage of all ACS housing units that do not have complete plumbing facilities." *Children in Poverty* is the "The percentage of children under age 18 living in households that are below the poverty line in the ACS." *No Computing Device* is the "Percentage of people that live in households that do not have computing device of any kind in the ACS." *No Internet* is the "Percentage of ACS households that have no Internet access." *Public Assistance* is the "The percentage of all ACS occupied housing units that receive public assistance income (general assistance and Temporary Assistance to Needy Families)." *Crowded Housing* is the "The percentage of ACS occupied housing units that have more than 1.01 persons per room." *No Health Insurance* refers to "The percentage of the ACS population that have no health insurance, public or private." *Single Female Head of Household* is the "The percentage of all ACS occupied housing units with a female householder and no spouse of householder present." *Unemployment* refers to "The percentage of ACS civilians ages 16 years and over in the labor force that are unemployed." *Disability* is the "The percentage of the ACS population who have one or more disabilities."

A number of variables were also taken from the Opportunity Atlas ³⁰. *Teenage Birth Rate* represents "Fraction of women who grew up in this area who claimed ever a child who was born when the women were between the ages of 13 and 19 as a dependent when filing taxes." *Incarceration Rate* represents "Fraction of children who grew up in this area who were in prison or jail on April 1, 2010." *Will Not make top 20 Percent of Earners* is 1 minus "Fraction of children who grew up in this area who have average individual income in 2014-15 (in their mid-30s) in the top 20 percent of the national income distribution for children born in the same year."

Health outcomes data was taken from the US Centers for Disease Control PLACES Project ³, which provides small area estimates for 27 chronic disease rates, health behaviors, and chronic conditions. The estimates are calculated using a multilevel regression and poststratification framework. These estimates have been independently validated ⁴.

Tooth Loss represents biennial prevalence of "Respondents aged ≥ 65 years who report having lost all of their natural teeth because of tooth decay or gum disease." divided by total "Respondents aged ≥ 65 years." *Currently Smoking* represents annual prevalence of "Respondents aged ≥ 18 years who report having smoked ≥ 100 cigarettes in their lifetime and currently smoke every day or some days" divided by "Respondents aged ≥ 18 years who reported information about cigarette smoking." *Poor Mental Health* represents annual prevalence of "Respondents aged ≥ 18 years who report 14 or more days during the past 30 days during which their mental health was not good" divided by "Respondents aged ≥ 18 years who report or do not report the number of days during the past 30 days during which their mental health was not good." *Obesity* represents the annual prevalence of "Respondents aged ≥ 18 years who have a body mass index (BMI) ≥ 30.0 kg/m² calculated from self-reported weight and height." divided by "Respondents aged ≥ 18 years for whom BMI can be calculated from their self-reported weight and height." This excluded the following: "data from respondents with heights less than 3 ft or ≥ 8 ft, data from respondents weighing less than 50 lbs or ≥ 650 lbs, data from respondents with BMI less than 12 kg/m² ≥ 100 kg/m², and pregnant women."

Linear Fits, Urban Definitions and Visualization

Supplementary Figures 1 to 7 and 10 to 18 show linear fits characterizing the variation of (components) of HDI with population and various population rates commonly used to express social disadvantage. Linear fits were performed in python using package *curvefit* from *scipy.optimize*.

Metropolitan and micropolitan population is the sum total of the population reported by the American Community Survey for each tract within a US Census defined Metropolitan or Micropolitan Statistical Area. These are functional definitions that define cities in terms of unified labor markets, meaning that they include in the same spatial unit both places of work and places of residence, determined based on measured commuting flows. In practice, this includes in the same urban definition central urban cores and suburbs and typically several political units such as "cities," townships and counties.

Though the term "metropolitan" is often used to refer to all these urban areas, in Supplementary Figures 3 to 7 we use it in its more specific meaning, to refer to urban areas so defined with populations above 50,000. Micropolitan Statistical Areas, or simply Micropolitan Areas refer to smaller functional cities with populations between about 10,000 and 50,000 people. The largest metropolitan area in the US is New York City with just over 20 million people. There are 381 metropolitan areas in our data set and 536 micropolitan areas, making up a total of 917 in total in the continental US and Alaska and Hawaii.

In statistical studies at the tract level, non-urban (micro or metropolitan) census tracts are also included, as shown in the map found at <https://communityhdi.org>. Linear fits are done in a similar way using the value of social indicators as the dependent variable and of the HDI as the independent variable, with data as census tracts. This procedure can be repeated at any scale, such as individual metropolitan areas, states, or political cities. Supplementary Tables 2 and 3 summarize the linear

best fits for the dependence of social disadvantage rates, computed as the population weighted community HDI in each tract in the urban area, versus total population.

Beta Distribution Estimation

To characterize the statistical non-linear dependence of various social disadvantage rate on the community HDI, we modeled these rates as stochastic variables following a Beta distribution. The Beta distribution is the most standard statistical model for variables that describe a continuous probability for an event, such as the probability of teenage pregnancy or incarceration for someone in a given community. In this sense, the Beta distribution for social disadvantage rates conditional of HDI also provides the Bayesian conjugate to many generative processes that can be used to generate event data, including binomial, negative binomial and geometric distributions.

To model the dependence of the two parameters of the Beta distribution on HDI, we estimated the parameters of the distribution for census tracts divided into a number of bins, shown in Figure 3a-b and Supplementary Figures 20 to 28 and 31 by their centers as red dots. For each of these intervals (bins) of HDI, we then collect all corresponding tracts and estimate parameters of the Beta distribution, see Supplementary Figure 29. We verified that the Beta distribution is a general good description of the frequency distribution of tracts for many social disadvantage rates and other variables using (Fit_Beta_2P, Fit_Everything) from the python library *reliability* and a Bayesian Information Criterion test, see Supplementary Figure 29 for an illustration. Supplementary Tables 4 and 5 give the values for Beta Average and Beta standard deviation, which are equivalent to the two parameters of the distribution but easier to interpret. We then fit both average and distribution by linear and sigmoid functions to obtain an estimate of the continuous variation of the distribution parameters on HDI. These estimates are shown as both the blue solid lines (linear fit) and red and green sigmoid curves in Figure 3a-b and Supplementary Figures 20 to 28, as well as Supplementary Figure 31. We see in all cases that the sigmoid curves (which have an extra parameter) give a better fit than the linear model, see Supplementary Tables 4 and 5.

Principal Component Analysis

In addition to giving a statistical characterization of pairwise relationships between HDI and social disadvantage rates, we also performed a principal component analysis (PCA) of these associations taking the set of variables in Figure 3 together with HDI at the tract level as separate dimensions. This makes for 18 separate dimensions, including HDI. A total of 71,436 census tracts with all variables given across the nation was then used as points, with variance to be accounted for via PCA analysis.

Supplementary Figure 30 shows the relative variance explained by the first principal components, as is usually shown in PCA analysis. We see that the first and second components are by far the most influential, accounting for 54.5% and 8.7% of the total variance at the census tract level. Other dimensions explore various covariations of social disadvantage rates in the 16-dimensional orthogonal directions to the first component.

The first PCA dimension accounts for the linear inverse correlation between the HDI (first element of the vector) and all other components, see Supplementary Table 6, showing the near proportionality of decreases in HDI and of *all* other rates of social disadvantage, supporting the pairwise results shown in Figure 3. The second component is “orthogonal” to the first in a number of dimensions, with coefficients of both signs, see Supplementary Table 6.

This analysis therefore supports, in our view, the arguments of the main paper that communities with HDI approaching unity should see predictably small rates of social disadvantage along many distinct dimensions.

Effects of Race and Ethnicity

Many studies of neighborhood effects have provided evidence of the association of social disadvantage rates and racial and ethnic segregation at the community level, especially of Black populations in specific cities^{5,6}. We explored the general influence of race and ethnicity rates (population fraction) with values of the HDI, which we show in the paper is systematically negatively correlated with many dimensions of social disadvantage, Figure 3.

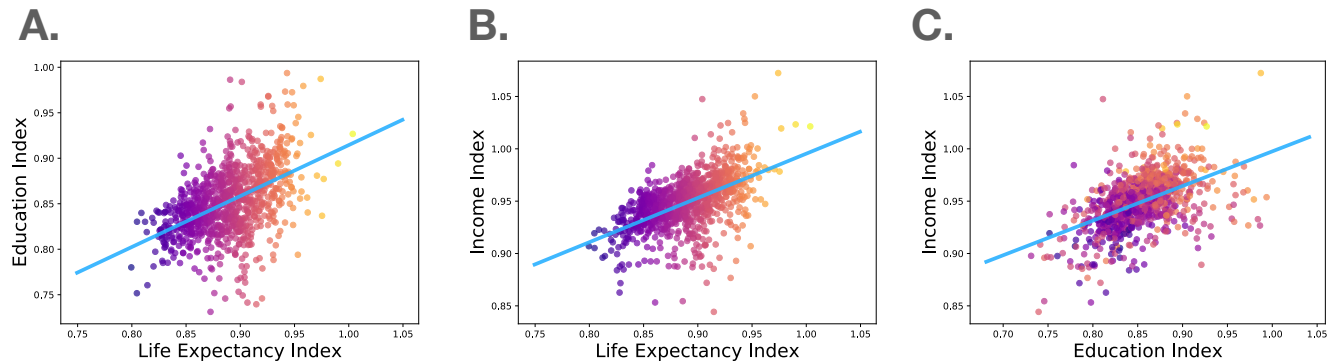
Specifically, Supplementary Figure 19 shows the correlation of the fraction of Black, and Hispanic population versus the value of the HDI at the metropolitan level. The correlation is very small (very low R^2), in effect because at low development there are cities with many different racial and ethnic makeups, some with very small Black or Hispanic populations and others with strong majorities, for example in the South and the border with Mexico, respectively.

The estimation of the correlation between the HDI and fraction Black or Hispanic at the community level (census tracts) reveals a similar pattern, with weak correlations ($R^2 = 0.143$ and 0.083 for Black and Hispanic respectively), see Supplementary Figure 31. Though there is some negative association at this level of minority concentration to HDI, especially for fraction of Black residents, the features of the statistics are as for Metropolitan areas, where low HDI tracts come in many different rates of race and ethnicity.

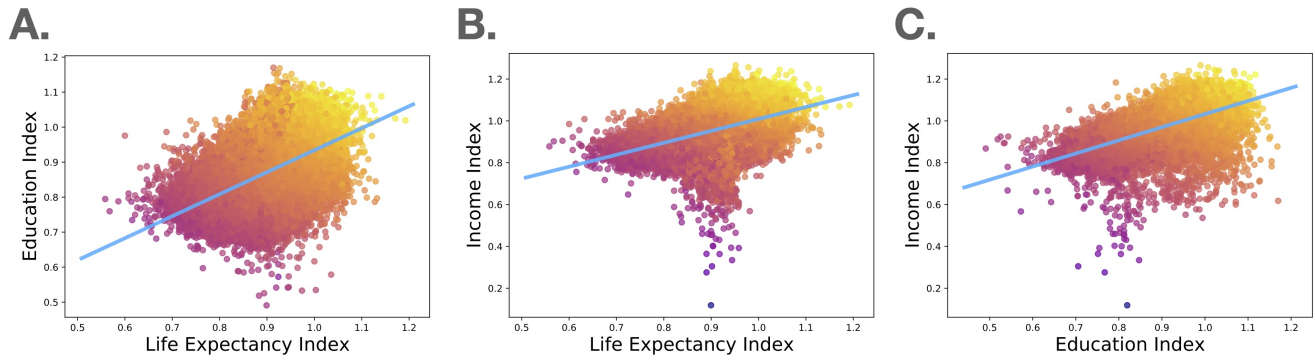
Within specific metropolitan areas (not shown) the correlation between these race and ethnicity variables at the tract level and the HDI is very context dependent. It is weak or insignificant in many urban areas such as New York City, but it is stronger in cities where racial segregation and associated poverty has been known to be stronger. Examples are Baltimore, Chicago or

Memphis for Black rates at the neighborhood level, and Los Angeles for Hispanic. Other variables accounting for the rates of foreign residents or English not spoken at home are even less correlated with HDI, and in some cases show in fact weak positive correlations.

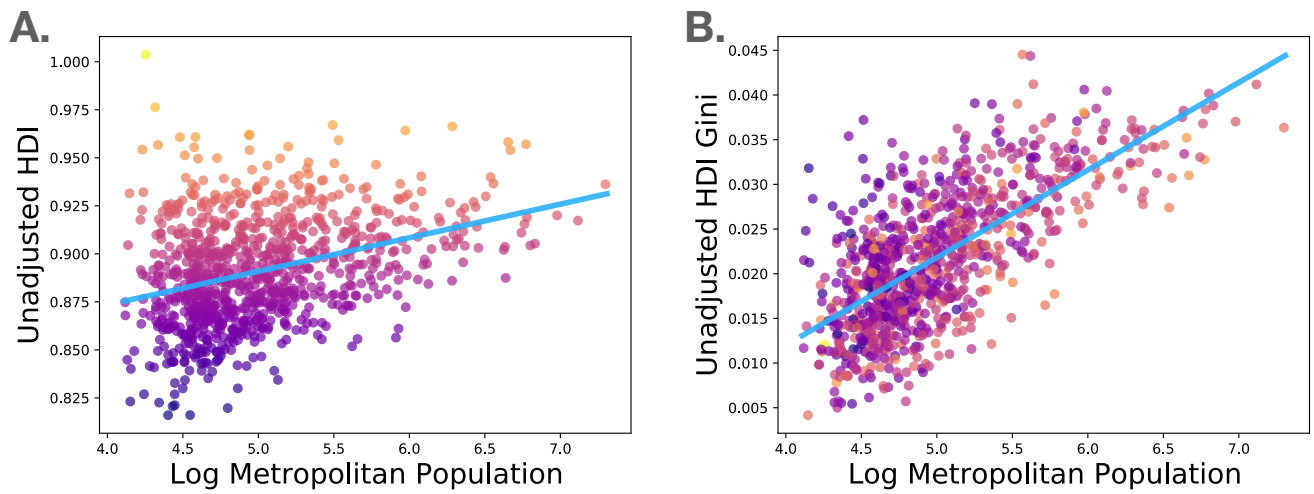
We conclude from this analysis that race and ethnicity variables are not significantly associated with changes in human development at the national level because low development situations are not *specific* to high rates of Black or Hispanic population in particular. Many places in the nation with very low development (for the US) have small or vanishing minority populations, such as Appalachia. At the same time, race and ethnicity can show strong associations with HDI in specific cities, many of which have been the focus of past studies and where race and poverty may be strongly segregated in small areas, the original motivation for the modern literature on neighborhood effects. A detailed analysis of these effects in the context of specific cities is therefore necessary and will be developed elsewhere.



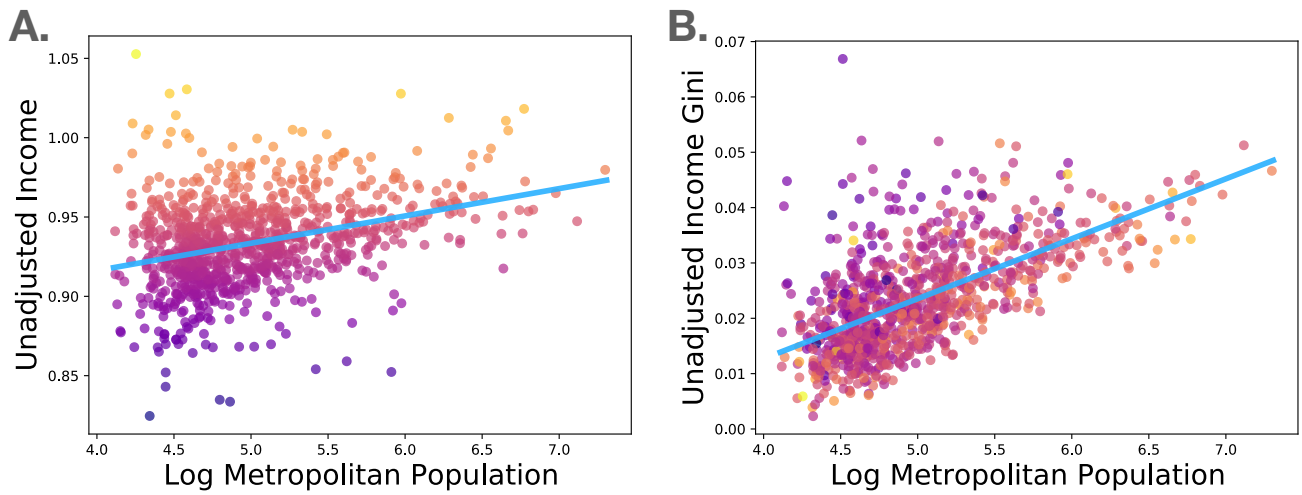
Supplementary Figure 1. Correlation of components of HDI for Metropolitan and Micropolitan Areas. Though the components of the Human Development Index (Education, Income, and Life Expectancy) are positively correlated with one another, there is a large degree of variance observed. A. Dependence of the Education Index (EI) on the Life Expectancy Index (LEI). The best fit line (blue) has intercept 0.354[0.293,0.414] and gradient 0.560[0.492,0.628] B. Dependence of the Income Index (II) on the Life Expectancy Index (LEI). The best fit line (blue) has intercept 0.572[0.533,0.611] and gradient 0.422[0.379,0.466] C. Dependence of the Income Index (II) on the Education Index (EI). The best fit line (blue) has intercept 0.666[0.633,0.699] and gradient 0.330[0.292,0.369]. Numbers in parentheses indicate the 95% confidence interval in the parameter estimates.



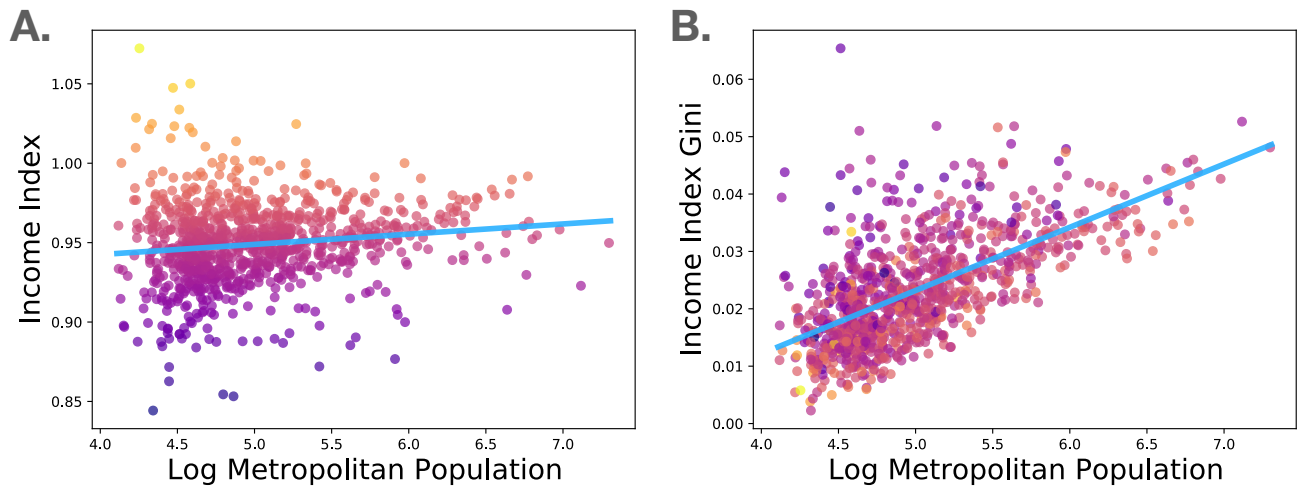
Supplementary Figure 2. Correlation of components of HDI at the census tract level. A higher degree of variance is observed between the quantities at the tract level than at larger geographies, such as metropolitan and micropolitan areas. This demonstrates the importance of working at the tract level, where measures are less correlated. A. Dependence of the Education Index (EI) on the Life Expectancy Index (LEI) for tracts. The best fit line (blue) has intercept 0.305 [0.298, 0.312] and gradient 0.628 [0.620, 0.636] B. Dependence of the Income Index (II) on the Life Expectancy Index (LEI) for tracts. The best fit line (blue) has intercept 0.438 [0.431, 0.445] and gradient 0.570 [0.562, 0.577] C. Dependence of the Income Index (II) on the Education Index (EI) for tracts. The best fit line (blue) has intercept 0.404 [0.400, 0.409] and gradient 0.627 [0.622, 0.632]. Numbers in parentheses indicate the 95% confidence interval in parameter estimates.



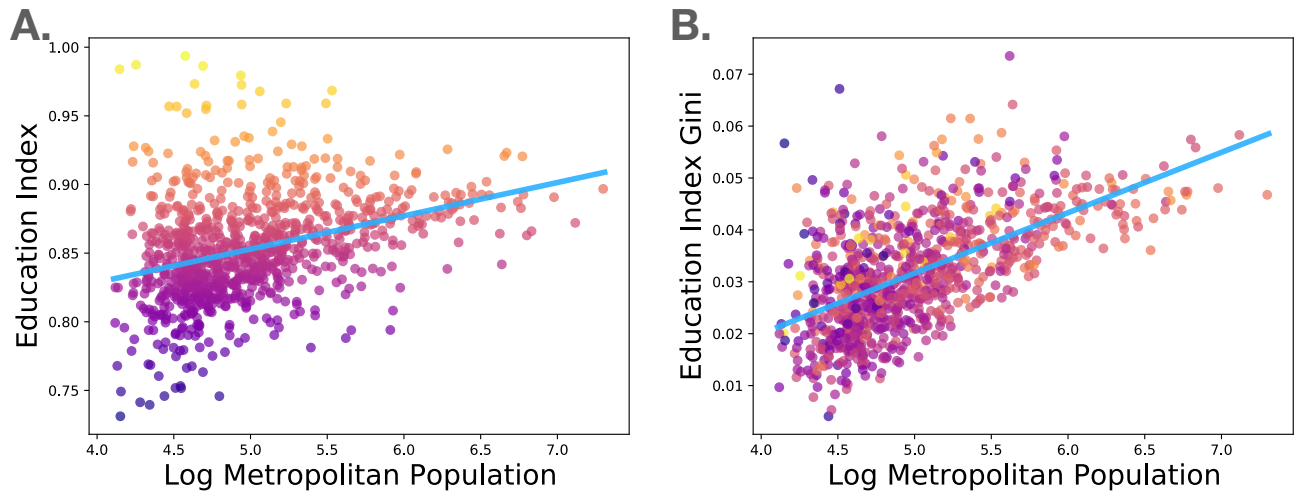
Supplementary Figure 3. The unadjusted HDI -computed using nominal income rather than with local purchasing power parity correction- for all metropolitan areas in the US. This includes so-called micropolitan areas and metropolitan areas. A. Average unadjusted HDI on city population size. The best fit line (blue) has intercept $0.803[0.787, 0.819]$ and gradient $0.017, [0.014, 0.021]$, $R^2 = 0.12$. B. The dependence of the unadjusted HDI Gini coefficient (inequality) on population size. The best fit line (blue) has intercept $-0.027, [-0.030, -0.024]$ and gradient $0.0097, [0.0091, 0.0105]$, $R^2 = 0.48$. Parenthesis indicate the 95% confidence interval in the estimates of both parameters.



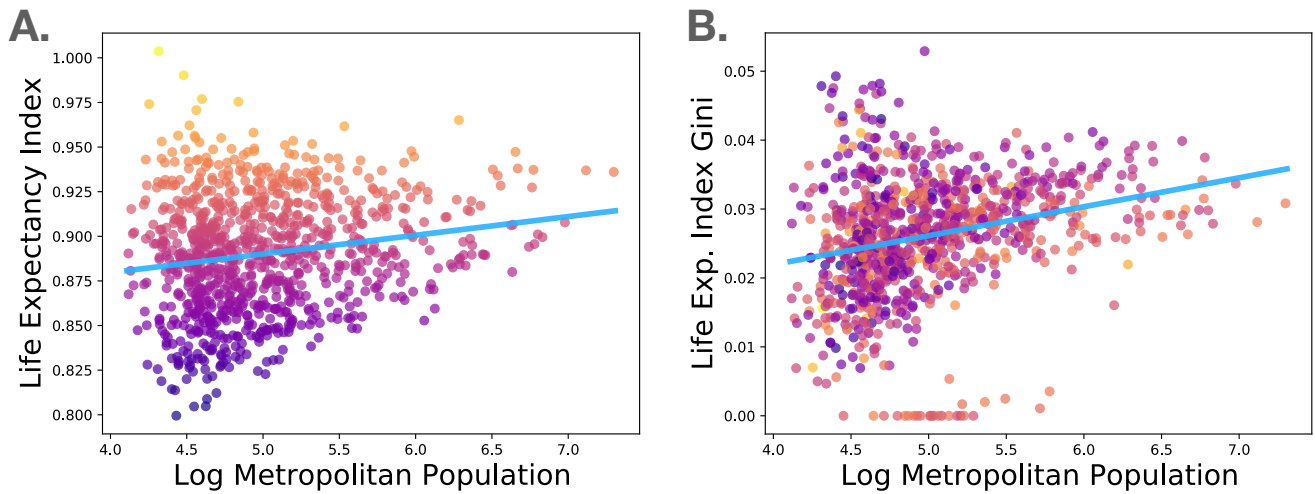
Supplementary Figure 4. The unadjusted income index -using nominal income rather than with local purchasing power parity correction- versus population for all metropolitan and micropolitan areas in the US. A. The average unadjusted income index on city population size. The best fit line (blue) has intercept 0.847, [0.831, 0.864] and gradient 0.017, [0.014, 0.020]. B. Scaling of unadjusted income index Gini coefficient with population size. The best fit line (blue) has intercept -0.031 , $[-0.035, -0.026]$ and gradient 0.0108, [0.0099, 0.0117]. Numbers in parentheses indicate the 95% confidence interval in the estimates of both parameters.



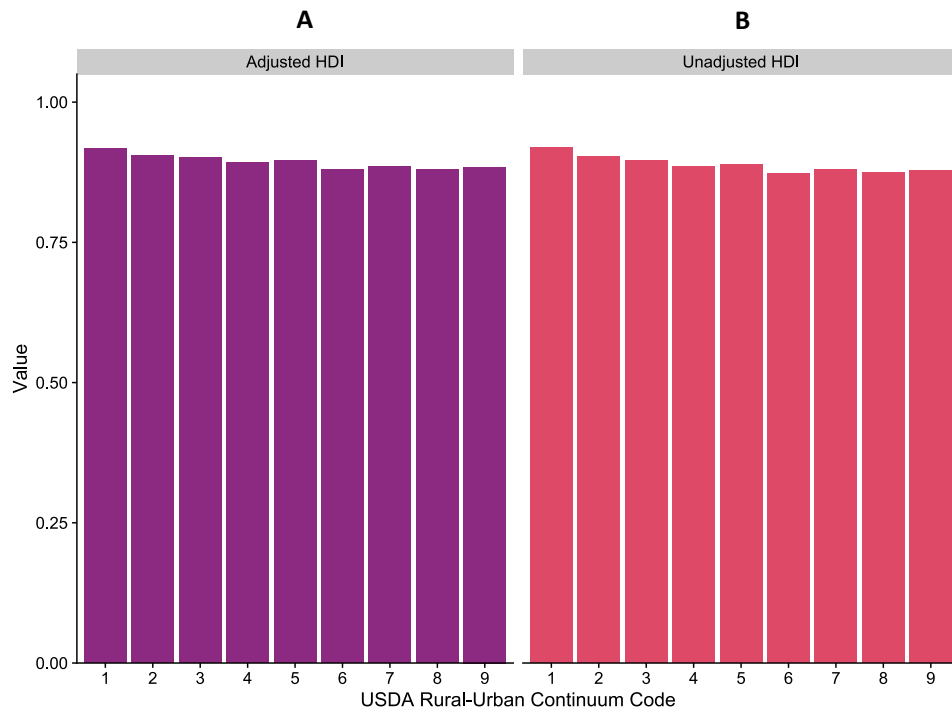
Supplementary Figure 5. The adjusted income index and its Gini coefficient versus population for metropolitan and micropolitan areas. A. The best fit line for the income index versus logarithmic of population has gradient 0.0064 [0.0033, 0.0095] and intercept 0.9168 [0.9012, 0.9322]. B. The dependence of the Gini coefficient of the income index on logarithm of populations has gradient 0.0110 [0.010, 0.01199173] and intercept -0.0319 [-0.0363 , -0.0275].



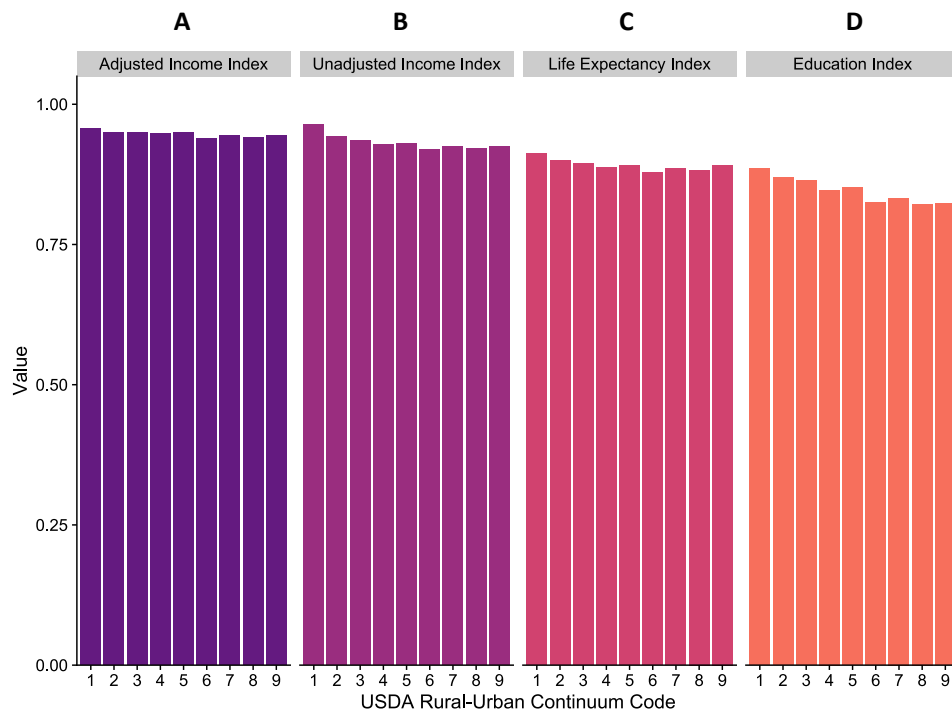
Supplementary Figure 6. The dependence of the education index and its Gini coefficient on population size for both metropolitan and micropolitan areas in the US. A. The dependence of the education index with logarithm of the population is characterized by a linear fit (blue line) with gradient 0.0243 [0.020, 0.0286] and intercept 0.7316 [0.7097, 0.7535]. B. The dependence of the Gini coefficient of the income index on the logarithm of population is characterized by a linear best fit (blue line) with gradient 0.0116 [0.0106, 0.0127] and intercept -0.0265 [$-0.0318, -0.0213$]



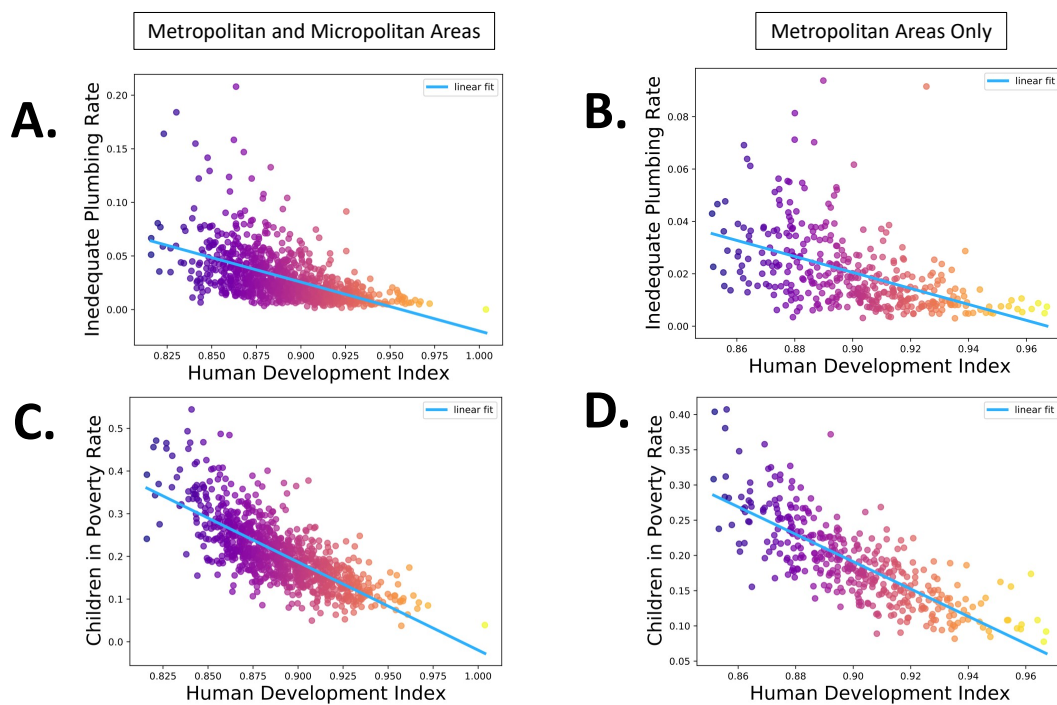
Supplementary Figure 7. The dependence of the life expectancy index and its Gini coefficient on the population size of metropolitan and micropolitan areas in the US. A. The best fit line (blue) for the life expectancy index on the logarithm of population has gradient 0.0105 [0.0066, 0.0144] and intercept 0.8377 [0.8181, 0.8574]. B. the Gini coefficient dependence on the logarithm of population (blue line) has gradient 0.0042 [0.0032, 0.0052] and intercept 0.0051 [0.0005, 0.0103]



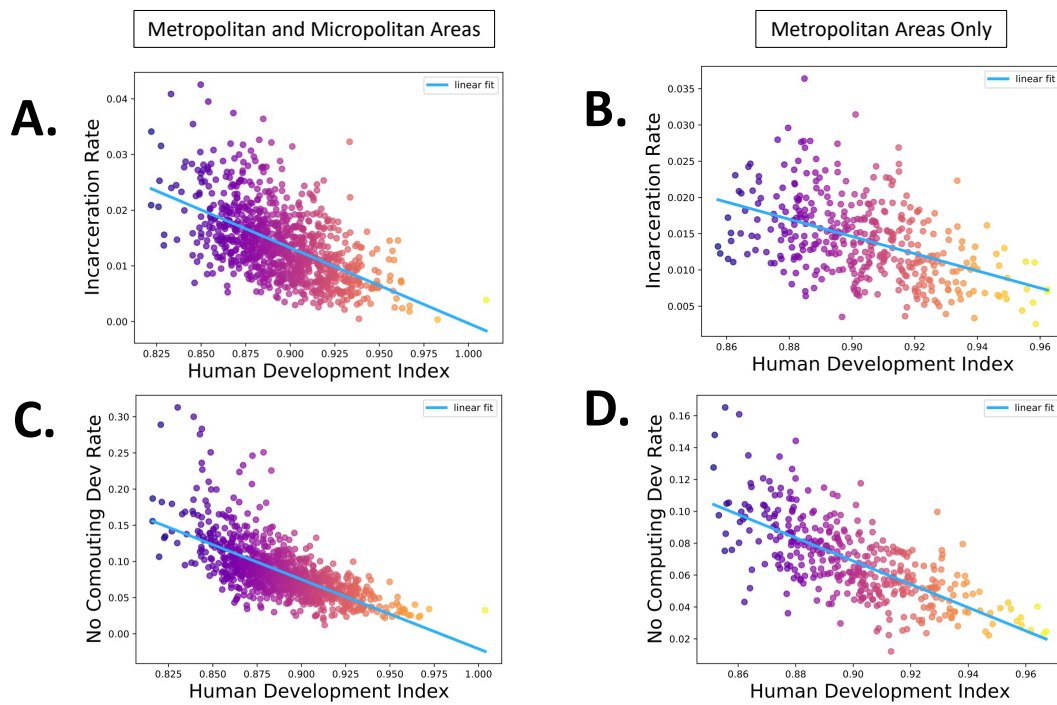
Supplementary Figure 8. Population-weighted HDI values of counties organized by United States Department of Agriculture (USDA) Rural-Urban Continuum codes, which classify counties based on their urbanization levels. The most urban counties are in Class 1 and the most rural counties are in Class 9. On average, HDI slightly decreases moving from urban to rural counties, both when (A) adjusted for local purchasing power parities and when (B) calculated using nominal income.



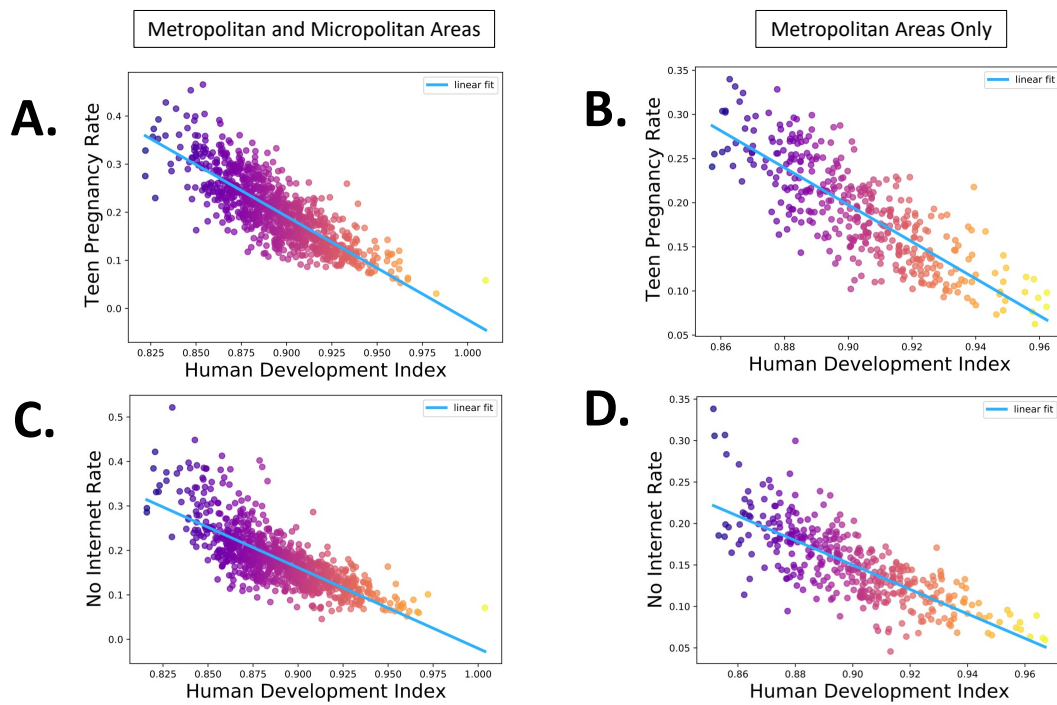
Supplementary Figure 9. Population-weighted values of HDI Components of counties organized by United States Department of Agriculture (USDA) Rural-Urban Continuum codes, which classify counties based on their urbanization levels. The most urban counties are in Class 1 and the most rural counties are in Class 9. On average, the income index (A) adjusted for local purchasing power parities and (B) unadjusted for local price differences, (C) the life expectancy index, and (D) the education index all decrease moving from urban to rural counties, with the education index having the largest differences between the counties on the extremes of the continuum.



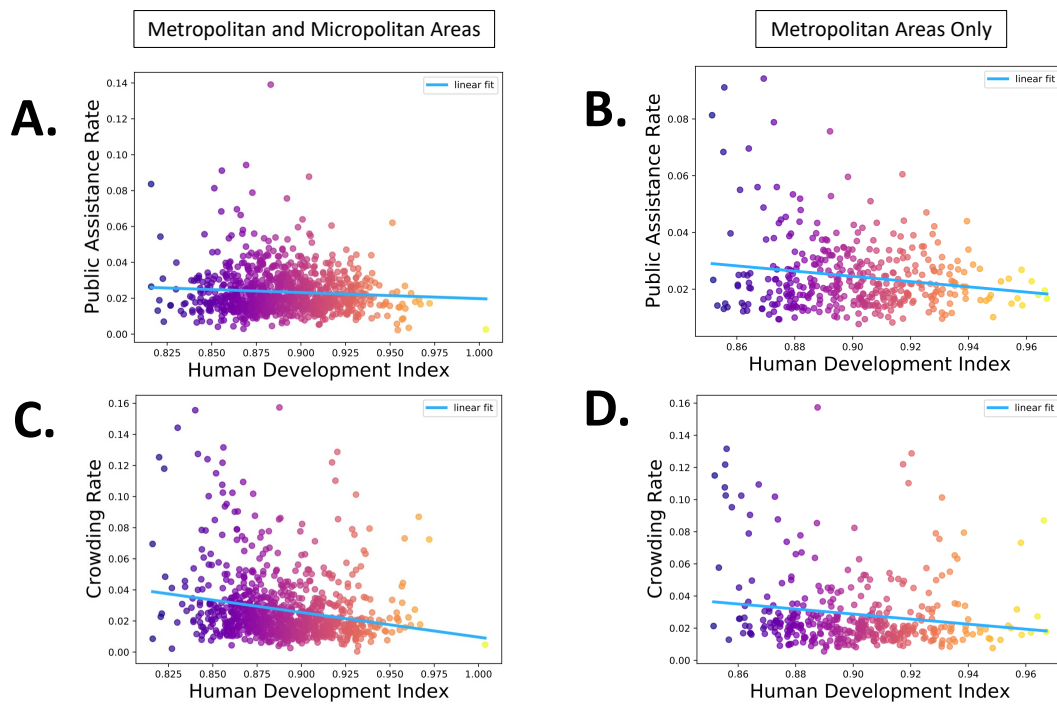
Supplementary Figure 10. Inadequate plumbing and children in poverty by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in Supplementary Table 3.



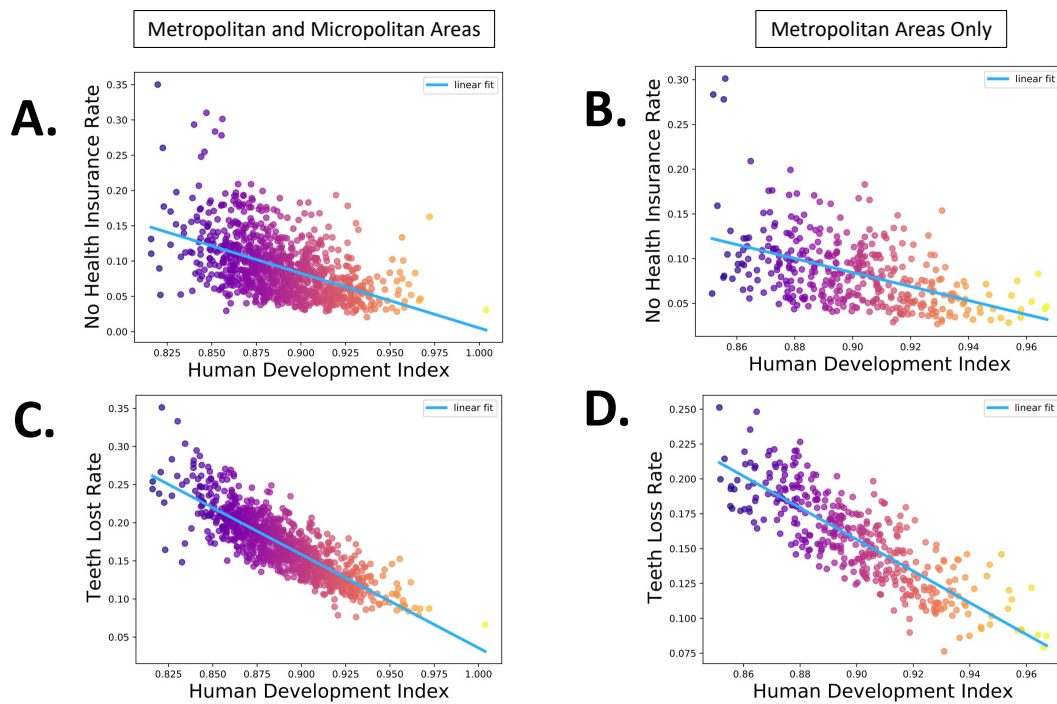
Supplementary Figure 11. Incarceration rate and fraction of individuals living in households with no computing device by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in [Supplementary Tables 2](#) and [3](#).



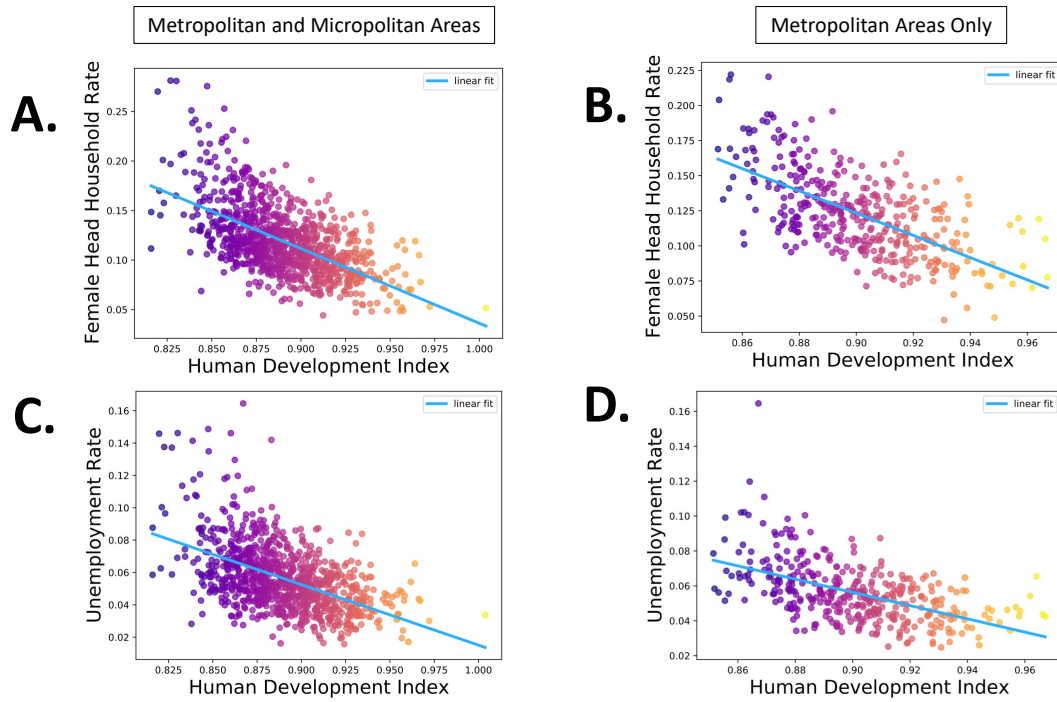
Supplementary Figure 12. Teenage pregnancy rate and fraction of households that have no internet access by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in Supplementary Tables 2 and 3.



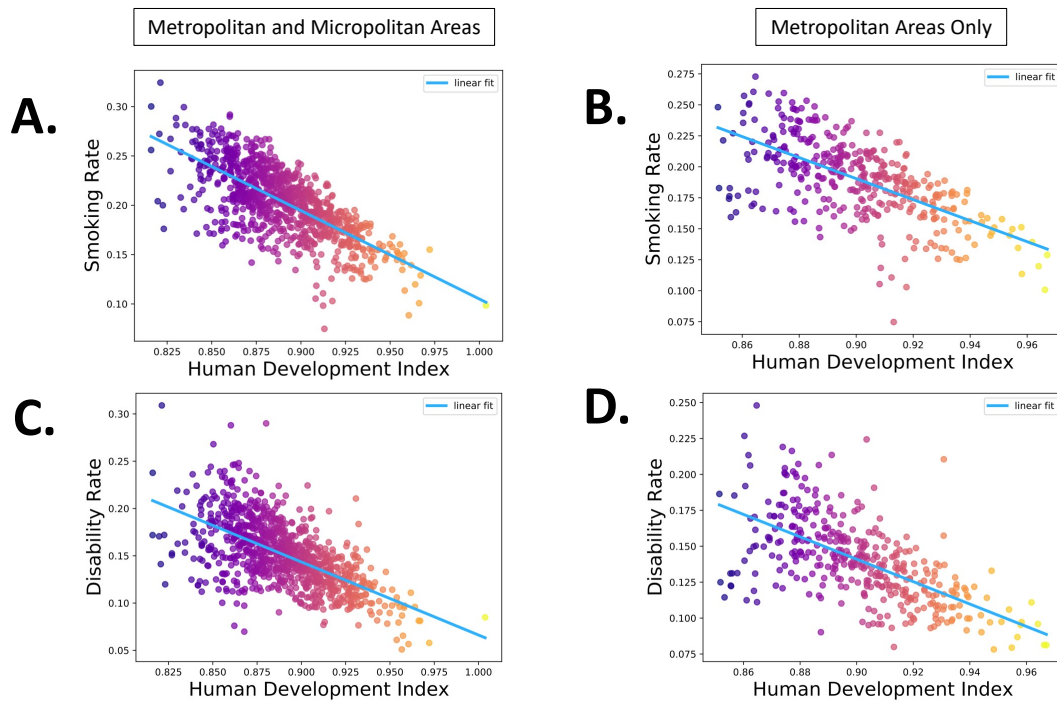
Supplementary Figure 13. Fraction of housing units that receive public assistance and fraction of households with crowding (> 1 person/room) by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in Supplementary Table 3.



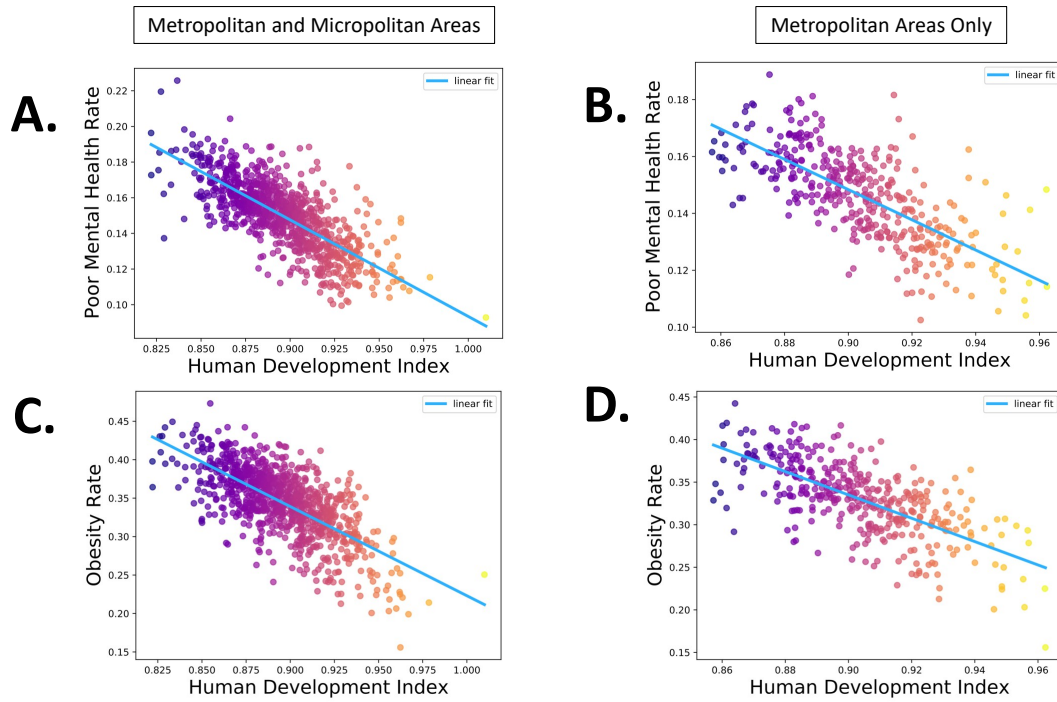
Supplementary Figure 14. Fraction of people with no health insurance coverage and teeth loss (fraction aged ≥ 65 years who report having lost all of their teeth) by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in Supplementary Tables 2 and 3.



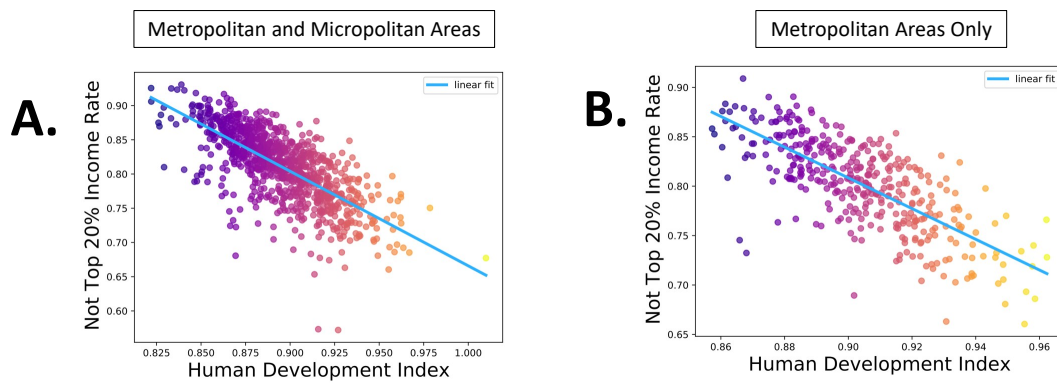
Supplementary Figure 15. Fraction of households with a single female householder and population aged ≥ 16 years in the labor force that are unemployed by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in Supplementary Tables 2 and 3.



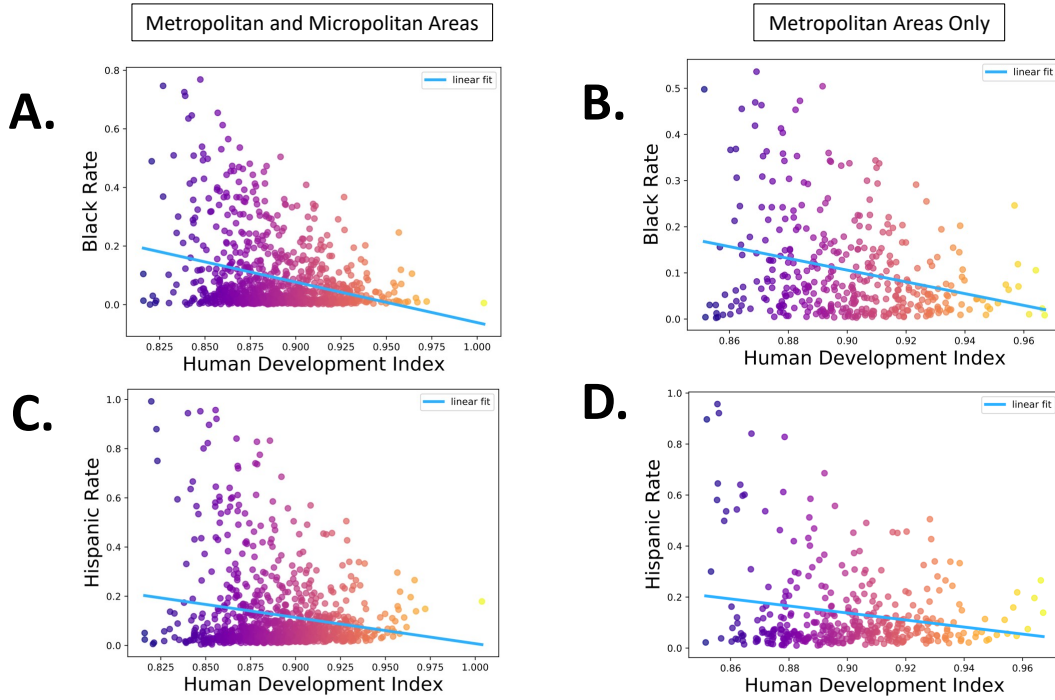
Supplementary Figure 16. Fraction of individuals who currently smoke and fraction of individuals who report one or more disabilities by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in [Supplementary Table 2](#).



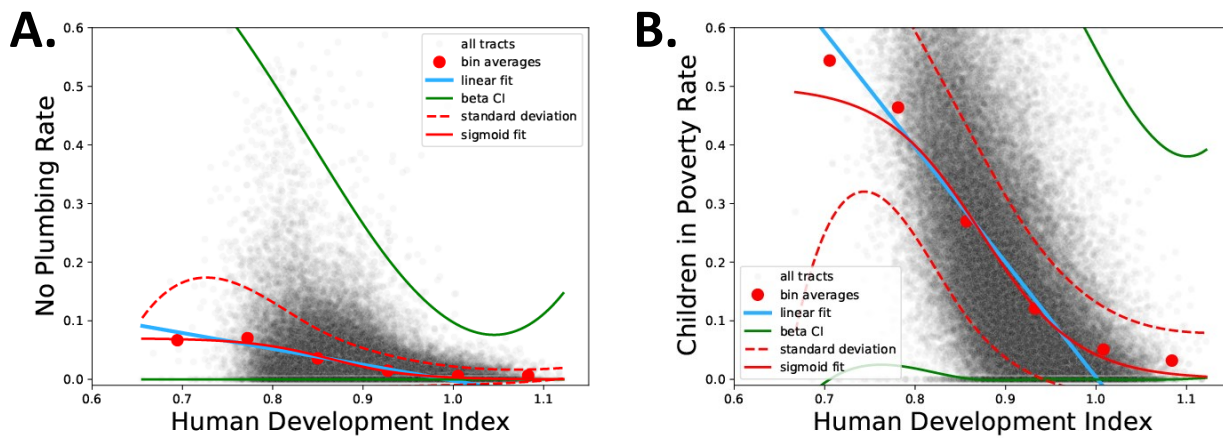
Supplementary Figure 17. Fraction of individuals with poor mental health (fraction who report 14 or more days during the past 30 days during which their mental health was not good) and fraction of individuals who are obese by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in [Supplementary Table 2](#).



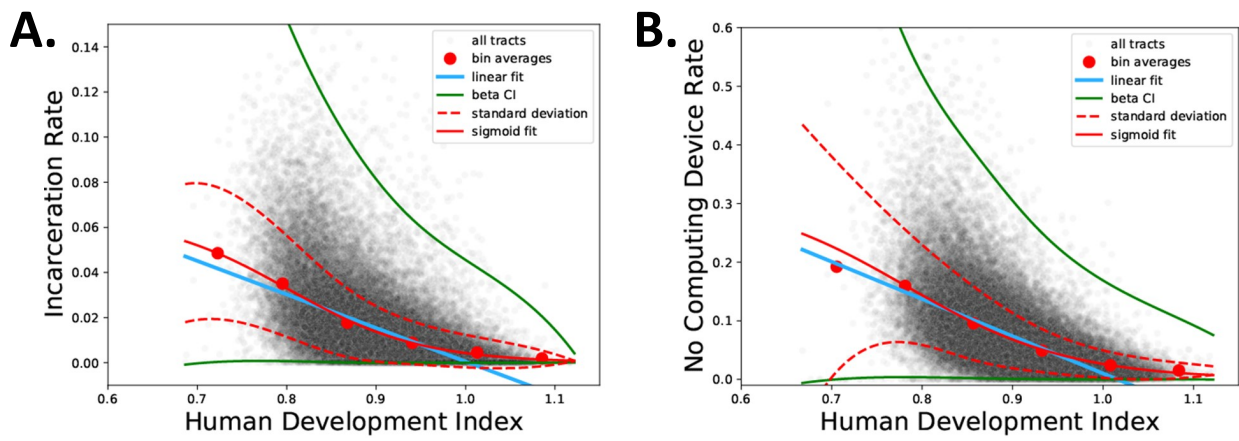
Supplementary Figure 18. Fraction of children who grew up in this area who do not reach individual income in 2014-15 in the top 20 percent of the national income distribution by Metropolitan and Micropolitan Area vs HDI. Best line fits (in blue) are given in [Supplementary Table 2](#).



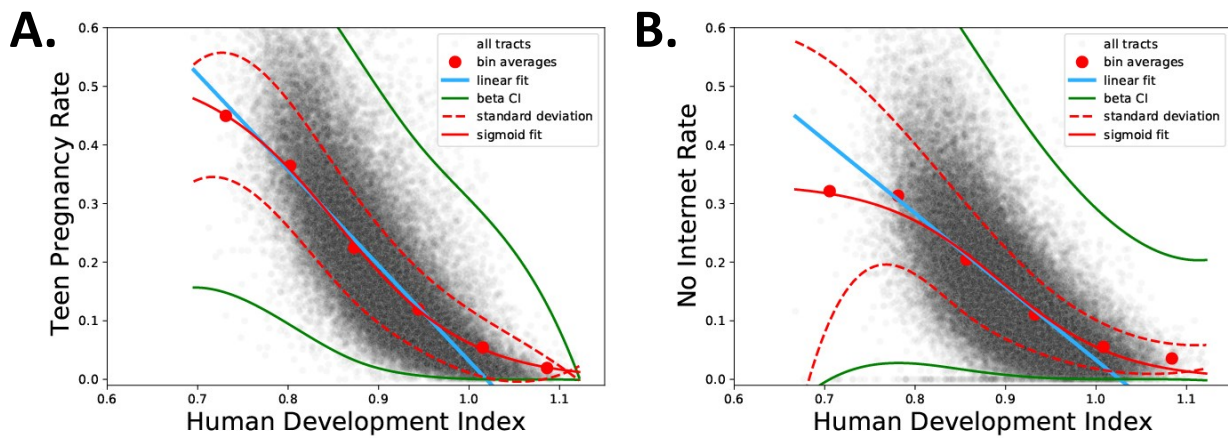
Supplementary Figure 19. The relationship between the Community Human Development Index (CHDI) and the fraction of Black (top) or Hispanic (bottom) population in 917 Metropolitan and Micropolitan areas (left) or limited to 381 Metropolitan areas (right). A. The linear relation (blue line) has gradient $-1.381(0.288)$ and intercept $1.319(0.257)$, with $R^2 = 0.091$; B. The linear relation (blue line) has gradient $-1.274(0.455)$ and intercept $1.253(0.410)$, with $R^2 = 0.076$; C. The linear relation (blue line) has gradient $-1.062(0.387)$ and intercept $1.069(0.345)$, with $R^2 = 0.032$; D. the linear relation (blue line) has gradient $-1.379(0.686)$ and intercept $1.379(0.618)$, with $R^2 = 0.0409$. In all cases the correlation is barely significant and largely the result of greater variation of population composition at lower HDI values, meaning that low development cities have many different racial and ethnic makeups, including some with relatively large Black or Hispanic populations. Note however that low HDI is not associated at this scale to mostly Black or mostly Hispanic urban areas.



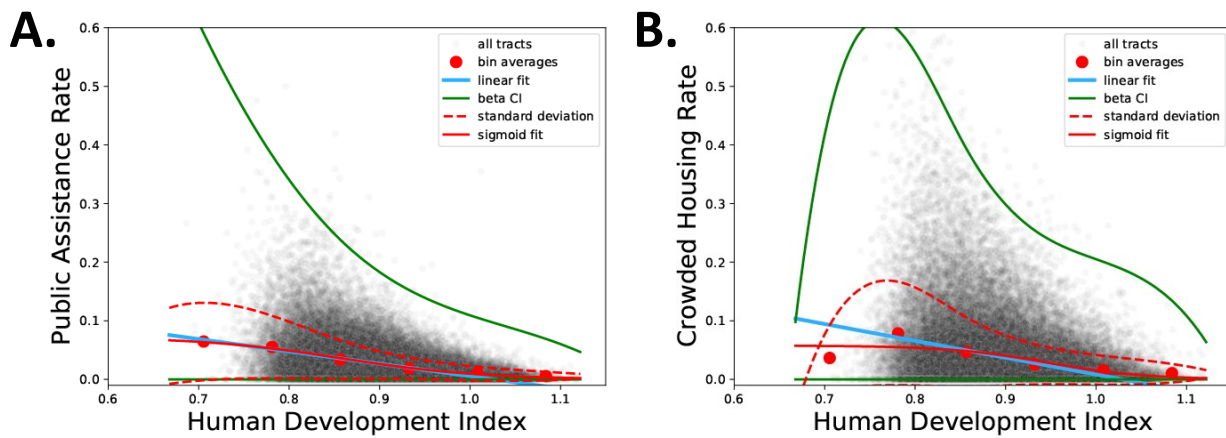
Supplementary Figure 20. Rates of A. households without plumbing and B. children in poverty versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in [Supplementary Table 5](#).



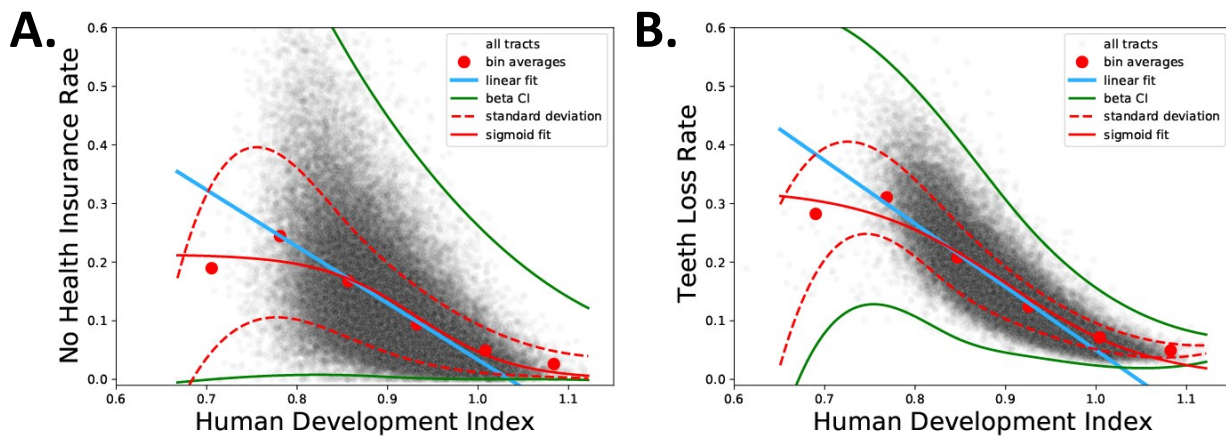
Supplementary Figure 21. Rates of A. incarceration per person and B. households without a computing device for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in Supplementary Tables 4 and 5.



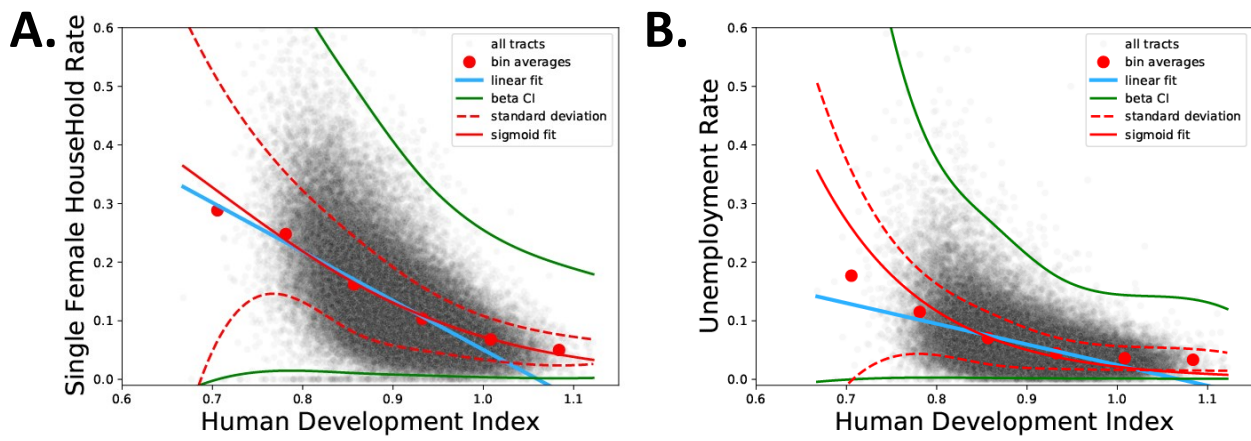
Supplementary Figure 22. Rates of A. teen pregnancy and B. households without internet access versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in Supplementary Tables 4 and 5.



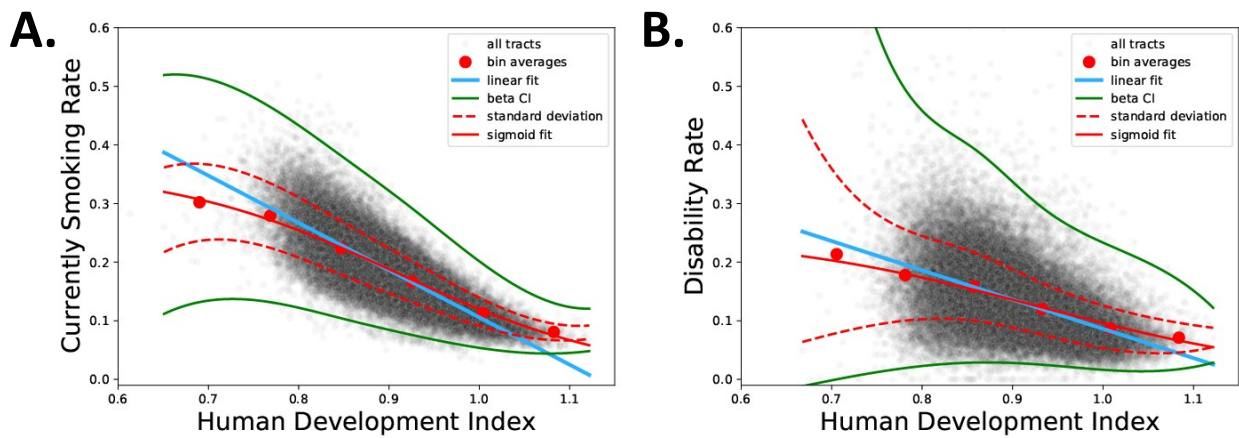
Supplementary Figure 23. Rates of A. people on public assistance and B. crowded households versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in [Supplementary Table 5](#).



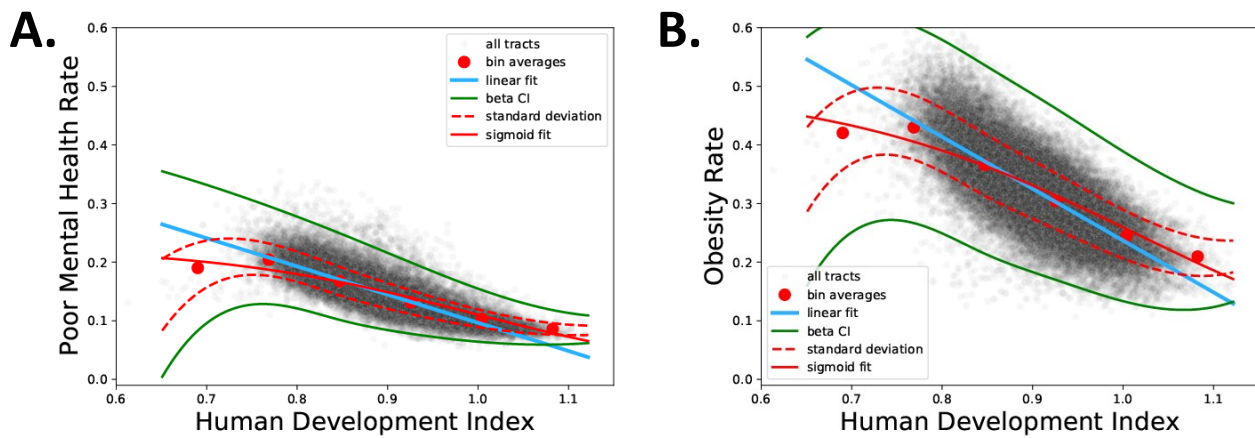
Supplementary Figure 24. Rates of A. people without health insurance and B. people with teeth loss versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in Supplementary Tables 4 and 5.



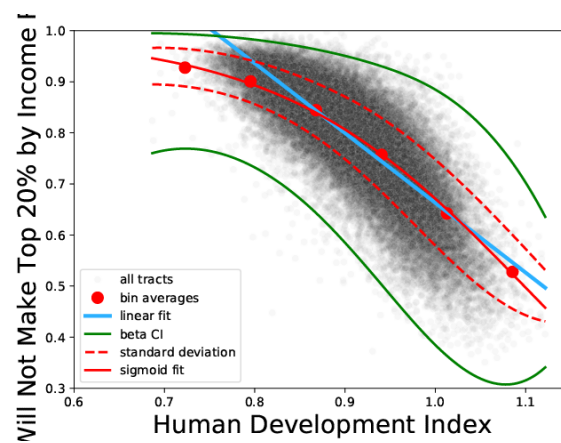
Supplementary Figure 25. Rates of A. single female headed households and B. unemployment versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in Supplementary Tables 4 and 5.



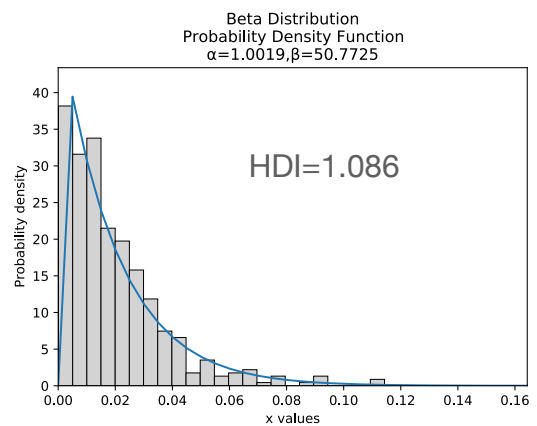
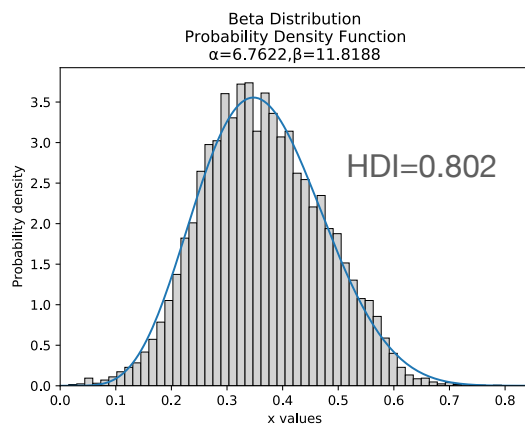
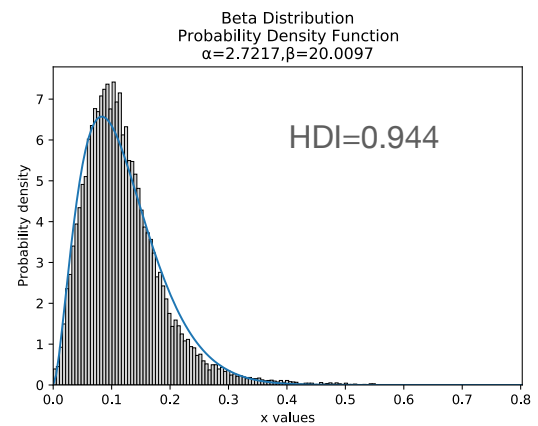
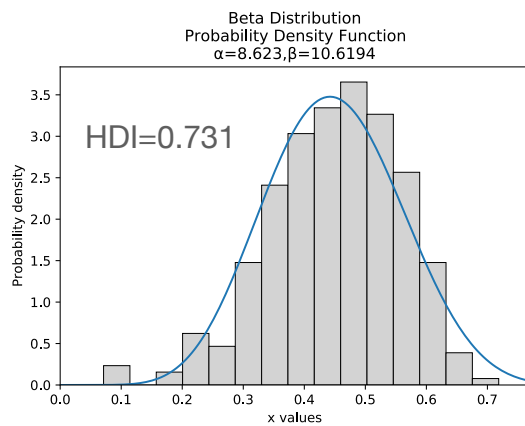
Supplementary Figure 26. Rates of A. people currently smoking and B. people with disability versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in [Supplementary Table 4](#).



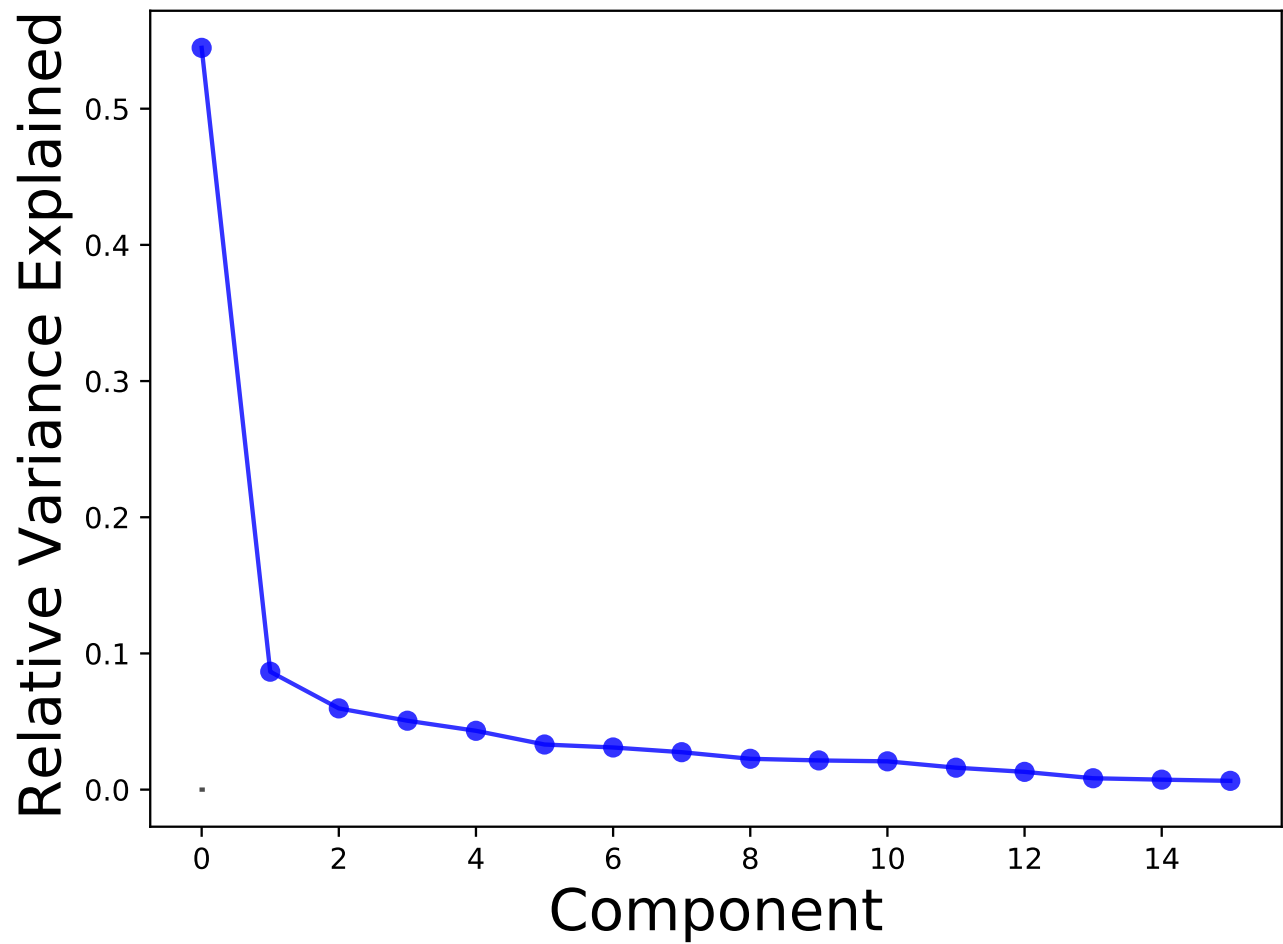
Supplementary Figure 27. Rates of A. poor mental health and B. obesity versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in [Supplementary Table 4](#).



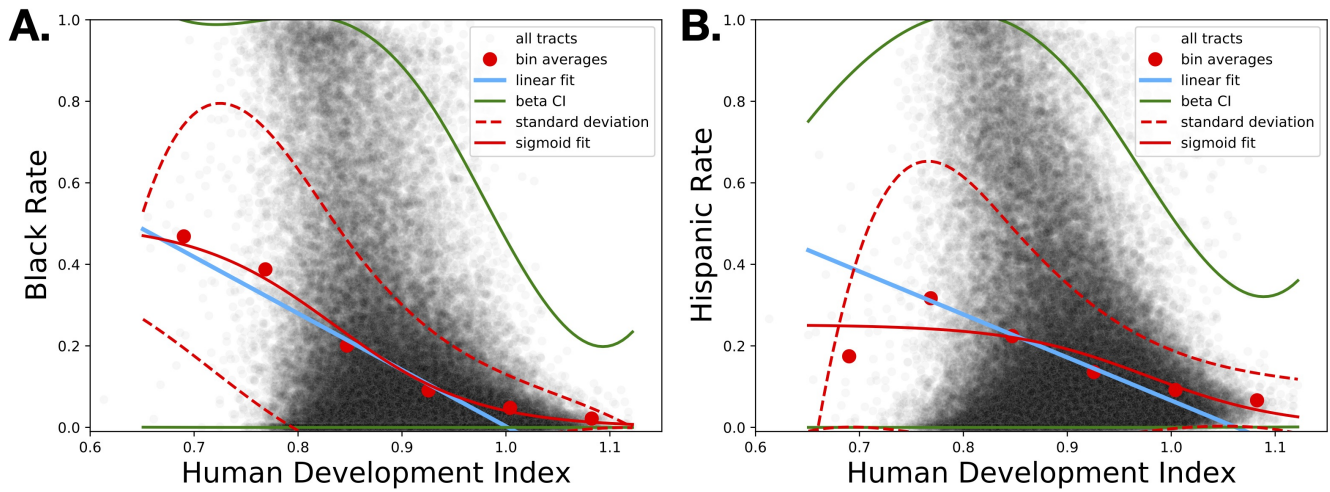
Supplementary Figure 28. Rates of people not making it to the top 20% of income versus HDI for census tracts nationwide. The blue line shows a linear fit, while the red and green lines show the estimation for Beta distribution mean (solid red), standard deviation (dashed red) and 95% confidence interval (green). The red dots show the bin averages used for the sigmoidal fits. Parameter estimations and goodness of fit are given in [Supplementary Table 4](#).



Supplementary Figure 29. Examples of Beta distribution fits for the variation in Teen Pregnancy rates for sets of tracts with different HDI. Note how the histograms changes shape and how the Beta distribution is able to estimate all cases reasonably well. See Supplementary Table 4 for parameter estimates.



Supplementary Figure 30. The relative variance explained by rank ordered PCA components for the variables of Figure 3. The first component corresponds to the decrease in all social disadvantage rates with increases in HDI, see also Supplementary Table 6.



Supplementary Figure 31. The correlation between the fraction of **A.** Black and **B.** Hispanic population fractions in 72349 census tracts nationwide versus the community HDI. While there is a small negative association in both cases (gradient= $-1.056(0.026)$, $R^2 = 0.142$ for Black and gradient= $-1.385(0.025)$, $R^2 = 0.083$ for Hispanic), the data clearly show that a linear fit is inadequate and that there are many different situations at low development, while at high HDI most tracts are mixed but fractions of minority population are small, especially for Black.

Supplementary Table 1. Table of Density Distribution best fits to HDI census tract data in the US. Parameter names are as conventionally listed for the distribution in the first column. Log-likelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Anderson-Darling statistic (AD) are different goodness of fit criteria for preferring a specific distribution given data. The 2 parameter Normal distribution is gives the best fit among distributions listed.

Distribution	α	β	γ	μ	Sigma	Log-likelihood	AICc	BIC	AD
Normal 2P				0.905097	0.0571608	104426	-208849	-208831	9.6342
Lognormal 2P				-0.101714	0.0633808	104312	-208620	-208601	16.5568
Lognormal 3P			0	-0.101714	0.0633808	104312	-208618	-208590	16.5568
Loglogistic 2P	0.903917	27.4721				103444	-206884	-206865	79.4194
Loglogistic 3P	0.903917	27.4721	0			103444	-206882	-206854	79.4194
Weibull 3P	0.487969	8.66643	0.442444			101928	-203849	-203822	372.56
Weibull 2P	0.932037	16.5051				100465	-200926	-200908	590.255
Gumbel 2P				0.933802	0.056969	98521.3	-197039	-197020	879.804

Supplementary Table 2. CHDI and Social Indicator Fits for Metropolitan and Micropolitan Areas Part 1

Dependent Variable vs. HDI	Linear Model for Metros and Micros	Linear Model for Metros Only
	$y = a - b \times hdi$	$y = a - b \times hdi$
Teen Pregnancy	$a = 2.019$ (0.045) $b = 2.041$ (0.050) $R^2 = 0.643$	$a = 1.911$ (0.065) $b = 1.911$ (0.072) $R^2 = 0.648$
Incarceration	$a = 0.135$ (0.012) $b = 0.135$ (0.014) $R^2 = 0.308$	$a = 0.121$ (0.010) $b = 0.118$ (0.011) $R^2 = 0.215$
Will Not Make Top 20% by Income	$a = 2.047$ (0.040) $b = 1.381$ (0.044) $R^2 = 0.508$	$a = 2.207$ (0.066) $b = 1.554$ (0.073) $R^2 = 0.540$
Poor Mental Health	$a = 0.635$ (0.014) $b = 0.541$ (0.016) $R^2 = 0.555$	$a = 0.626$ (0.024) $b = 0.531$ (0.027) $R^2 = 0.500$
Obesity	$a = 1.383$ (0.036) $b = 1.160$ (0.040) $R^2 = 0.472$	$a = 1.569$ (0.069) $b = 1.371$ (0.077) $R^2 = 0.453$
Teeth Loss	$a = 1.261$ (0.023) $b = 1.225$ (0.026) $R^2 = 0.694$	$a = 1.178$ (0.036) $b = 1.135$ (0.040) $R^2 = 0.672$
Currently Smoking	$a = 1.000$ (0.026) $b = 0.895$ (0.029) $R^2 = 0.498$	$a = 0.953$ (0.048) $b = 0.847$ (0.053) $R^2 = 0.395$
Unemployment	$a = 0.389$ (0.018) $b = 0.374$ (0.021) $R^2 = 0.254$	$a = 0.397$ (0.028) $b = 0.379$ (0.031) $R^2 = 0.280$
Disability	$a = 0.839$ (0.029) $b = 0.772$ (0.033) $R^2 = 0.370$	$a = 0.842$ (0.045) $b = 0.779$ (0.050) $R^2 = 0.388$

Supplementary Table 3. CHDI and Social Indicator Fits for Metropolitan and Micropolitan Areas Part 2

Dependent Variable vs. HDI	Linear Model for Metros and Micros	Linear Model for Metros Only
	$y = a - b \times hdi$	$y = a - b \times hdi$
Children in Poverty	$a = 2.044$ (0.055) $b = 2.063$ (0.061) $R^2 = 0.547$	$a = 1.939$ (0.072) $b = 1.943$ (0.080) $R^2 = 0.606$
No Health Insurance	$a = 1.327$ (0.058) $b = 1.340$ (0.065) $R^2 = 0.312$	$a = 1.320$ (0.096) $b = 1.329$ (0.106) $R^2 = 0.289$
No Computing Device	$a = 0.938$ (0.031) $b = 0.959$ (0.034) $R^2 = 0.452$	$a = 0.726$ (0.035) $b = 0.730$ (0.039) $R^2 = 0.475$
Single Female Household	$a = 0.790$ (0.030) $b = 0.753$ (0.034) $R^2 = 0.345$	$a = 0.0836$ (0.045) $b = 0.792$ (0.050) $R^2 = 0.393$
Public Assistance	$a = 0.053$ (0.013) $b = 0.033$ (0.014) $R^2 = 0.005$	$a = 0.107$ (0.024) $b = 0.092$ (0.026) $R^2 = 0.030$
Crowded Housing	$a = 0.168$ (0.022) $b = 0.159$ (0.024) $R^2 = 0.042$	$a = 0.169$ (0.044) $b = 0.156$ (0.049) $R^2 = 0.025$
No Plumbing	$a = 0.436$ (0.022) $b = 0.456$ (0.024) $R^2 = 0.270$	$a = 0.295$ (0.025) $b = 0.305$ (0.027) $R^2 = 0.241$
No Internet	$a = 1.796$ (0.045) $b = 1.816$ (0.051) $R^2 = 0.579$	$a = 1.477$ (0.058) $b = 1.475$ (0.064) $R^2 = 0.579$

Supplementary Table 4. CHDI and Social Indicator Fits at Tract Level Part 1

Dependent Variable vs. HDI	Linear Model $y = a - b \times hdi$	Beta Average $y = \frac{y_0}{(1 + e^{k(hdi - hdi_0)})}$	Beta Standard Deviation
Teen Pregnancy	$a = 1.662$ (0.004) $b = 1.630$ (0.005) $R^2 = 0.596$	$y_0 = 0.532$ (0.017) $k = 13.872$ (0.673) $hdi_0 = 0.853$ (0.006) $R^2 = 0.999$	$y_0^{std} = 0.116$ (0.004) $k_0^{std} = 13.317$ (1.375) $hdi_0^{std} = 0.971$ (0.008) $R^2 = 0.995$
Incarceration	$a = 0.149$ (0.0007) $b = 0.148$ (0.0008) $R^2 = 0.285$	$y_0 = 0.065$ (0.006) $k = 13.400$ (1.371) $hdi_0 = 0.801$ (0.018) $R^2 = 0.997$	$y_0^{std} = 0.159$ (0.050) $k_0^{std} = 7.610$ (0.405) $hdi_0^{std} = 0.572$ (0.062) $R^2 = 0.999$
Will Not Make Top 20% by Income	$a = 2.028$ (0.003) $b = 1.365$ (0.003) $R^2 = 0.642$	$y_0 = 0.991$ (0.015) $k = 7.339$ (0.470) $hdi_0 = 1.100$ (0.004) $R^2 = 0.998$	$y_0^{std} = 0.086$ (0.018) $k_0^{std} = -8.753$ (5.403) $hdi_0^{std} = 0.785$ (0.059) $R^2 = 0.870$
Poor Mental Health	$a = 0.577$ (0.001) $b = 0.480$ (0.001) $R^2 = 0.683$	$y_0 = 0.225$ (0.039) $k = 7.009$ (2.854) $hdi_0 = 0.993$ (0.058) $R^2 = 0.949$	$y_0^{std} = 2.613e+03$ (1.693e+08) $k_0^{std} = 3.410$ (2.181) $hdi_0^{std} = -2.559$ (1.902e+04) $R^2 = 0.969$
Obesity	$a = 1.120$ (0.002) $b = 0.883$ (0.002) $R^2 = 0.567$	$y_0 = 0.500$ (0.073) $k = 5.972$ (2.010) $hdi_0 = 1.012$ (0.053) $R^2 = 0.971$	$y_0^{std} = 0.069$ (0.006) $k_0^{std} = 5.265$ (1.427) $hdi_0^{std} = 1.070$ (0.034) $R^2 = 0.984$
Teeth Loss	$a = 1.127$ (0.002) $b = 1.078$ (0.002) $R^2 = 0.699$	$y_0 = 0.325$ (0.047) $k = 12.660$ (4.140) $hdi_0 = 0.901$ (0.035) $R^2 = 0.959$	$y_0^{std} = 0.155$ (0.042) $k_0^{std} = 7.366$ (1.395) $hdi_0^{std} = 0.758$ (0.078) $R^2 = 0.992$
Currently Smoking	$a = 0.911$ (0.002) $b = 0.805$ (0.002) $R^2 = 0.647$	$y_0 = 0.362$ (0.024) $k = 7.787$ (0.838) $hdi_0 = 0.909$ (0.021) $R^2 = 0.996$	$y_0^{std} = 0.074$ (0.003) $k_0^{std} = 7.988$ (0.548) $hdi_0^{std} = 0.904$ (0.013) $R^2 = 0.998$
Unemployment	$a = 0.376$ (0.002) $b = 0.352$ (0.002) $R^2 = 0.222$	$y_0 = 6.746e+04$ (1.736e+10) $k = 8.426$ (4.684) $hdi_0 = -7.744e-01$ (3.061e+04) $R^2 = 0.966$	$y_0^{std} = 5.723e+04$ (1.933e+10) $k_0^{std} = 1.450e+01$ (1.243e+01) $hdi_0^{std} = -1.3847e-01$ (2.334e+04) $R^2 = 0.967$
Disability	$a = 0.585$ (0.002) $b = 0.499$ (0.003) $R^2 = 0.247$	$y_0 = 0.248$ (0.028) $k = 6.538$ (1.124) $hdi_0 = 0.929$ (0.040) $R^2 = 0.992$	$y_0^{std} = 4.161e+04$ (1.184e+10) $k_0^{std} = 6.429$ (4.237) $hdi_0^{std} = -1.226$ (4.436e+04) $R^2 = 0.949$

Supplementary Table 5. CHDI and Social Indicator Fits at Tract Level Part 2

Dependent Variable vs. HDI	Linear Model $y = a - b \times hdi$	Beta Average $y = \frac{y_0}{(1 + e^{k(hdi - hdi_0)})}$	Beta Standard Deviation
Children in Poverty	$a = 1.965$ (0.007) $b = 1.961$ (0.008) $R^2 = 0.427$	$y_0 = 0.500$ (0.041) $k = 18.757$ (4.159) $hdi_0 = 0.872$ (0.015) $R^2 = 0.986$	$y_0^{std} = 1.982e+04$ (1.117e+09) $k_0^{std} = 4.580$ (2.625) $hdi_0^{std} = -1.695$ (1.233e+04) $R^2 = 0.968$
No Health Insurance	$a = 0.998$ (0.004) $b = 0.965$ (0.005) $R^2 = 0.332$	$y_0 = 0.213$ (0.034) $k = 18.602$ (10.268) $hdi_0 = 0.932$ (0.035) $R^2 = 0.896$	$y_0^{std} = 0.299$ (0.026) $k_0^{std} = 7.812$ (0.468) $hdi_0^{std} = 0.764$ (0.024) $R^2 = 0.999$
No Computing Device	$a = 0.645$ (0.002) $b = 0.635$ (0.003) $R^2 = 0.340$	$y_0 = 0.318$ (0.020) $k = 11.037$ (0.624) $hdi_0 = 0.781$ (0.013) $R^2 = 0.999$	$y_0^{std} = 7.556e+04$ (1.883e+10) $k_0^{std} = 9.672$ (4.514) $hdi_0^{std} = -5.973e-01$ (2.582e+04) $R^2 = 0.980$
Single Female Household	$a = 0.887$ (0.003) $b = 0.836$ (0.004) $R^2 = 0.346$	$y_0 = 0.650$ (0.168) $k = 6.959$ (0.822) $hdi_0 = 0.701$ (0.070) $R^2 = 0.997$	$y_0^{std} = 7.868e+04$ (2.182e+10) $k_0^{std} = 8.734$ (5.239) $hdi_0^{std} = -7.218e-01$ (3.184e+04) $R^2 = 0.961$
Public Assistance	$a = 0.216$ (0.001) $b = 0.210$ (0.001) $R^2 = 0.167$	$y_0 = 0.072$ (0.007) $k = 13.045$ (2.290) $hdi_0 = 0.856$ (0.022) $R^2 = 0.990$	$y_0^{std} = 0.379$ (0.159) $k_0^{std} = 7.018$ (0.483) $hdi_0^{std} = 0.538$ (0.088) $R^2 = 0.999$
Crowded Housing	$a = 0.295$ (0.002) $b = 0.287$ (0.003) $R^2 = 0.105$	$y_0 = 0.057$ (1.813e-02) $k = 18.572$ (2.114e+01) $hdi_0 = 0.945$ (7.318e-02) $R^2 = 0.639$	$y_0^{std} = 0.080$ (0.023) $k_0^{std} = 13.413$ (10.606) $hdi_0^{std} = 0.944$ (0.072) $R^2 = 0.775$
No Plumbing	$a = 0.268$ (0.002) $b = 0.270$ (0.002) $R^2 = 0.136$	$y_0 = 0.070$ (8.362e-03) $k = 22.253$ (8.558) $hdi_0 = 0.863$ (2.149e-02) $R^2 = 0.962$	$y_0^{std} = 0.131$ (0.014) $k_0^{std} = 12.826$ (2.020) $hdi_0^{std} = 0.824$ (0.023) $R^2 = 0.993$
No Internet	$a = 1.283$ (0.004) $b = 1.25101972$ (0.004) $R^2 = 0.480$	$y_0 = 0.334$ (0.035) $k = 15.32755914$ (3.960) $hdi_0 = 0.894$ (0.023) $R^2 = 0.977$	$y_0^{std} = 7.865e+04$ (1.875e+10) $k_0^{std} = 7.166$ (3.627) $hdi_0^{std} = -1.039$ (3.334e+04) $R^2 = 0.969$

Supplementary Table 6. Principal Components

Variables	First Component	Second Component
Explained Relative Variance	54.5%	8.7%
HDI	1.00	1.00
Teen Pregnancy	-0.956	-2.034
Incarceration	-0.749	-1.928
Will Not Make Top 20% by Income	-0.896	0.032
Poor Mental Health	-0.999	-0.425
Obesity	-0.929	3.113
Teeth Lost	-1.047	0.478
Currently Smoking	-0.968	3.739
Unemployment	-0.683	-2.041
Disability	-0.652	8.628
Children in Poverty	-0.880	-2.639
No Health Insurance	-0.667	-5.061
No Computing Device	-0.802	4.791
Single Female Head Household	-0.759	-6.677
Public Assistance	-0.539	-4.978
Crowded Housing	-0.318	-12.448
No Plumbing	-0.556	6.678
No Internet	-0.903	3.769

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