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Calculating and Applying the Tract-Based Concentrated Poverty Index

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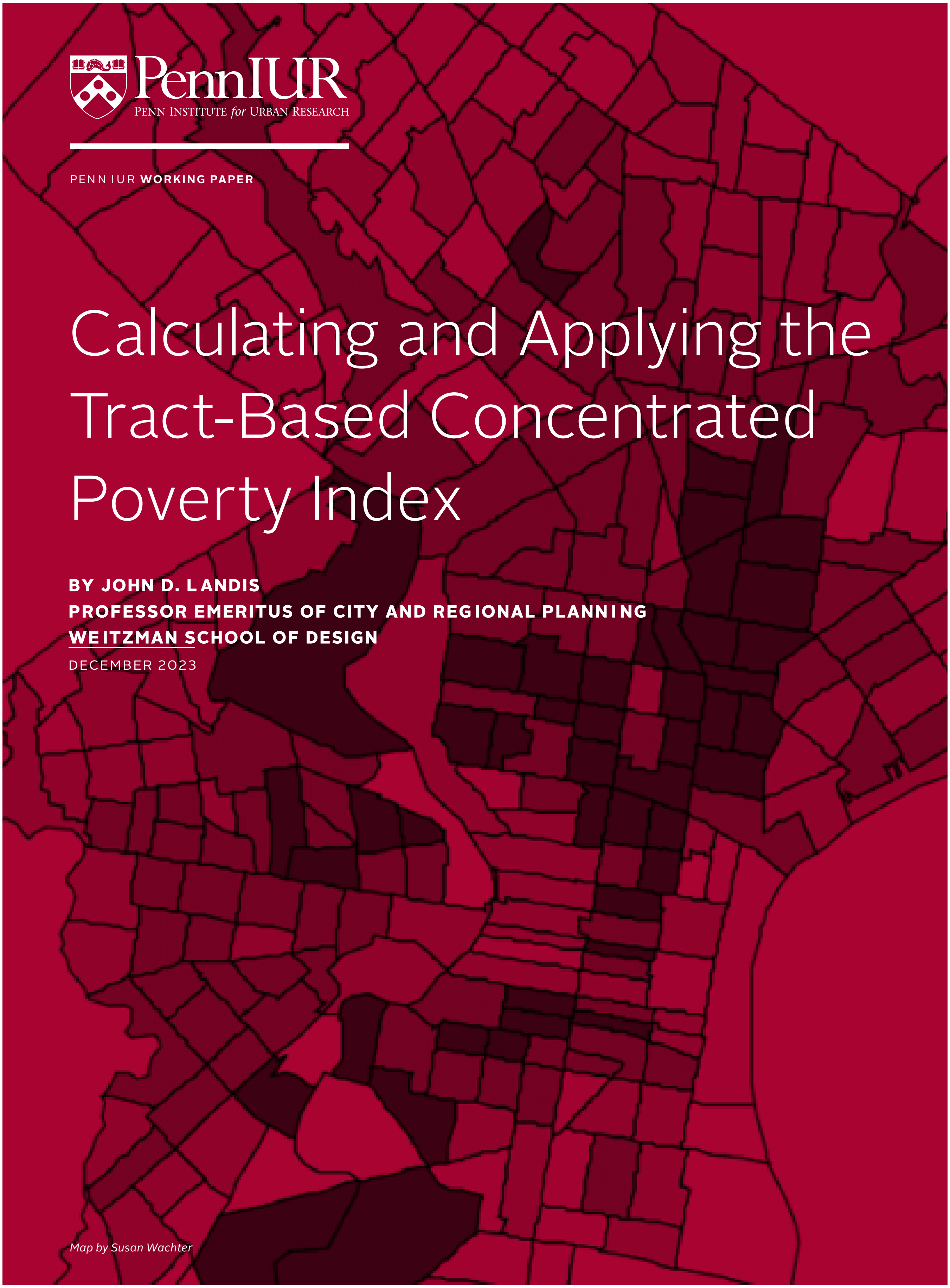


Map by Susan Wachter

Urban sociologists, economists, and community development scholars write convincingly about the dangers of concentrated poverty, especially in cities. Concentrated poverty prevents local labor and housing markets from functioning efficiently or equitably (Wilson 1987, O'Regan 1993, Rosenbaum 1995, Goetz 2000, Galster et al. 2006, McClure 2008, Quigley et al. 2008); contributes to worsening residential segregation (Massey 1990, Jargowsky 1997, Lichter et al. 2012, Quillian 2012); aggravates crime and other social pathologies (Lee 2000, Hipp & Yates 2011, Chamberlain & Hipp 2015); limits equitable access to education, public and health services (Orfield & Lee 2005, Roscigno et al. 2006, Sims et al. 2008, Sampson et al. 2008, Ludwig et al. 2012, Gennetian et al. 2013, Gaskin et al. 2014); mitigates against community engagement in governance (Alex-Assensoh 1997, Stoll 2001, Joassart-Marcelli et al. 2005, Silver & Messerri 2014); and perhaps most perniciously of all, functions to replicate itself over multiple generations (Pebbly & Sastry 2003, Sharkey 2008, Chetty & Hendren 2018, Levy 2019). After declining nationwide during the 1990s (Jargowsky 2003, Galster 2005), the incidence of concentrated poverty began rising in the mid-2000s as well as extending outward from cities to suburbs (Kneebone & Nadeau 2015, Iceland & Hernandez 2017).

Unfortunately, neither of the indicators used most often to measure poverty fully communicates both its incidence and magnitude. The first of the two, the poverty rate, measures the share of a local population with an income below the federal poverty line. It works well for city and county-level comparisons but is more problematic at the neighborhood level where it fails to account for population size.[1] A second measure, the share of the overall poverty population living in a particular district or neighborhood, is likewise more useful for comparing relative magnitudes than for communicating numerical levels.

What is needed is something like the Gini coefficient, which summarizes the degree to which a given share of income or wealth is held by a similar or lesser proportion of the population. Created by Italian statistician Corrado Gini in 1912, the Gini coefficient's ability to concisely communicate absolute as well as relative income and wealth concentrations across diverse spatial units makes it popular among both scholars and policy professionals (Yitzhaki & Schechtman 2013, Mukhopadhyay & Sengupta 2021). Varying linearly between 0 (complete equality) and 1 (total inequality), the Gini coefficient is calculated by plotting the cumulative population share against the cumulative income or wealth share, and then dividing the geometric area between the resulting curve—known as the Lorenz Curve after the American economist Max Lorenz who developed it—and the 45-degree diagonal by the triangular area under the diagonal. When the share of cumulative income or wealth is comparable to the cumulative population share, the Lorenz curve runs close to the diagonal, yielding a Gini coefficient close to zero and indicative of relative income or wealth equality. When the cumulative income share is much less than the comparable population share, the Lorenz curve hews closer to axes, causing the Gini coefficient to rise, and indicating greater inequality.

As helpful as Gini coefficients are for summarizing income and wealth inequality, they cannot be easily adapted for use with poverty statistics. This is because poverty status is typically measured in nominal rather than interval terms, as when a person (or household) either possesses or lacks

[1] Consider the case of two neighborhoods, A and B, both located in the same city. Neighborhood A has a population of one hundred, ten of whom are poor. Neighborhood B has a population of 10,000, one thousand of whom are poor. From a poverty rate perspective, both neighborhoods are equally poor, but from an aggregated hardship perspective, neighborhood B is 100 times as poor as neighborhood A.

the minimum income required to buy a government-specified basket of goods and services. Measured this way, people fall either above or below the poverty line; there is no in-between. When aggregated by place, the incidence of poverty is expressed as the share of persons or households (or some other group such as children) whose incomes put them below the poverty line; and shares, unfortunately, cannot be used to construct Gini coefficients.

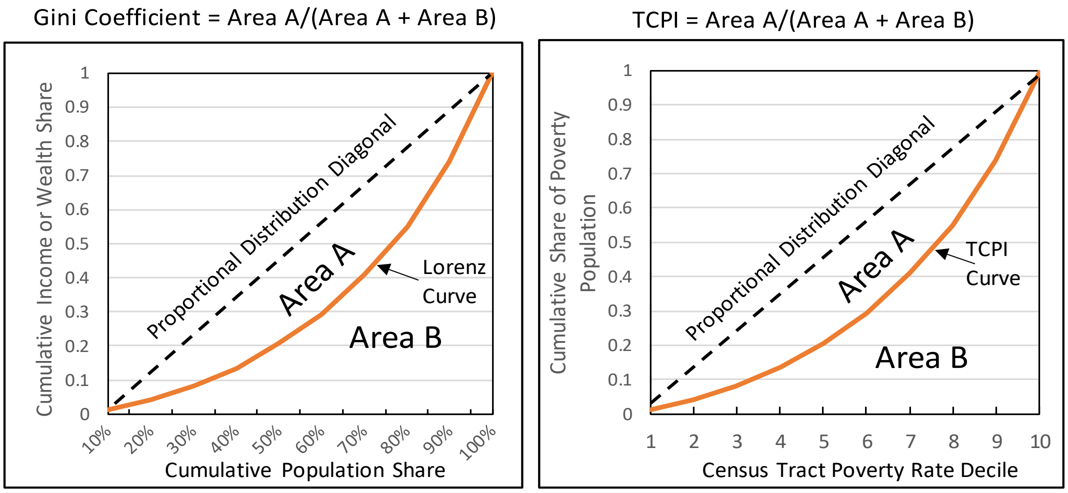
This brief working paper presents a Gini-like poverty concentration measure known as the Tract-based Concentrated Poverty Index, or TCPI, which can be calculated using census tract-level poverty rate data from the Decennial Census and American Community Survey (ACS). TCPI values reflect the share of a given population living in low-poverty versus high-poverty districts and can be interpreted like Gini coefficients, meaning that they vary in a manner indicating relative concentrations. The balance of this paper proceeds in five parts. Part I explains how TCPIs are calculated using large urban counties as units of analysis and comparison. It also compares poverty concentrations as indicated by TCPI values to poverty clustering as indicated by poverty rate Moran's I values. Part II looks at how county-level TCPI values changed between 2000 and 2021, and Part III compares TCPI values by race and ethnicity. Part IV looks at the associations between TCPI values and racialized homeownership, income, and life expectancy disparities. A concluding section, Part V, offers a summary assessment of whether TCPIs add to contemporary policy discussions around alleviating poverty and reducing poverty-related outcome disparities. The upshot of these comparisons is that TCPIs are so far more useful for comparing the incidence of poverty between places and years than they are for informing anti-poverty policies and programs. Hopefully, this will change as researchers accumulate additional experience using TCPIs and similar measures to track how anti-poverty experiments like the Universal Basic Income program are affecting poverty's local magnitude and incidence.

I. CALCULATING AND COMPARING TCPI VALUES AMONG PLACES

The TCPI differs conceptually from the Gini coefficient in two ways. The first is that it compares poverty rates rather than income or wealth levels. The second is that whereas Gini coefficients are calculated using individual-level observations, the TCPI is calculated using poverty rate deciles. Both compare the cumulative distribution of observations as typically plotted on the x-axis to the cumulative outcome share plotted on the y-axis. For the Gini coefficient, the x-axis is the cumulative population share sorted by income or wealth level and the y-axis is the cumulative income or wealth share. For the TCPI case, the x-axis is census tract poverty rate deciles (sorted from low to high) and the y-axis is the cumulative share of persons or households living below the poverty line. Once the poverty decile share curve has been plotted, the TCPI is calculated by dividing the geometric area below the 45-degree diagonal proportional distribution line into the area between the diagonal and the poverty decile curve (The Gini coefficient is calculated similarly: by comparing the area under the 45-degree diagonal, and the area between the diagonal and the Lorenz Curve.). **Figure 1** graphically compares the derivation of the Gini coefficient and TCPI, while Appendix A explains how the TCPI can be calculated using downloadable ACS data.

TCPIs, like Gini coefficients, vary linearly between 0 and 1. A TCPI value of zero indicates that the poverty population of a city, county, or metro area is evenly distributed throughout its constituent census tracts regardless of how rich or poor they are. A TCPI value of one indicates that the poverty population is entirely concentrated among census tracts in its uppermost

Figure 1: Graphical Comparison of Gini Coefficient and TCPI Derivations



poverty rate decile. Higher TCPI values indicate that poverty is highly concentrated among relatively few census tracts; lower values indicate that it is more dispersed.

How Concentrated is Poverty Among Large Urban Counties? Table 1 reports 2021 TCPI values for the 66 U.S. counties that are home to one or more cities with at least 300,000 inhabitants.[2] [3] Added together, they included 31% of the U.S. population in 2021. Four counties are home to more than one large city: Orange County in California is home to the cities of Anaheim, Santa Ana, and Irvine; Maricopa County in Arizona is home to Phoenix and Mesa; Clark County in Nevada is home to the cities of Las Vegas and Henderson; and Tarrant County in Texas is home to the cities of Ft. Worth and Arlington. Separate TCPI values are also reported for each of New York City's four largest counties: Brooklyn (Kings), Queens, New York (Manhattan), and the Bronx.

The average 2021 TCPI value for the counties listed in Table 1 is 0.348. Among individual counties, TCPI values range from a high of 0.463 in Hennepin County, which includes the city of Minneapolis, to a low of just 0.064 in Allegheny County, the home county to Pittsburgh. Not coincidentally, Minneapolis has a long-standing history of racial strife—culminating in the 2020 murder of George Floyd by four Minneapolis Police Department officers—while Pittsburgh does not, despite being much poorer. In addition to Hennepin County, the list of counties in which poverty is highly concentrated includes Mecklenburg (Charlotte), Fulton (Atlanta), the District of Columbia, Dallas, Douglas (Omaha), and Travis (Austin). In addition to Allegheny, the group of counties in which poverty is relatively dispersed include Hamilton (Cincinnati), Arapahoe (Aurora), St. Louis, and Denver.

[2] I originally intended to estimate TCPI values for individual cities, but because census tract boundaries do not consistently conform to city boundaries (especially in faster-growing regions), to avoid biasing the results by misallocating tract populations to the wrong municipalities, I instead estimated county-level TCPI values.

[3] Several well-known central cities (and their counties) fall below the 300,000-inhabitant threshold, including Greensboro, Buffalo, Madison, Toledo, Jersey City, Boise, Spokane, Richmond, and Salt Lake City.

Table 1: 2021 Tract-based Poverty Concentration Index Values for Large Urban Counties

County & State	Principal Cities	2021 TCPI Value	County & State	Principal Cities	2021 TCPI Value
Hennepin, MN	Minneapolis	0.463	Fresno, CA	Fresno	0.352
Mecklenburg, NC	Charlotte	0.450	Orange, FL	Orlando	0.350
Fulton, GA	Atlanta	0.447	Nueces, TX	Corpus Christi	0.347
District of Columbia	Washington, DC	0.435	Duval, FL	Jacksonville	0.346
Dallas, TX	Dallas	0.428	Queens, NY	New York	0.345
Douglas,NE	Omaha	0.420	Bernalillo, NM	Albuquerque	0.344
Tarrant, TX	Fort Worth & Arlington	0.417	Wake, NC	Raleigh	0.343
Travis, TX	Austin	0.416	Miami-Dade, FL	Miami	0.341
Pima, AZ	Tucson	0.415	Marion, IN	Indianapolis	0.340
Manhattan, NY	New York	0.411	Philadelphia, PA	Philadelphia	0.339
Brooklyn, NY	New York	0.409	Multnomah, OR	Portland	0.337
Maricopa, AZ	Phoenix & Mesa	0.406	Los Angeles,CA	LA & Long Beach	0.335
Franklin, OH	Columbus, OH	0.403	Wayne, MI	Detroit	0.331
Honolulu, HI	Honolulu	0.403	Bronx, NY	New York	0.330
Ramsey, MN	St. Paul	0.398	Suffolk, MA	Boston	0.328
San Diego, CA	San Diego	0.394	Virginia Beach, VA	Virginia Beach	0.326
Kern, CA	Bakersfield	0.392	Cook, IL	Chicago	0.326
Fayette, KY	Lexington	0.384	Hillsborough, FL	Tampa	0.324
Orange, CA	Anaheim, Santa Ana & Irvine	0.376	Shelby, TN	Memphis	0.319
Davidson, TN	Nashville	0.376	San Joaquin, CA	Stockton	0.316
Harris,TX	Houston	0.371	Milwaukee, WI	Milwaukee	0.315
Alameda, CA	Oakland	0.371	El Paso, CO	Colorado Springs	0.314
Tulsa, OK	Tulsa	0.368	Bexar, TX	San Antonio	0.309
Jackson, MO	Kansas City	0.366	San Francisco, CA	San Francisco	0.305
Sedgewick, KS	Wichita	0.361	Baltimore City, MD	Baltimore	0.301
Santa Clara, CA	San Jose	0.361	Riverside, CA	Riverside	0.301
Oklahoma, OK	Oklahoma City	0.360	Orleans, LA	New Orleans	0.301
King, WA	Seattle	0.357	El Paso, TX	El Paso	0.296
Clark, NE	Las Vegas & Henderson	0.356	Denver, CO	Denver	0.258
Essex, NJ	Newark	0.356	St. Louis City, MO	St. Louis	0.226
Cuyahoga, OH	Cleveland	0.355	Arapahoe, CO	Aurora	0.201
Sacramento, CA	Sacramento	0.354	Hamilton, OH	Cincinnati	0.104
Jefferson, KY	Louisville	0.3527	Allegheny, PA	Pittsburgh	0.064
(listing continues to the right)					

Other than because of historical circumstances, the reasons why poverty should be more concentrated in some counties than others are not immediately obvious. Household location patterns are typically path-dependent—meaning that current household location decisions are strongly influenced by past ones. Still, contemporary forces and factors are not irrelevant. To see which matters most statistically, I compared the TCPI values listed in Table 1 to various county-level population, demographic, economic, housing, and regulatory measures. The results are presented in **Table 2** in the form of correlation coefficients. Of all the county-level TCPI relationships identified in Table 2, the only one that is statistically significant is the rate of recent

Table 2: Population, Demographic & Economic Correlates with 2021 County-Level TCPI Values

Variable Type	Variable (all values are for 2021 unless otherwise noted)	Correlation Coefficient with 2021 TCPI Value
Population, Size, Growth Rate & Density	Population	0.103
	Percent Population Change, 2010-2020	0.305*
	Population Density (persons/sq.mile)	0.109
Demographic Characteristics	Black/White Dissimilarity Index (2018)	-0.107
	Hispanic/non-Hispanic Dissimilarity Index (2018)	0.162
	(Non-Hispanic) White Population Share	-0.122
	Black Population Share	-0.056
	Hispanic Population Share	0.063
Economic Characteristics	Median Household Income	0.170
	Gross Regional Product per Capita (2019)	0.129
	Labor Force Participation Rate	-0.022
	Income Inequality: 95th-to-20th Percentile Income Ratio	-0.047
	Poverty Rate Dissimilarity Index (2018)	-0.060
	Overall Poverty Rate	-0.089
	Homeownership Rate	-0.110
Housing Market Characteristics	Median Gross Rent	0.176
	Annual Mortgage Cost-to-Rent Ratio	0.174
	Median Home Value	0.158
	Ratio of Median Home Value to Median Income	0.154
	Up-for-Growth Housing Production Deficit (2019)	0.079

* indicates correlation coefficient is statistically significant at the .05 level

population growth; and the fact that this relationship is positive suggests that population growth serves to concentrate poverty rather than disperse it.

Among the variables observed *not* to be correlated with county-level TCPI values are population size, population density, various measures of racial composition and segregation, median household income, poverty rates, homeownership rates, and multiple measures of housing cost and value. The fact that these associations are not statistically significant when measured at the county level does not mean they do not have profound neighborhood-level effects. When measured at the neighborhood and individual levels, there is considerable statistical evidence linking concentrated poverty to lower homeownership rates and housing values (Wallace 2016); lower household incomes, and higher unemployment rates (Kasarda 1993, O'Regan 1993); to higher levels of racial and ethnic segregation (Lichter et al. 2012); to a higher incidence of chronic health problems and lower quality medical care (Wurth 2004); to higher homicide rates (Lee 2000); and among children, to lower earnings as adults (Chetty & Hendren 2018). What Table 2 does indicate is that these localized associations are not evident when the data is aggregated at the county level. Simply put, higher levels of concentrated poverty have more of an effect on individual and neighborhood outcomes than on city-level or county-level ones.

Concentrated Poverty Versus Clustered Poverty: TCPI values indicate whether poverty is concentrated in a few neighborhoods, not whether those neighborhoods are spatially clustered. To understand the difference between concentration and clustering, **Figure 2** compares four large urban counties with high and low TCPI values and with high and low levels of poverty clustering. Poverty clustering is measured using the Moran's I statistic, which is an indicator of spatial autocorrelation that tracks the tendency of populations or groups with similar attributes to locate adjacent to one another. Moran's I varies nonlinearly between -1 and +1, with a value of +1 indicating complete spatial concentration and a value of -1 indicating complete spatial dispersion.[4]

Panel A of Figure 2 shows the distribution of 2021 poverty rates by census tract in Orleans Parish, Louisiana, the home county of New Orleans. Compared to other counties, poverty in Orleans Parish is unconcentrated and un-clustered as indicated by the checkerboard pattern of census tract poverty rates as well as by the parish's low TCPI and Moran's I values. Panel B shows the census tract distribution of poverty rates for Honolulu County, in which poverty is moderately concentrated but not spatially clustered. Compared to Orleans Parish, there are proportionately more high-poverty tracts in Honolulu County but they are widely dispersed. Panel C shows the distribution of poverty rates in the City of St. Louis, in which poverty is moderately clustered but not highly concentrated. Compared to Orleans Parish, there are a similar number of high-poverty tracts in St. Louis, but they are more highly clustered. Finally, Panel D shows the distribution of poverty rates in Hennepin County (the home county of Minneapolis) in which poverty is both highly concentrated and highly clustered. Compared to Orleans Parish, there are many more high-poverty census tracts and they are much more tightly clustered. Comparing 2021 TCPI and 2020 poverty rate Moran's I values across a sample of the 66 largest urban counties yields a correlation coefficient of just .30, indicating that while there is some overlap between the two measures, they mostly measure different things.[5] Appendix B includes a side-by-side listing of county TCPI and poverty rate Moran's I values.

II. PATTERNS OF TCPI CHANGE

Average TCPI values for the counties included in this analysis declined ever so slightly between 2000 and 2021, falling from .361 in 2000 to .348 in 2021. The three counties in which TCPI values fell the most—indicating a decline in concentrated poverty—were Hamilton, the home county to Cincinnati (-.29); Allegheny, the home county to Pittsburgh (-.28); and Arapahoe, the home county to Aurora, Colorado (-.27). The four counties in which TCPI values increased most were Fulton, home county to Atlanta (+.16); Washington, DC (+.11), Santa Clara, home county to San Jose (+.11). and Mecklenburg, home county to Charlotte (+.10). Overall, TCPI values declined in thirty-four counties and increased in 25; there were 7 counties in which TCPI values were unchanged between 2000 and 2021.

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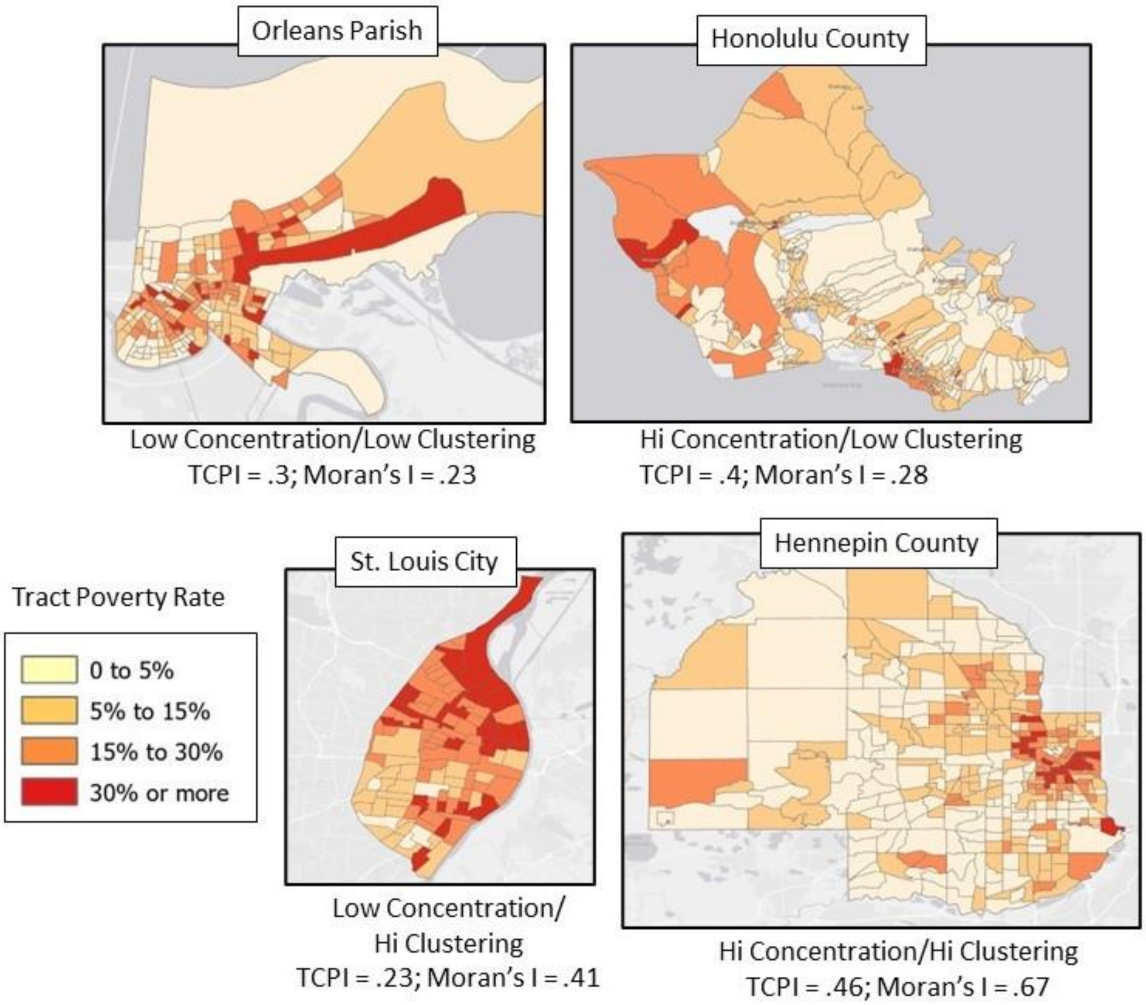
[4] A Moran's value of zero indicates that the observations are located randomly with respect to the attribute of interest.

[5] The average poverty rate Moran's I value in the sample of 66 large urban counties is 0.43. This compares with an average TCPI value of 0.36. Whereas the TCPI is linear, Moran's I is not, so care should be taken when comparing the two measures directly.

Figure 2: Four Combinations of High and Low Poverty Concentrations and Clustering



To determine whether there was any pattern to these changes, I used regression analysis to compare them to various measures of demographic and economic change as compiled by county from the Decennial Census and American Community Survey. These measures include:

i. **The initial TCPI value for the year 2000:** Extreme values of any type are difficult to maintain amidst ongoing change. In counties where TCPI values were initially high, I expect them to have fallen; in places where they were initially low, I expect them to have risen.

ii. **Initial population:** I Included this variable to see whether there was any association between county size and subsequent changes in concentrated poverty.

iii. **Initial poverty rates**: I included this variable to see whether there was any association between county poverty rates in 2000 and subsequent changes in concentrated poverty.

iv. **The rate of population change between 2000 and 2020:** Population growth creates new opportunities which may accelerate residential resorting. Depending on the county, this could manifest itself as either an increase or decrease in concentrated poverty.

v. **Poverty rate changes between 2000 and 2020:** All else being equal, I expect counties where poverty declined between 2000 and 2020 to also have experienced a decline in concentrated poverty.

vi. **Residential segregation levels:** For reasons discussed previously, concentrated poverty often goes hand-in-hand with residential segregation. Accordingly, I expect poverty concentrations to have increased in counties that are highly segregated as measured by the 2000 Black-White Dissimilarity Index.[6]

vii. **Residential mobility:** Poverty de-concentration opportunities should be greater in places where people move more frequently. This variable, which is drawn from the American Community Survey, indicates the share of county households in 2015 who lived in the same house a year earlier.

viii. **The share of gentrification-eligible census tracts in 2000 gentrified by 2013.** Gentrification should function to de-concentrate poverty. A 2015 study by *Governing Magazine* identified the share of gentrification-eligible[7] census tracts among the fifty largest U.S. cities that gentrified between 2000 and 2013.

ix. **State and local income support and health expenditures.** The periodic *Census of Government Finance*s reports state and local government expenditures by category and state. The most recent year for which this data is available is 2020. Other factors being equal, I would expect concentrated poverty levels to be lower among counties in states that spend more per capita on income support and other related programs.

Because *Governing Magazine's* gentrification rate estimates are only available for the fifty largest U.S. cities, I tested two regression models. Model A includes *Governing Magazine's* gentrification measure and covers just forty-nine counties. Model B does not include *Governing Magazine's* gentrification measure and covers all sixty-six counties.

The results of both regression models are presented in **Table 3.** The nine variables in Model A explain 60% of the variation in the change in TCPI values between 2000 and 2021. Not including the gentrification variable (Model B) increases the sample size to 66 counties but because the additional counties are a diverse lot, it reduces the model's r-squared value to 0.38. Except for the initial TCPI value (in Models A and B) and the 2018 Black-White Dissimilarity Index (in Model A),

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[6] The most used measure of segregation, dissimilarity indices (DIs) vary between 0 and 1 and measure the proportion of two population groups that would have to change location to achieve complete integration. Linear in nature, a Black-white DI value of .5 means that half of the Black and white households in a place would have to move for it to be fully integrated. According to Brown University's Diversity and Disparity Project, the median Black-white DI for large U.S. metro areas in 2020 was 0.52 down from 0.58 in 2010. Among the 66 counties in our sample, the average 2018 Black-white DI was .50; the average Hispanic DI was .40. DI values for the sample counties are listed in Appendix B.

[7] *Governing Magazine* regards a census tract to be "gentrification-eligible" if it had a population of at least 500 residents at the beginning and end of a decade and was located within a central city, and if its median household income and median home value were in the bottom 40th percentile when compared to all tracts within its metro area at the beginning of the decade.

Table 3: Factors Associated with 2000-2021 Changes in TCPI Values: Regression Results

Dependent Variable: Change in TCPI Value between 2000 and 2021	Model A (Includes Gentrification Variable) N=49		Model B (Does Not includes Gentrification Variable) N=66	
Independent Variables (sorted by statistical significance)	Standardized Coefficient	Prob. Value	Standardized Coefficient	Prob. Value
TCPI (2000)	-0.51**	0.00	-0.54**	0.00
Black-White Dissimilarity Index (2000)	0.19*	0.04	0.06	0.66
Pct. Change in County Population (2000-2020)	0.16	0.17	0.20	0.16
Change in County Poverty Rate (2000-2020)	-0.18	0.21	-0.13	0.46
Poverty Rate (2000)	-0.12	0.32	0.07	0.67
Population (2000)	-0.06	0.42	0.02	0.84
Per capita State & Local Income Support and Health Expenditures (2020)	0.05	0.52	0.00	0.97
Pct. of Residents in Same House in 2015 & One Year Earlier	-0.05	0.61	-0.08	0.55
Share of Eligible Census Tracts Experiencing Gentrification	0.00	0.98	not included	
Intercept	0.33	0.23	0.33	0.23
r-squared	0.60		0.38	

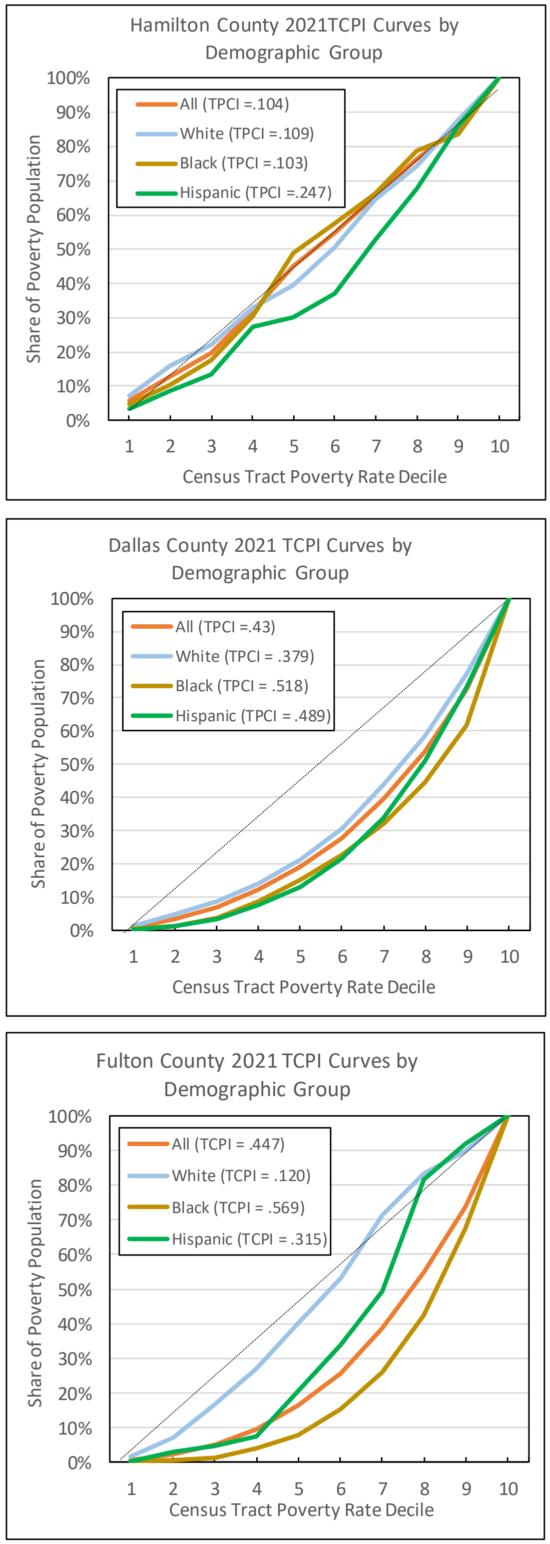
** indicates coefficient is statistically significant at the .01 probability level
* indicates coefficient is statistically significant at the .05 probability level

none of the independent variables are statistically significant. The coefficient of the 2000 TCPI value is strongly negative, indicating that the higher the initial level of concentrated poverty, the greater the subsequent decline. The coefficient of the 2015 Black-White Dissimilarity Index value is positive, indicating that counties that were more segregated along Black-White lines in 2000 were also more likely to have experienced an increase in concentrated poverty. None of the other independent variables are close to being statistically significant in either Model A or Model B, meaning that they are unconnected to changes in county-level TCPI values between 2000 and 2021. When it comes to deconcentrating poverty in America's largest urban counties, neither population growth nor gentrification nor higher state and local anti-poverty spending has any effect.

III. COMPARING TCPI VALUES BY RACE AND ETHNICITY

With a little added effort, TCPIs can also be used to compare poverty concentrations among different demographic groups. In this instance, instead of calculating the share of all poor people residing in each census tract, I calculate the poverty shares of whites, Black people, and non-white Hispanics. The resulting shares can then be used to construct poverty concentration curves by race and ethnicity. These curves can be compared to each other for particular places, compared across places by race and ethnicity, or used to calculate group-and-place specific TCPI values. **Figure 3** presents three such groups and curves: the top panel for Hamilton County (Ohio) depicts a situation in which Black, white, and Hispanic poverty populations are all relatively dispersed; a middle panel for Dallas County (Texas) indicates the case in which all three poverty populations are concentrated; and a bottom panel for Fulton County (Georgia) is emblematic of cases in which the incidence of concentrated poverty differs categorically by race and ethnicity.

Figure 3: Comparisons of 2021 TCPI Curves by Race and Ethnicity Between Hamilton, Dallas & Fulton Counties



Comparing average TCPI values among whites, Black people, and Hispanics, (**Table 4**), we observe Black poverty to be twice as concentrated as white poverty (0.45 vs. 0.23) and Hispanic poverty to be 80 percent more concentrated (0.40 vs. 0.23). These are significant differences and they are indicative of the systematic ways in which poor Black people and Hispanics are trapped in high-poverty neighborhoods compared to poor whites. Beyond comparing sample averages, several counties stand out for their higher poverty concentrations across two or more racial or ethnic groups. These include the Borough of Manhattan in New York City (whites and Blacks), Hennepin County in Minnesota (Blacks and Hispanics), Douglas County in Nebraska (Blacks and Hispanics), Maricopa and Pima Counties in Arizona (whites and Hispanics), and Tarrant County in Texas (whites and Hispanics). At the more benign end of the poverty concentration spectrum, several counties stand out for their lower Black and Brown poverty concentration levels, including Arapahoe County in Colorado and Hamilton County in Ohio. Generally speaking, the counties in which poor Black people are more concentrated are the same ones in which poor Hispanics are more concentrated. The reverse is not true: the counties in which poor Black people are more dispersed are not the same ones in which poor Hispanics are more dispersed. To the degree that concentrated poverty reinforces the effects of racism and discrimination, these results provide additional evidence of the systematic ways America's largest cities and urban counties have evolved to limit the economic and social opportunities available to poor Black people and Hispanics compared to poor whites.

Table 4: 2021 White, Black, and Hispanic TCPII Values: Most and Least Concentrated Counties

	Concentrated Poverty among WHITES		Concentrated Poverty among BLACKS		Concentrated Poverty among HISPANICS	
	County & Primary City	**TCPI**	**County & Primary City**	**TCPI**	**County & Primary City**	**TCPI**
10 Counties in Which Poverty is MOST Concentrated	Manhattan (NYC)	0.41	Douglas (Omaha)	0.64	Mecklenburg (Charlotte)	0.58
	Kern (Bakersfield)	0.39	Hennepin (Minneapolis)	0.62	Maricopa (Phoenix)	0.56
	Fayette (Lexington)	0.38	Tulsa	0.60	Manhattan (NYC)	0.55
	Dallas	0.38	King (Seattle)	0.59	Douglas (Omaha)	0.55
	Travis (Austin)	0.37	Cook (Chicago)	0.58	Hennepin (Minneapolis)	0.54
	San Diego	0.36	Davidson (Nashville)	0.57	Tarrant (Ft. Worth)	0.54
	Pima (Tucson)	0.35	Manhattan (NYC)	0.57	Philadelphia	0.53
	Maricopa (Phoenix)	0.34	Ramsey (St. Paul)	0.57	Orange (Anaheim)	0.51
	Tarrant (Ft.Worth)	0.33	Fulton (Atlanta)	0.57	Sedgwick (Wichita)	0.50
	Fresno	0.33	Duval (Jacksonville)	0.56	Pima (Tucson)	0.49
10 Counties in Which Poverty is LEAST Concentrated	Philadelphia, PA	0.12	The Bronx (NYC)	0.37	Dade (Miami)	0.31
	Hamilton (Cincinnati)	0.11	Queens (NYC)	0.35	Cook (Chicago)	0.29
	Cuyahoga (Cleveland)	0.10	Bexar (San Antonio)	0.35	Shelby (Memphis)	0.26
	Cook (Chicago)	0.06	Riverside	0.34	District of Columbia	0.26
	District of Columbia	0.06	Honolulu	0.33	Arapahoe (Aurora)	0.25
	Milwaukee	0.05	Denver, CO	0.31	Hamilton (Cincinnati)	0.25
	Shelby (Memphis)	-0.02	Arapahoe (Aurora)	0.28	Baltimore City	0.23
	Baltimore City	-0.02	Hamilton (Cincinnati)	0.10	Orleans Parish (N. Orleans)	0.21
	St. Louis City	-0.08	El Paso (Texas)	0.08	Allegheny (Pittsburgh)	0.06
	Orleans Parish (N. Orleans)	-0.09	Allegheny (Pittsburgh)	-0.12	St. Louis City	-0.01

These recurrent racial and ethnic concentrated poverty patterns raise questions about the correspondence between concentrated poverty and segregation. Specifically, does concentrated poverty among Black people and Hispanics go hand-in-hand with higher levels of racial and ethnic segregation as measured by Black/White and Hispanic/non-Hispanic dissimilarity indices? Judging from the correlation coefficients reported in Appendix C, the answer to this question is not so much. Black poverty is no more or no less concentrated in counties in which Black people account for a larger share of the population. The same is also true for Hispanics. Nor do Black and Hispanic poverty concentration levels appear to be systematically higher in counties in which Black-white and Hispanic/non-Hispanic segregation levels are higher as measured using dissimilarity indexes.

As for income and poverty, there are no statistically significant associations between Black or Hispanic TCPI values and Black or Hispanic median income and poverty levels when compared at the county level. Black and Hispanic poverty levels are slightly lower in counties where white poverty is more concentrated, but the associations are only borderline significant. In terms of county population size and growth, there are consistent associations between high white and Hispanic TCPI values and county population growth rates, meaning that counties that grew faster between 2010 and 2020 were those with higher white and Hispanic TCPI values. In which directions these relationships go and whether they are in any way causal, I cannot say. White, Black, and Hispanic TCPI values are not notably correlated with county population size.

IV. CONCENTRATED POVERTY AND RACIALIZED OUTCOMES

Are higher levels of concentrated and racialized poverty associated with less equitable outcomes? To find out, I used regression analysis to compare 2021 white, Black, and Hispanic TCPI values to four commonly cited racial and ethnic disparity measures: (i) the ratio of Black-to-white and Hispanic-to-white homeownership rates; (ii) the ratio of Black-to-white and Hispanic to non-Hispanic poverty rates;[8] (iii) the ratio of Black-to-white and Hispanic to non-Hispanic median household income; and the ratio of Black-to-white and Hispanic-to-white life expectancy.

The homeownership, poverty rate, and median income comparisons are based on 2020 American Community Survey tabulations. The life expectancy comparisons are drawn from county-level vital statistics data compiled by the Institute for Health Metrics and Evaluation Institute at the University of Washington and are current as of 2014 (Dwyer-Lindgren et al. 2017). Whatever the outcome measure chosen, we should expect higher levels of concentrated poverty to be associated with bigger racial and ethnic disparities.

To remind readers of just how deeply embedded racial and ethnic disparities are in American urban life, let us take a moment to review how widely these eight racial and ethnic equity ratios vary among the sixty-six counties included in this analysis. In terms of magnitudes, lower Black-white and Hispanic-white homeownership, median household income, and life expectancy ratios indicate greater inequality while lower poverty-rate ratios indicate lesser inequality. Starting with homeownership, the ratio of Black to white homeownership rates in 2020 ranged from a low of .26 in Ramsey County (the home county of St Paul, Minnesota) to a high of .82 in Queens, New York City. Comparing Hispanics to whites, the 2020 Hispanic-white homeownership rate ratio

[8] The non-Hispanic grouping includes people of all races who do not self-identify as Hispanic or Latino, including whites, Black people, Asians, Pacific Islanders, and Native Americans.

ranged from a low of .26 in Manhattan (in New York City) to a high of 1.02 in El Paso County, Texas.[9] The average 2019 Black-to-white homeownership ratio for the entire sample of counties was .55; for Hispanics, it was .68.

In terms of poverty, the 2020 ratio of Black poverty rates to white poverty rates ranged from a high of 4.55 in the District of Columbia to a low of .84 in Jackson County (Kansas City), Missouri. The average Black-white poverty ratio was 2.2, meaning that Black poverty rates on average were more than twice as high as white poverty rates. Comparing poverty rates between Hispanics and non-Hispanics, the ratio of one to the other varied from a high of 4.83 in Essex County, New Jersey (the home county of Newark) to a low of 1.12 in Jackson County, Missouri, the home county of Kansas City.

There were also stark differences between Black people, whites, and Hispanics in terms of median income. Excluding El Paso County because of its extremely small Black population, among the counties included in this analysis, the 2020 ratio of Black-to-white median household income varied from a low of 0.29 in Nueces County, Texas (the home county of Corpus Christi) to a high of .90 in Sacramento County. Nueces County was also the county with the lowest Hispanic-to-non-Hispanic median income ratio (.38), while Fayette County in Kentucky was the county with the highest (.95). On average, Hispanic households earned seventy-five cents for every dollar earned by non-Hispanic households while Black households earned 61 cents for every dollar earned by white households.

The disparities between Black people, whites, and Hispanics in terms of life expectancy are similarly startling. On average, whites in the counties included in this study live an average of 4.1 years or 5% longer than Black people, while Hispanics live an average of 5.2 years or 7% longer than whites Percentage differences in Black-white life expectancy range from +1% in Brooklyn to -17% in Washington DC. Hispanics living in Baltimore live an average of 17 years or 23% longer than whites, while Hispanics living in Manhattan live an average of 1.6 years or 2% less. Because life expectancy is a function of many factors in addition to place of residence—including background, work history, lifestyle, and culture—readers should be careful not to over-attribute these differences to where people live vis a vis the local availability and cost of healthcare.

The regression results are presented in **Table 5**. In addition to Black, Hispanic, and white TCPI values, the regression models summarized in Table 5 include county-specific 2020 poverty rate Moran's I values measuring the extent to which poverty is spatially clustered. To make it easier to interpret the results, where relationships are statistically significant, I have indicated in italics whether higher TCPI or Moran's I values are associated with greater or lesser outcome equity.

For Hispanics, there are no statistically significant associations between 2021 county-level TCPI values and differences in homeownership rates, poverty rates, median household income, or life expectancy compared to whites. For Hispanics, moving to a county in which poverty is highly concentrated will not, on average, widen the economic and life expectancy disparities they face when compared to whites. Likewise moving to a county in which poverty is less concentrated will not help narrow those gaps.

[9] El Paso was the only county in the sample in which the Hispanic homeownership rate was greater than the white homeownership rate.

Table 5: TCPI Contributions to Black-White and Hispanic/non-Hispanic Outcome Disparities: Regression Results

Depedent Variable: 2019 County-level Equity Ratio or Difference (Data Sources: ACS; University of Washington, NEAP)	Improved Equity is Associated with:	Coefficient Estimates & Statistics						
		Constant	Black TCPI Coefficient	Hispanic TCPI Coefficient	White or Non-Hispanic TCPI Coefficient	Poverty Rate Moran's I Coefficient	r-squared	County Observations
County-level Ratio of Black-to-White **Homeownership Rates**	Larger Values	.85**	-.25* *Less equitable*	Not entered	-0.15	-.34** *Less equitable*	0.24	63
County-level Ratio of Black-to-White **Poverty Rates**	Smaller Values	1.75**	1.79* *Less equitable*	Not entered	-1.89	0.1	0.11	63
County-level Ratio of Black-to-White **Median Household Incomes**	Larger Values	.73**	-0.27	Not entered	0.28	-0.15	0.10	63
County-level Percentage Difference in Black vs. White **Life Expectancy**	Smaller Values	-0.01	-.14** *Less equitable*	Not entered	.136** *Less equitable*	-0.02	0.38	63
County-level Ratio of Hispanic-to-non-Hispanic **Homeownership Rates**	Larger Values	.67**	Not entered	0.34	-0.16	-0.02	0.04	63
County-level Ratio of Hispanic-to-non-Hispanic **Poverty Rates**	Smaller Values	2.14**	Not entered	-1.97	1.15	1.24	0.04	63
County-level Ratio of Hispanic-to-non-Hispanic **Median Household Incomes**	Larger Values	.74**	Not entered	0.16	-0.14	-0.07	0.01	63
County-level Percentage Difference in Hispanic vs. White **Life Expectancy**	Smaller Values	.09*	Not entered	-0.12	-0.04	0.08	0.11	63

** indicates coefficient is statistically significant at the .01 probability level
* indicates coefficient is statistically significant at the .05 probability level

The story is different for Black people. For Black people, higher levels of concentrated poverty at the county level are associated with wider Black-white homeownership, poverty rate, and life expectancy disparities, but not wider median income gaps. For the three economic measures, the associations between higher levels of concentrated poverty and Black-white disparities are not large, but they are statistically significant and notable. In terms of life expectancy, Black people who live in predominantly poor neighborhoods have notably shorter life expectancies than whites who live in poor neighborhoods.

What is even more notable, as evident from the constant terms in the various regression models is how large and consistent these disparities are regardless of county or location. Black homeownership rates are consistently 15% lower than white rates regardless of county of residence or the extent of concentrated poverty while Hispanic homeownership rates are consistently 33% lower. Black poverty rates are consistently 75% higher than white rates and Hispanic poverty rates are consistently 114% higher than non-Hispanic rates. On average, Black and Hispanic median household incomes are 27% and 26% lower than White and non-Hispanic median household incomes.

These baseline disparities may increase or decrease slightly as other factors are considered, but overall, the story is one in which a household's race and ethnicity are the dominant determinants of how likely they are to be a homeowner, live above the poverty line, or earn a decent income. As noted previously but bears repeating, readers should be especially careful interpreting results such as these. Among the things they reliably tell us is there is a loose association between living in a place in which Black poverty is concentrated in a few neighborhoods and wider disparities between Black people and whites in terms of homeownership, poverty, and life expectancy when compared at the county level. No such associations are apparent for Hispanics. To the extent that countywide averages matter when designing, implementing, or evaluating anti-poverty and racial equity policies, this is useful information.

Among the many things, these findings do not tell us are whether individuals of a particular race or ethnicity living in high-poverty neighborhoods are more likely than inhabitants of low-poverty neighborhoods to own a home, escape the effects of poverty, or live a longer and healthier life than individuals living in lower-poverty neighborhoods. They also do not tell us of the effects of concentrated poverty on individual outcomes or racial/ethnic disparities when measured at the neighborhood level. This last set of results suggests that policies and programs intended to reduce poverty and racial or ethnic outcome disparities are better targeted at the individual or neighborhood level than at the city or county level. When it comes to addressing poverty and equity issues, the finer the spatial scale, the better.

V. CONCLUDING THOUGHTS: THE TCPI IS STILL A WORK IN PROGRESS

As Princeton sociologist Matthew Desmond writes in his 2023 book, *Poverty, by America*, the problem of poverty in America—especially urban poverty—is not that we do not understand its causes, incidence, or effects, or that we have failed to identify effective programs for reducing it. Rather, it is that as a nation, we lack the collective will to pay the costs of undertaking and completing those programs; and that we have come to regard poverty and wealth inequality as the unavoidable price of maintaining a competitive economy. All the while conveniently choosing to overlook who benefits from that economy and who does not. Viewed in this context, it is indeed reasonable to ask what value yet another poverty measure adds to the policy mix, especially one that tends to gloss over individualized and locally based differences in how poverty is experienced or escaped.

My response to this skepticism is three-fold. The first is that poverty, like many other urban attributes, overwhelmingly occurs as a spatial phenomenon, with high-poverty neighborhoods existing—often for no obvious reason other than history--within throwing distance of low-poverty ones. Such spatial heterogeneity is easy to indicate on a map but is more difficult to express or to compare across places and times using easy-to-understand summary statistics. This is where the TCPI comes in. As this working paper has shown, like any good indicator, TCPIs provide a concise and intuitively understandable way to compare poverty concentrations over time and between places.

Second, as this working paper has also demonstrated, the TCPI (and the Lorenz Curve-like diagrams it is calculated from) provide a more complete means of understanding the demographic incidence of poverty than simple poverty rates. This should prove helpful when targeting anti-poverty policies and programs to particular locales and groups. Third, like any robust and easy-to-construct summary indicator, the TCPI should, in time, find additional and relevant uses as poverty researchers and policy scholars connect the individual causes and effects of poverty with more granular presentations of its incidence at larger spatial scales.

Still, at some point, over-measuring a problem can distract from addressing it. Given the current indifference of Congress and many state legislatures to the plight of the poor in America, any tool that can help build a larger political constituency to lessen that plight should be welcome. Just as the Gini coefficient is now widely used to communicate the extent of income inequality by place and group—thereby helping bring together disparate groups and places around a common issue, so too I hope that the TCPI and other similar measures be used to help build a broader constituency for political and policy efforts intended to combat poverty.

Appendices can be viewed by clicking here.

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