Spatially-concentrated Poverty and Metropolitan & Individual Economic Outcomes

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*PPEI Working papers express the views of the authors and not the University of Pennsylvania or the Department of City and Region Planning.

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INTRODUCTION

The United States has made noteworthy progress during the last thirty years reducing Black-White residential segregation (Fischer et al., 2004; Landis, 2019). It has made less progress reducing income segregation. Indeed, by some accounts, income segregation among U.S. metropolitan areas is now greater than at any time since 1970 (Jargowsky, 1996, 2002, 2014; Wheeler and La Jeunesse, 2008; Watson, 2009). With income inequality rising across the globe (Reardon and Bischoff, 2011; Picketty, 2014), and with such meager progress having been made in America's 50-year fight against urban poverty[1], concerns are mounting in the U.S. and globally about the mutually-reinforcing nature of income inequality, income segregation, and spatially-concentrated poverty (Hoeller, Joumard, and Koske, 2014). Policymakers worry that programs that redistribute income without also deconcentrating poverty or income segregation will ultimately fail, as will programs that try to reduce income segregation without also redistributing income.

Income segregation is best understood as the spatial clustering of households by income and/or wealth level. Typically, this involves upper-income households using their wealth and power—principally by enacting large-lot zoning—to create high-income enclaves, thereby limiting middle- and lower-income households to less-desirable neighborhoods (Rothwell and Massey, 2010; Rothwell, 2011). This behavior is then repeated by middle-income households who zone-out apartments and oppose subsidized housing, leaving poor households clustered in the least preferable locations.

Economists, sociologists and urban planners agree that such exclusionary activities impose significant economic and social costs. For economists, the principle problem is reduced economic opportunity and spillovers. Residents of lower-income neighborhoods typically have many fewer entrepreneurial and job opportunities within their neighborhoods, requiring them to travel longer-than-necessary distances in search of good jobs, retail opportunities, and public services. In addition to limiting job opportunities, urban economists have documented the adverse effects of economic segregation on children's educational attainment levels and upward economic mobility (Cutler and Glaeser, 1997; Quillian, 2007; Mayer, 2010).

For sociologists, this type of spatial sorting inevitably leads to an "us-versus-them" mentality in which residents of other neighborhoods (defined as those who do not live in "our" neighborhood) are seen as intrinsically inferior and therefore not to be trusted. As a result, residents of lower-income neighborhoods suffer from reduced individual and group aspirations, as well as being cut off from supportive services and civic institutions. While the literature on these "neighborhood effects" connecting social norms and aspirations to individual outcomes remains contested (Sampson et al., 2002; Sampson, 2011), there is a growing body of evidence linking deficient social capital to a reduced intergenerational economic mobility (Chetty et al., 2017). Anti-social behaviors such as crime and delinquency come to be seen as adverse pathologies to be contained to lower-income neighborhoods rather than as problems to be solved on a citywide basis.

For planners concerned with promoting improved housing and neighborhood quality, and with providing high-quality public services, the problem with economic segregation is that it limits needed private investment in housing and local businesses, thereby shifting the investment and public services burden entirely to the public sector (Galster, Tatian, and Accordino, 2006; McClure, 2008; Bramley, 2012; Galster, 2013).

This working paper explores the most extreme form of economic segregation: the case in which most of a community's poor residents are concentrated in just one or a few neighborhoods. Among geographers, this is known as spatially-concentrated poverty. While much research has tackled and problematized spatially-concentrated poverty, the nature and scale of its pernicious effects are not yet completely understood. To understand why this is the case, consider the following thought experiment. There are two metropolitan areas in which the poverty rate is 20 percent. The poverty population of Metro Area A is homogeneously distributed throughout the metro while in Metro Area B the poverty population is completely concentrated in a single neighborhood. Which case is worse and in what ways?

The answer depends on the spatial scale one considers. From a neighborhood perspective, Metro Area B is infinitely worse. As countless empirical studies have documented (see for example: Ellen and Turner, 1997; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2013), residents of metro area B's single high-poverty neighborhood will suffer from all manner of adverse economic and social outcomes when compared to residents of neighborhoods in which poverty is less spatially-concentrated. These include higher unemployment rates, reduced amounts of private investment, a lack of good-quality affordable housing, higher crime rates, worse schools, and lower educational attainment levels. These outcomes may be mitigated somewhat by effective government programs and policies, but except for crime reduction, the success rates of such interventions are regrettably low (Partridge and Rickman, 2006; Ellen, Horn, and Reed, 2017).

What about from the perspective of the larger metropolitan area? Do residents of metro areas in which poverty is spatially concentrated face systematically worse economic and social outcomes than residents of metro areas in which poverty populations are more uniformly distributed?

Likewise, what about individuals? Do children brought up in communities in which poverty is spatially concentrated suffer from less economic mobility as adults when compared to otherwise similar children raised in communities where poverty is less spatially concentrated?

The purpose of this working paper is to use the most recent data available to answer these two questions. First, to what extent is spatially-concentrated poverty associated with reduced metropolitan-level outcomes? And second, to what extent is spatially-concentrated poverty associated with reduced individual outcomes, especially for Blacks and Latinos?

To answer the first question, we draw on current population and poverty data from the American Community Survey as well as a series of statistical measures used by quantitative geographers to measure spatial concentrations. Our efforts to answer the second question draw on recent work by Harvard University economists Raj Chetty and Nathaniel Hendren (2014a; 2014b; 2016; 2018), which finds the socioeconomic conditions in the places where children spend their childhood and adolescence to play a major—and in the cases of Blacks and Latinos, dominant—role in determining their economic mobility and success as a young adult.

The balance of this working paper is organized into five parts. In Part I, we explain how we measure spatially-concentrated poverty. In Part II, we rank the nation's 107 largest metro areas according to the degree to which their poor residents are spatially-concentrated in one-or-a-few neighborhoods, versus being more widely distributed throughout the metropolitan area. In Part III, we use regression analysis to assess the degree to which spatially-concentrated poverty is correlated with reduced economic performance when measured at the metropolitan scale. In Part IV, we turn our attention to the connection between concentrated poverty and individual outcomes when measured at the neighborhood level. Finally, in Part V, we draw some preliminary connections between our empirical findings and potential policy interventions.

I. MEASURING SPATIALLY-CLUSTERED POVERTY

We begin by asking how best to measure the extent of spatially-concentrated poverty. In their seminal study of racial segregation in America, Massey and Denton (1988: 283-297) identified five types of separation and segregation measures, including evenness, exposure, concentration, centralization, and clustering. *Evenness* compares the spatial distributions of two or more groups within a given spatial region. The most widely-used evenness measure is the dissimilarity index, which calculates the percentage of each group's population that would have to change location to achieve the same neighbourhood and regionwide percentage. *Exposure* measures the degree of potential contact or possibility of interaction between members of majority and minority groups. Although highly correlated, evenness and exposure measures have some subtle differences: exposure measures depend on the relative sizes of the two groups being compared, while evenness measures do not. *Concentration* refers to the amount of physical space within a spatial region occupied by one or more groups. Groups of the same relative size occupying comparatively less space are more concentrated. *Centralization* is the degree to which a group is spatially located near the geographic center of a region. Absolute centralization considers the spatial distribution of just the minority population, whereas relative centralization compares the areal profile of both the majority and minority populations. *Clustering* measures the extent to which areal units inhabited by minority group members adjoin one another. Massey and Denton (p. 293) refer to a high degree of clustering as constituting an "enclave." Low-income racial, ethnic, and religious enclaves have historically been referred to as ghettos.

This working paper is principally concerned with the fifth of these dimensions: clustering, or the degree to which observations with similar attributes (e.g., poverty rate or median household income) are either adjacent or proximate to one other. Clustering can be measured nominally, as when members of a particular group (e.g., African-Americans or high-income households) are co- or near-located; or along as scale, as when similarly-attributed individuals live and work closer or farther away from one another.

Geographers and statisticians refer to this second scalar form of clustering as *spatial auto-correlation.* In non-statistical terms, spatial auto-correlation measures the degree to which similarly-valued observations co-locate or near-locate—that is, the degree to which high-valued observations locate near other high-valued observations, leaving lower-valued observations to near-locate (or not) with other lower-valued observations.

Spatial auto-correlation can be measured regionally (or, in some cases, globally), meaning that all similarly-valued observations co- or near-locate across a region; or locally, meaning that high-valued individual observations are more likely to locate near other high-valued individual observations. Regional spatial auto-correlation is typically measured using a statistic known as Moran's I, while local clustering can be measured using the Local Moran's I statistic, also known as Anselin's Local Moran's I.

(Global) Moran's I values are calculated by comparing the attribute value differences between nearby and faraway observations.[2]

When any local differences are small relative to the differences among faraway observations (meaning that nearby observations vary less among themselves than more distant observations), Moran's I takes a positive value. When they are large, Moran's I takes a negative value. Moran's I values typically vary between -1 and +1: a Moran's I value of 1 indicates that a population or activity is perfectly clustered. A Moran's I value of 0 indicates that a population or activity is located randomly in space, while a Moran's I value of -1 indicates complete dispersal, like the black-red patterns of a checkerboard.

Properly interpreting Moran's I values requires some caution. Moran's is non-linear: a Moran's I value of 0.5 does not indicate five times the clustering power of a Moran's I value of 0.1. Second, Moran's I does not provide any information about the composition of the clusters it measures; that is, whether the clustering is of high values or low values. On the positive side, Moran's I is a statistic, meaning that calculations of Moran's I values are always accompanied by probabilities indicating whether or not those values are statistically significant.

Anselin's Local Moran's I is calculated for each spatial observation as the difference between its own attribute value and the mean attribute values of its immediate neighbors (as weighted by the distance between them, and then normalized by a measure of the attribute variance). Each observation's Local Moran's I value is accompanied by a Z-score which indicates whether that observation is surrounded by other observations with similarly high values (i.e., "High-high") or similarly low ("Low-low") values, or whether high values are surrounded by low values ("High-low") or whether low values are surrounded by high values ("Low-high").

Figures 1 and 2 graphically summarize the differences between the two measures. Figure 1a presents a thematic map of 2017 poverty rates for every census tract in the Detroit metropolitan area. Detroit is not only the nation's poorest large metropolitan area, but with a Moran's I value of .73, exhibits the highest level of spatially-concentrated poverty of any large U.S. metro areas. This is evident from the evenness of the poverty rate hotspot map presented in Figure 1b[3].

Figure 1c is based on the same census tract poverty rate information as Figures 1a and 1b, but uses Anselin's Local Moran's I to present it in a more nuanced fashion: as a map indicating whether each tract is part of a local "high-high" cluster as indicated in dark red (that is, a high-poverty rate surrounded by other high-poverty rate tracts), a local "low-low" tract as indicated in dark blue (a low-poverty rate tract surrounded by other low-poverty rate tracts), a "high-low" tract as indicated in light red, a "low-high" as indicated in light blue, or an un-clustered tract as indicated in yellow. Figures 2a, 2b, and 2c present comparable information for the Portland (Oregon) metropolitan area, which, among large U.S. metro areas, has the lowest level of spatially-concentrated poverty.

Equipped with Moran's I and Anselin's Local Moran's I (henceforth, MI and ALMI), we downloaded 2017 and 2000 poverty rates[4] and median household income estimates for every U.S. census tract.[5] The 2000 data were collected as part of the 2000 Decennial Census, while the 2017 data were estimated as part of the Census Bureau's annual American Community Survey (ACS). Because the ACS is

Figure 1A: 2016 Census Tract Poverty Rates for the Central Detroit Metro Area

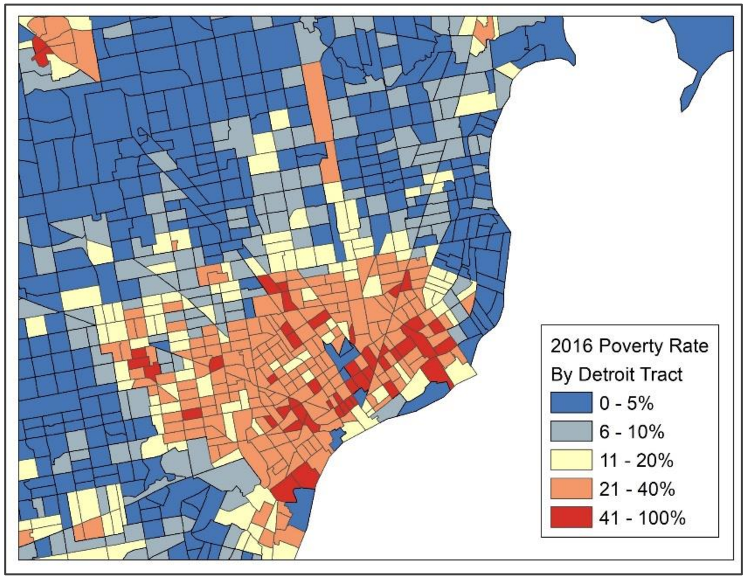


Figure 1B: 2016 Census Tract Poverty Rate Getis-Ord Hot Spot Analysis for the Central Detroit Metro Area

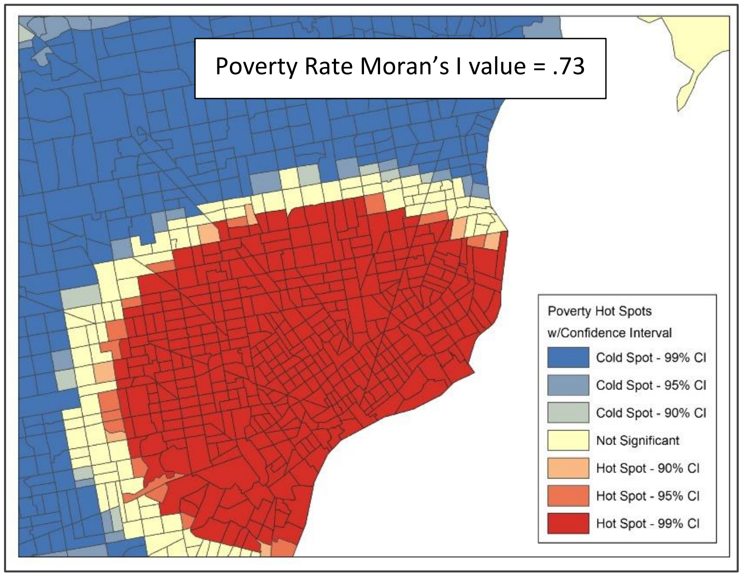


Figure 1C: Anselin's Local Moran's I Poverty Rate Clusters for the Central Detroit Metro Area

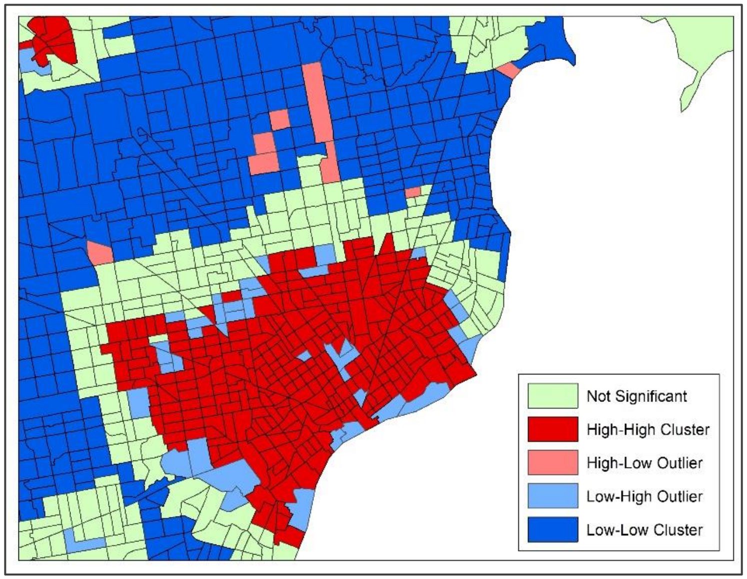


Figure 1D: Poverty Rate Clusters & Opportunity Tracts in the Central Detroit Metro Area

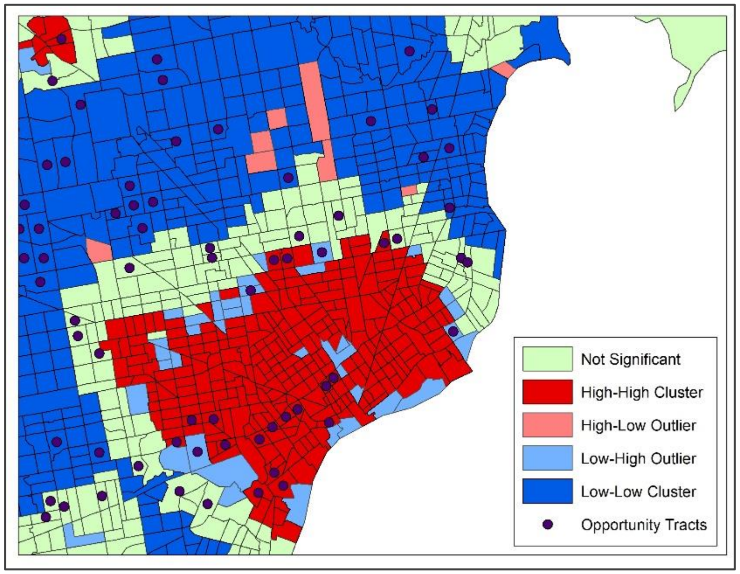


Figure 2A: 2016 Census Tract Poverty Rates for the Central Portland Metro Area

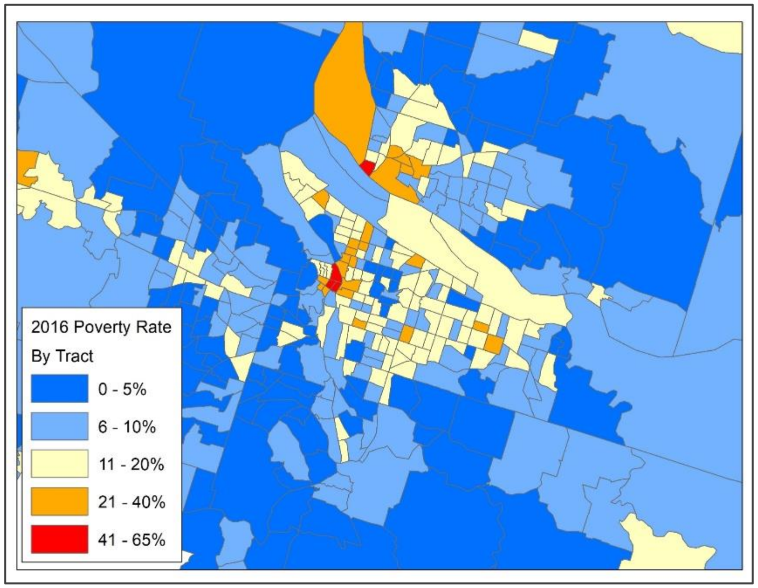


Figure 2B: 2016 Census Tract Poverty Rate Getis-Ord Hot Spot Analysis for the Central Portland Metro Area

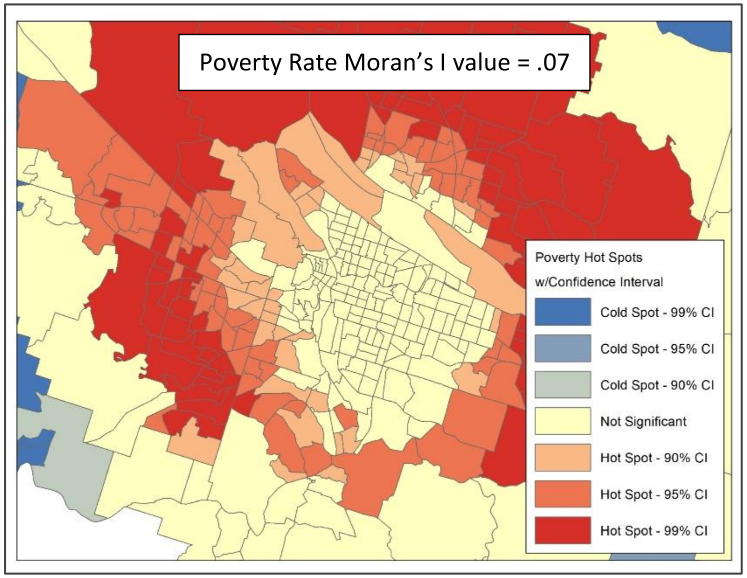


Figure 2C: Anselin's Local Moran's I Poverty Rate Clusters for the Central Portland Metro Area

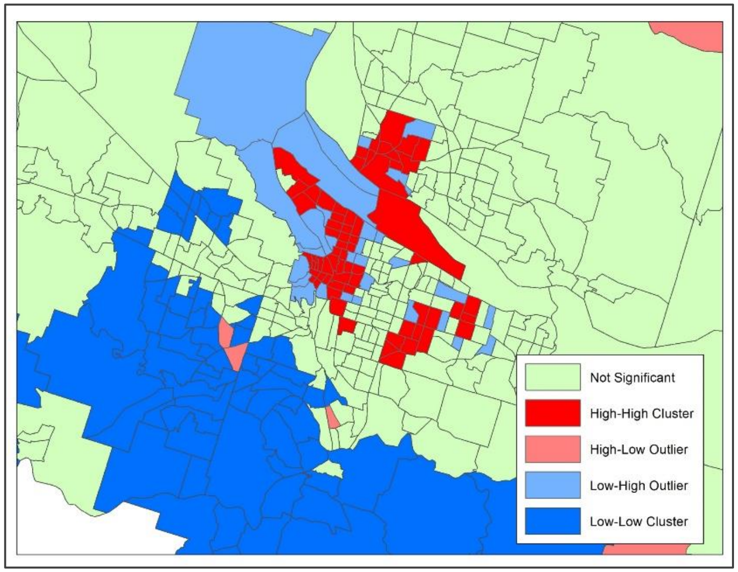
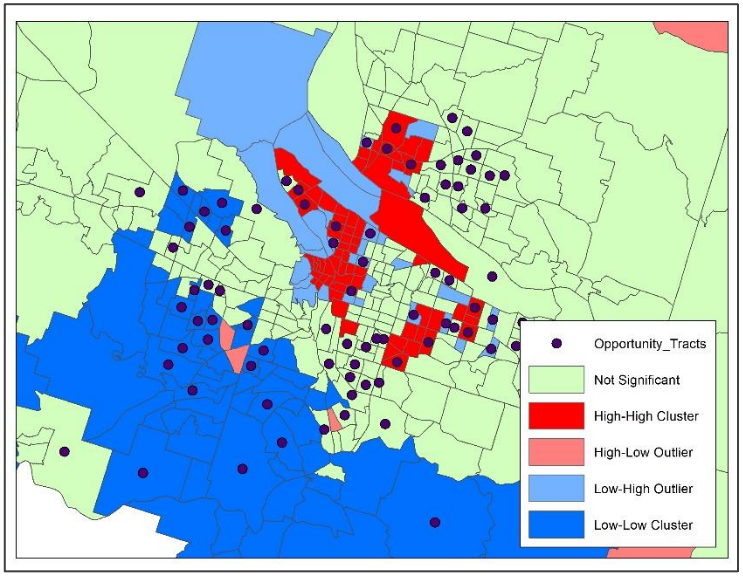


Figure 2D: Poverty Rate Clusters & Opportunity Tracts in the Central Portland Metro Area



based on a sample[6], every ACS value is reported with a margin of error estimate to account for sample size-based differences in accuracy. Because poverty rates and household income levels vary widely by race and ethnicity, we downloaded separate estimates for Whites, African-American and Latino residents. To explore the potential relationships between spatially-concentrated poverty and individual outcomes, we make extensive use of a remarkable dataset produced by Raj Chetty and Nathaniel Hendren and their colleagues at Harvard University, and distributed publicly via the Opportunity Insights website (https://opportunityinsights.org/). This dataset assigns a value to every U.S. census tract based on whether a White or minority child growing up in that census tract in the mid-to-late 1980s had a better-than-average or worse-than-average likelihood of attaining a particular income level as an adult.

Unlike prior opportunity studies that were limited to assessing the role of subsidized housing programs in avoiding negative outcomes, Chetty and Hendren's work looks at opportunity in terms of achieving greater economic mobility. Drawing on the Chetty and Hendren's Opportunity Insights database, we identified 16,232 separate census tracts as "opportunity tracts" for Black and Hispanic children. These are the census tracts in which a Black or Hispanic child growing up in the 1980s and early 1990s could be expected to achieve an adult income falling within the 75th-or-higher percentile of their particular age and race cohort.

Figures 1d and 2d identify the locations of these opportunity tracts as purple dots against poverty rate ALMI maps for Detroit and Portland. To the degree that concentrated poverty serves to limit individual opportunities, we would expect to observe little or no overlap between these Chetty and Hendren's opportunity tracts and tracts identified as "high poverty-high poverty"; that is, high-poverty tracts surrounded by other high-poverty tracts. Following Jargowsky (2002, 2014), we would expect to observe a significant overlap between opportunity tracts and those tracts identified as "low-poverty-low-poverty" based on the ALMI statistic.

II. WHERE IS POVERTY CLUSTERED?

Table 1 lists poverty rate Moran's I (MI) values for the 107 U.S. metro areas with more than 500,000 residents. As noted previously, these values were estimated using 2017 poverty rates as reported at the census tract level in the American Community Survey. Also listed are symbols indicating whether there has been a significant change in MI value between 2000 and 2017: the "---" symbol indicates that a metro area's MI value declined by more than 0.2 between 2000 and 2017 (indicating a sharp decline in the spatial concentration of poverty); the "--" symbol indicates an MI decline of 0.1 to 0.2; the "-" symbol indicates an MI decline of 0.04 to 0.1; a "0" indicates an MI value change between -0.04 and +0.04; the "+" symbol indicates a MI increase of between 0.04 and 0.1; the "++" symbol indicates an MI increase of 0.1 to 0.2; and the "+++" symbol indicates a MI increase of more than 0.2. To reflect the sensitivity of MI values to the number of observations (in this case, census tracts), these results are further organized into three metropolitan area size categories. Metro areas with a 2017 population of two million or more residents are designated as "Very Large," those with one to two million residents are designated as "Large," and those with 500,000 to a million residents are identified as "Middle-sized." Altogether, our sample includes 32 Very Large metro areas, 19 Large metro areas, and 52 Medium-sized metro areas.

Among Very Large metropolitan areas, poverty is most clustered among census tracts in Detroit (MI = .73) and Baltimore (MI=.68).[7] Rounding out the top five list of extreme poverty clustering are Philadelphia (MI=.65), Boston (MI=.52), and Indianapolis MI (.50). At the other end of the Very Large metro poverty clustering spectrum, the spatial distribution of poverty tends toward a more a random distribution among census tracts in Seattle, Orlando, Riverside-San Bernardino and Portland.

Among Large metro areas, poverty is most clustered in Hartford, Rochester, and Jacksonville, and least clustered in New Orleans, San Jose, and Salt Lake City. Among Middle-sized metro areas (those with populations between a half-million and one million residents), poverty is most spatially clustered in Portland (Maine), Lancaster, and Akron. By contrast, in Modesto, Baton Rouge, and McAllen, the spatial pattern of poverty is closer to random.

Poverty Clustering and Poverty Rates

The New Orleans and San Jose results provide a useful reminder that poverty and poverty clustering do not automatically coincide. New Orleans has one of the country's highest poverty rates, but because poor households reside throughout the metropolitan area, a low level of poverty clustering. Poverty is also highly dispersed in the San Jose metro area, which, in contrast to New Orleans, has a very low poverty rate. The lack of correlation between poverty rates and poverty clustering is shown graphically in Figure 3, which compares 2017 poverty rates (on the x-axis) with 2017 poverty rate Moran's I values (on the y-axis) for each group of Very Large, Large, and Mid-sized metropolitan areas. To the degree that there is any relationship between poverty rates and poverty clustering, it is most notable among Mid-sized metro areas.

Table 2 takes the comparison between poverty rates and poverty clustering a step further by classifying metro areas according to how they rank on both poverty and poverty clustering.

Table 1: Poverty Rate Moran's I Values in Large and Middle-sized U.S. Metropolitan Areas

Very Large Metro Areas (2+ Million Residents)	2017 Poverty Rate Moran's I Value	Change Since 2000
Detroit MI	0.73	--
Baltimore MD	0.68	0
Philadelphia PA-NJ-DE	0.59	---
Boston MA-NH	0.52	--
Indianapolis IN	0.50	--
Cincinnati OH-KY	0.49	-
Columbus OH	0.43	0
Atlanta GA	0.40	---
Cleveland OH	0.40	---
Kansas City MO-KS	0.39	--
Washington DC-VA-MD	0.39	-
Tampa-St. Petersburg FL	0.38	--
Chicago IL	0.35	--
Dallas-Fort Worth TX	0.30	-
Austin TX	0.29	-
New York City-Newark NY-NJ	0.29	-
Pittsburgh PA	0.27	0
San Antonio TX	0.25	-
Charlotte NC-SC	0.24	--
Sacramento CA	0.22	+
Las Vegas NV	0.20	0
Houston TX	0.19	--
Phoenix AZ	0.19	0
Los Angeles-Long Beach CA	0.18	-
San Francisco-Oakland CA	0.18	0
Miami-Ft. Ld.-W. Plm Bch FL	0.16	--
San Diego CA	0.16	-
Denver CO	0.14	-
Seattle-Tacoma WA	0.13	-
Orlando FL	0.11	0
Riverside-S. Bernardino CA	0.11	0
Portland OR-WA	0.07	-

Large Metro Areas (1-2 Million Residents)	2017 Moran's I Value	Change Since 2000
Hartford CT	0.60	---
Rochester NY	0.55	+
Jacksonville FL	0.53	++
Providence	0.50	++
Louisville–Jefferson County K	0.42	+
Milwaukee	0.40	---
Raleigh VA	0.39	0
Nashville TN	0.37	-
Birmingham AL	0.35	+
Grand Rapids MI	0.34	-
Richmond VA	0.32	-
Buffalo NY	0.29	--
Tucson AZ	0.20	0
Norfolk-Vir.Beach	0.19	-
Oklahoma City OK	0.18	-
Salt Lake City UT	0.18	-
San Jose CA	0.15	0
New Orleans LA	0.04	---
Memphis TN		

Middle-sized Metro Areas (0.5 - 1 Million Residents)	2017 Poverty Rate Moran's I Value	Change Since 2000
Portland ME	0.90	+
Lancaster PA	0.87	---
Akron OH	0.73	0
Bridgeport CT	0.64	-
Allentown PA	0.64	++
Knoxville TN	0.62	--
New Haven CT	0.58	-
Dayton OH	0.58	+
Worcester MA	0.54	+++
Winston-Salem NC	0.50	0
Syracuse NY	0.49	0
Madison WI	0.49	++
Albany NY	0.44	0
Chattanooga TN	0.43	+
Springfield MA	0.42	+
Omaha NE	0.40	0
Provo-Orem UT	0.37	-
Toledo OH	0.36	--
Stockton CA	0.36	+
Jackson MS	0.35	-
Daytona Beach FL	0.35	--
Youngstown OH	0.33	0
Greenville SC	0.29	-
Greensboro NC	0.29	+
Ogden UT	0.29	+
Scranton–Wilkes Barre PA	0.28	+
Harrisburg PA	0.27	-
Des Moines IA	0.26	0
Fayetteville AR	0.26	-
Little Rock AR	0.26	--
Wichita KS	0.26	+
Sarasota fl	0.25	++
El Paso TX	0.24	0
Augusta, GA-SC	0.23	--
Colorado Springs CO	0.22	0
Tulsa OK	0.21	0
Fresno CA	0.21	-
Bakersfield CA	0.20	0
Charleston SC	0.20	--
Columbia SC	0.18	--
Lakeland FL	0.17	-
Cape Coral FL	0.17	---
Oxnard-Ventura CA	0.16	-
Spokane WA	0.15	0
Boise ID	0.14	+
Durham NC	0.13	-
Palm Bay FL	0.13	--
Albuquerque NM	0.11	-
Modesto CA	0.11	-
McAllen TX	0.05	-
Baton Rouge LA	0.02	---
Honolulu HI		0

Key to changes: --- indicates MI decline by more than .2; -- indicates MI decline by .1 to .2; - indicates MI decline by .04 to .1; 0 indicates +.03 to -.03 MI change; + indicates MI increase by .04 to .1; ++ indicates MI increase by .1 to .2; +++ indicates MI increase by more than .2.

Figure 3:
Comparison of 2017 Metro Area Poverty Rates (x-axis) vs. 2017 Poverty Rate Moran's I Values (y-axis), by Metro Area Size Category

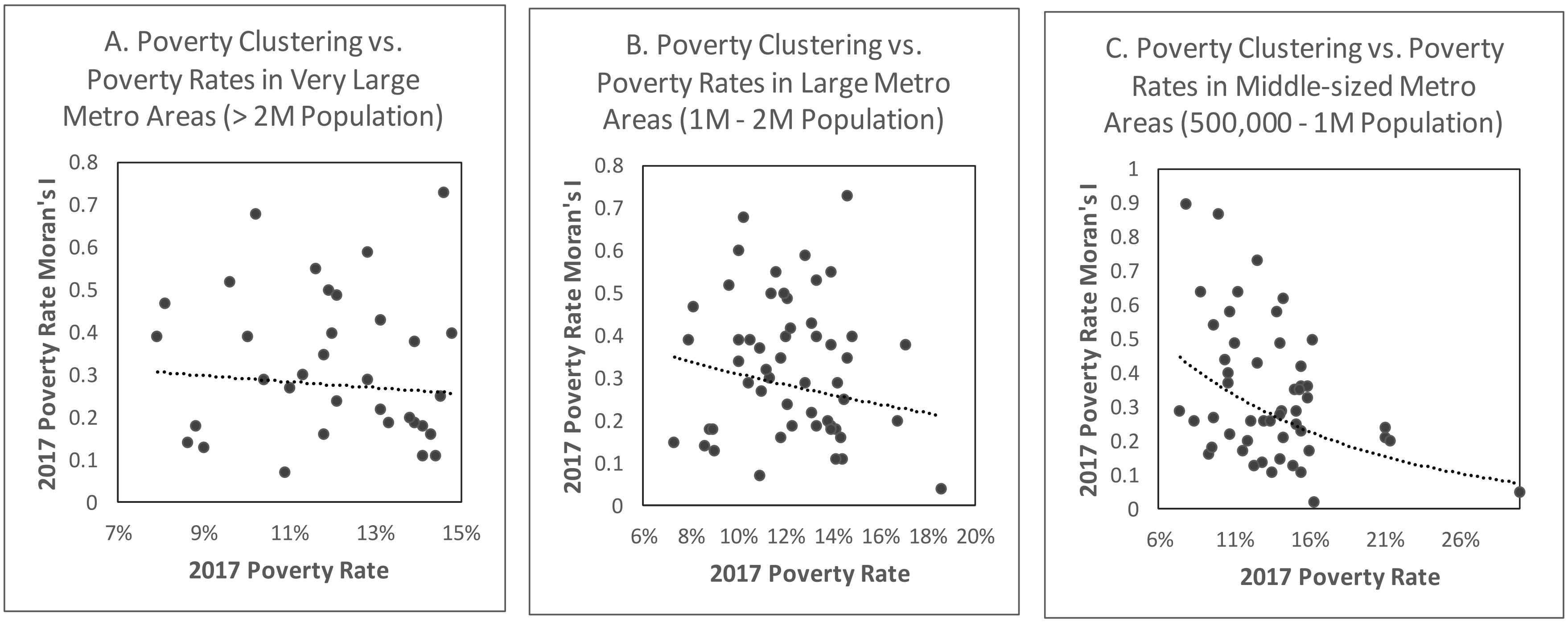


Table 2: 2017 Poverty Rates & Poverty Clustering: How the Nation's Largest Metro Areas Compare

	Metro Areas in Which Poverty is NOT Spatially-concentrated	Metro Areas in Which Poverty is SOMEWHAT Spatially-concentrated	Metro Areas in Which Poverty is VERY Spatially-concentrated
Low Poverty Rate Metro Areas	Colorado Springs CO Salt Lake City UT San Francisco-Oakland CA Columbia SC Thousand Oaks-Ventura CA San Jose CA Denver CO Seattle-Tacoma WA Portland OR	Worcester MA Washington DC Kansas City MO Raleigh NC Nashville TN Provo-Orem UT Grand Rapids MI Richmond VA Ogden UT Austin TX Harrisburg PA Pittsburgh PA Des Moines IA	Portland ME Lancaster PA Baltimore MD Bridgeport CT Allentown PA Hartford CT New Haven CT Omaha NE Boston MA Madison WI Albany NY
Moderate Poverty Rate Metro Areas	Sacramento CA Tulsa OK Las Vegas NV Charleston SC Norfolk-Virginia Beach VA Phoenix AZ Houston TX Los Angeles-Long Beach CA Oklahoma City OK Cape Coral-Ft.Myers FL San Diego CA Miami-Ft. Lauder.-Palm Beach FL Spokane WA Boise ID Palm Bay-Melbourne FL Modesto CA Riverside-San Bernardino CA Orlando FL	Atlanta GA Milwaukee WI Tampa-St. Petersburg FL Chicago IL Dallas-Fort Worth TX Buffalo NY Greenville SC New York City-Newark NY-NJ Scranton–Wilkes Barre PA Wichita KS Little Rock AR Fayetteville AR Charlotte NC	Akron OH Knoxville TN Philadelphia PA Dayton OH Rochester NY Jacksonville FL Indianapolis IN Providence Ri Cincinnati OH Syracuse NY Columbus OH Chattanooga Louisville–Jefferson Cnty KY
High Poverty Rate Metro Areas	Fresno CA Bakersfield CA Tucson AZ Lakeland FL Durham-Chapel Hill NC Albuquerque NM McAllen TX New Orleans LA Baton Rouge LA	Cleveland OH Toledo OH Stockton CA Daytona Beach FL Jackson MS Birmingham AL Youngstown OH Greensboro-High Point NC Sarasota FL San Antonio TX El Paso TX Augusta GA	Detroit MI Winston-Salem NC Springfield MA

The nine metro areas in the upper left-hand corner of Table 2 had low 2017 poverty rates *and* low levels of poverty clustering. Except for Columbia, South Carolina, they consist entirely of large urban centers along the Pacific Coast and in the Inter-mountain West.

By contrast, the eleven metro areas in the upper-right corner of Table 2, those with lower poverty rates and higher levels of poverty-clustering, mostly consist of medium-sized and older metropolitan areas in the New England and Middle Atlantic states. Except for Durham-Chapel Hill, the nine high poverty rate-low poverty clustering metro areas identified in the lower left-hand corner of Table 2 are all middle-sized and located in the South or Southwest. Detroit, Winston-Salem, and Springfield (Massachusetts), the three high-poverty/high-poverty-clustering metro areas in the lower right-hand corner of Table 2 are each still struggling to recover from the Great Recession.

Nor is poverty clustering an unambiguous function of metro area size. Among the metro areas listed in Table 1, the average Moran's I value for Very Large metro areas (those with more than two million residents) is 0.31. This compares to values of 0.33 for Large metro areas and 0.34 for Middle-sized ones. Neither is poverty clustering related to the size of the poverty population. Except for Detroit, all the metro areas with very large poverty populations (e.g., New York, Chicago, Los Angeles, Houston, San Francisco-Oakland, Dallas-Ft. Worth, Atlanta, or Washington, DC) fall into Table 2's middle categories.

Poverty Clustering and Race

Combining generations of racially discriminatory practices with the opportunity-robbing effects of poverty, we might expect to observe higher levels of spatial clustering among poor African-Americans than among poor Whites or poor Latinos.

As Figure 4 and Table 3 reveal, this is not the case. Figure 4 compares poverty rate MI values for Whites (on the x-axis) to poverty rate MI values for African-Americans (on the y-axis); poverty rate MI values for Whites to poverty rate MI values for Latinos; and poverty rate MI values for African-Americans to poverty rate MI values for Latinos.[8] Table 3 lists the 30 top metro areas according to their White, Black, and Hispanic poverty MI values. Among the 96 metro areas with statistically significant White poverty MI values, the average MI value was 0.56. Among the 62 metro areas with statistically significant Black poverty MI values, the average was 0.29. Among the 50 metro areas with statistically significant Latino poverty MI values, the average was 0.28. Comparing average White, Black, and Latino poverty MI values, we can conclude that poverty is significantly more spatially concentrated among poor Whites than among poor Blacks and Latinos.

Eight of the ten metro areas with the very highest White poverty MI values—those in the left-hand column of Table 3—are in the Northeast and Midwest. Among them are Madison (with a White poverty MI value of 3.38[9]), Portland, Maine (1.77), Columbus, Ohio (1.43), Springfield, Massachusetts (1.21), Indianapolis (1.16), and New York City-Newark (1.0). Among Whites, the extent of poverty clustering seems to have more to do with growth than with race or housing costs. Except for Provo-Orem and Ogden (both in Utah), and Houston, all the metro areas in the top half of the left-hand column of Table 3 are slow-

Table 3 : Top 30 Metro Areas Sorted by Poverty Clustering Level & Neighborhood Racial Makeup					
Top 30 Metro Areas sorted by Poverty Clustering Level Among Predominantly WHITE Census Tracts	Moran's I Value	Top 30 Metro Areas sorted by Poverty Clustering Level Among 2X BLACK Census Tracts	Moran's I Value	Top 30 Metro Areas sorted by Poverty Clustering Level Among 2X LATINO Census Tracts	Moran's I Value
Madison WI	3.38	Nashville TN	0.61	Baltimore MD	0.66
Charleston SC	3.05	Washington DC	0.61	Madison WI	0.60
Portland ME	1.77	Raleigh NC	0.59	Greenville SC	0.53
Provo-Orem UT	1.45	Atlanta GA	0.58	Los Angeles-Long Beach CA	0.50
Columbus OH	1.43	Baltimore MD	0.57	El Paso TX	0.46
Springfield MA	1.21	Cincinnati OH	0.54	New York-Newark NY-NJ	0.45
Indianapolis IN	1.16	Memphis TN	0.46	Philadelphia PA	0.43
New York-Newark NY-NJ	1.14	Springfield MA	0.42	Omaha NE	0.42
Hartford CT	1.00	Winston-Salem NC	0.42	Spokane WA	0.41
Albany NY	0.98	Palm Bay FL	0.38	San Diego CA	0.40
Allentown PA	0.96	Philadelphia PA	0.38	Fresno CA	0.39
Durham-Chapel Hill NC	0.90	New York-Newark NY-NJ	0.37	Provo-Orem UT	0.37
Omaha NE	0.86	Orlando FL	0.37	Detroit MI	0.35
Providence RI	0.81	Richmond VA	0.37	San Antonio TX	0.35
Pittsburgh PA	0.78	Cleveland OH	0.35	Springfield MA	0.35
Minneapolis-St. Pau MN	0.77	Bridgeport CT	0.34	Bridgeport CT	0.34
Houston TX	0.76	Columbia SC	0.32	Tucson AZ	0.32
Wichita KS	0.76	Dallas-Fort Worth TX	0.32	Houston TX	0.31
Ogden UT	0.75	New Haven CT	0.32	New Haven CT	0.31
Syracuse NY	0.75	Modesto CA	0.31	San Francisco-Oakland CA	0.31
Grand Rapids MI	0.74	Worcester MA	0.31	Boston MA	0.30
Knoxville TN	0.73	Hartford CT	0.30	Austin TX	0.28
Los Angeles-Long Beach CA	0.73	Milwaukee WI	0.30	Stockton CA	0.28
Dayton OH	0.72	Denver CO	0.30	Miami-Ft. Lauderdale FL	0.28
Milwaukee WI	0.69	Indianapolis IN	0.29	Orlando FL	0.27
Columbia SC	0.68	Durham-Chapel Hill NC	0.28	Albuquerque NM	0.25
Richmond VA	0.66	Miami-Ft. Lauderdale FL	0.28	Sacramento CA	0.24
Boise ID	0.61	Harrisburg PA	0.27	Phoenix AZ	0.23
New Haven CT	0.61	Minneapolis-St. Paul MN	0.27	Tampa-St. Petersburg FL	0.23
Boston MA	0.60	St. Louis MO	0.26	Hartford CT	0.23

growing. Likewise, except for New York City, Los Angeles, and Boston, housing prices and rents in the top 30 metro areas with high White poverty MI values are all affordable.

The list of top 30 metro areas in which poor African-Americans are spatially clustered is more distinct. The metro areas occupying the top five positions are all large and in or near Southern states. They include Nashville (with a Black poverty MI value of 0.61), Washington, DC (0.61), Raleigh (0.59), Atlanta (0.58), and Baltimore (0.57). Except for Springfield, Massachusetts, all the metros with Black poverty MI values greater than 0.40 are racially as well as poverty segregated.

The top 30 list of metros in which poor Latinos are spatially clustered is different still. At the top of the list are three metro areas in the West

(Los Angeles-Long Beach, Spokane, and San Diego), three Mid-Atlantic metro areas (Baltimore, New York City-Newark, and Philadelphia), two in the South (Greenville and El Paso), and two in the Midwest (Madison and Omaha). Los Angeles, El Paso, and New York City all have large numbers of Latino residents, whereas the numbers of Latinos in Madison, Greenville and Omaha is slight.

Last, it is important to remember what the MI values in Table 3 do and don't measure. They do measure the degree to which poor Whites live near other poor Whites (and likewise, poor Blacks and poor Latinos). They do not measure the extent to which Whites as a demographic group are segregated from Blacks and/or Latinos.

This brings us to the related question of whether metro areas characterized by a high degree of spatial clustering among poor Whites are also characterized by spatial clustering among poor Blacks and/or poor Latinos. As indicated by the trendlines in Figure 4, which plots White poverty MI values against Black poverty MI values and Latino poverty MI values, the answer to this question, is mostly no. As panel A of Figure 4 indicates, there is no relationship between a metro area's White poverty rate MI value and its Black poverty MI value. Nor is there any relationship between White and Latino poverty MI values, as indicated in panel B. As indicated in panel C, there is a very weak positive relationship between Black and Latino poverty MI values. In sum, poverty populations do indeed seem to be clustered by race, but the factors driving that clustering are different for Whites, Blacks, and Latinos.

Changes in Poverty Clustering Over Time

In terms of changes over time, poverty clustering mostly declined between 2000 and 2016. Among Very Large metro areas, Moran's I values declined between 2000 and 2017 by 0.1 or more in 12 metro areas, while increasing by 0.1 or more in just one metro area. Among Large metro areas, Moran's I declined by 0.1 or more in four metro areas while increasing by 0.1 or more in two metro areas. Lastly, among Medium-sized metro areas, Moran's I values declined by 0.1 or more in eleven metro areas while increasing by 0.1 or more in four metro areas.

Among individual metro areas, poverty clustering declined most between 2000 and 2017 in Atlanta (falling from a Moran's I value of 1.0 in 2000 to 0.40 in 2017), followed by Cleveland (declining from .80 in 2000 to 0.4 in 2017) and Philadelphia (falling from 0.85 in 2000 to 0.59 in 2017). To a modest degree, those metro areas with the highest level of poverty clustering in 2000 saw the biggest declines by 2017. As the three interpolated trend lines in Figure 5 reveal, this negative relationship was most apparent among Very Large metro areas and least apparent among Mid-sized metros.

Simple Correlation Analysis

Having previously noted the lack of a systematic connection between poverty rates and poverty clustering, we now turn our attention to other demographic and socio-economic measures that might be correlated with clustered poverty.

Along these lines, Table 4 presents a series of correlation coefficients comparing 2017 poverty

Figure 4: Comparison of 2017 Metro Area Poverty Rate Moran’s I Values by Race

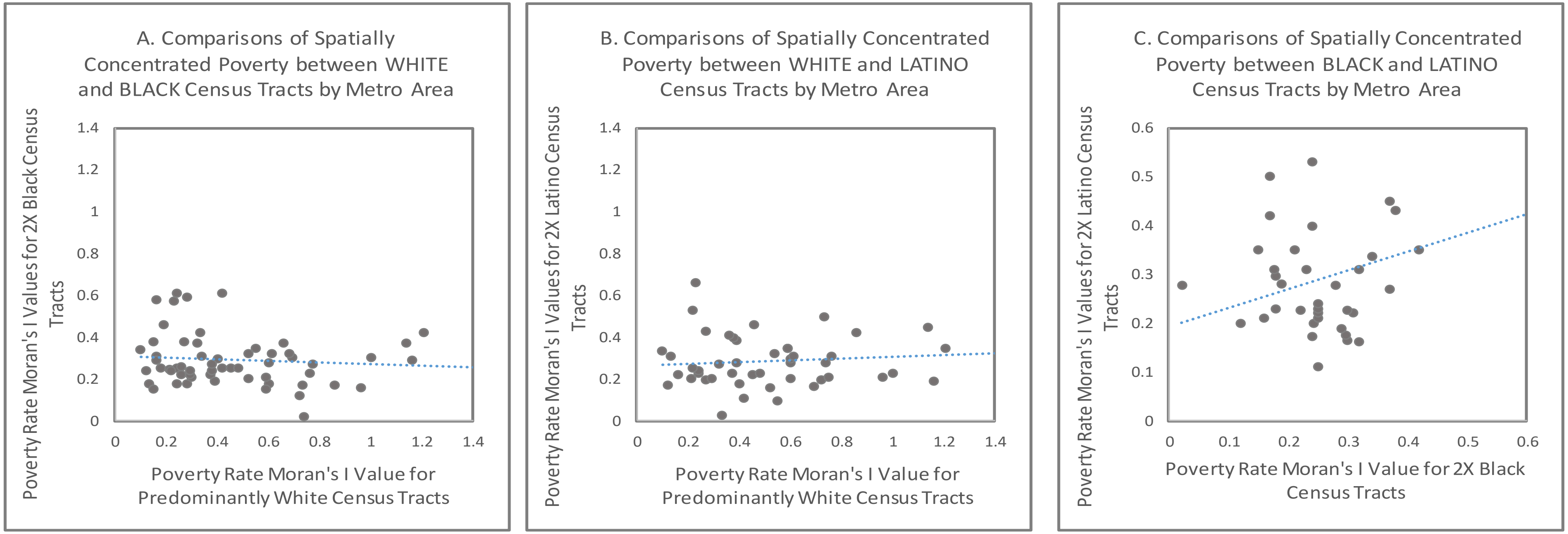
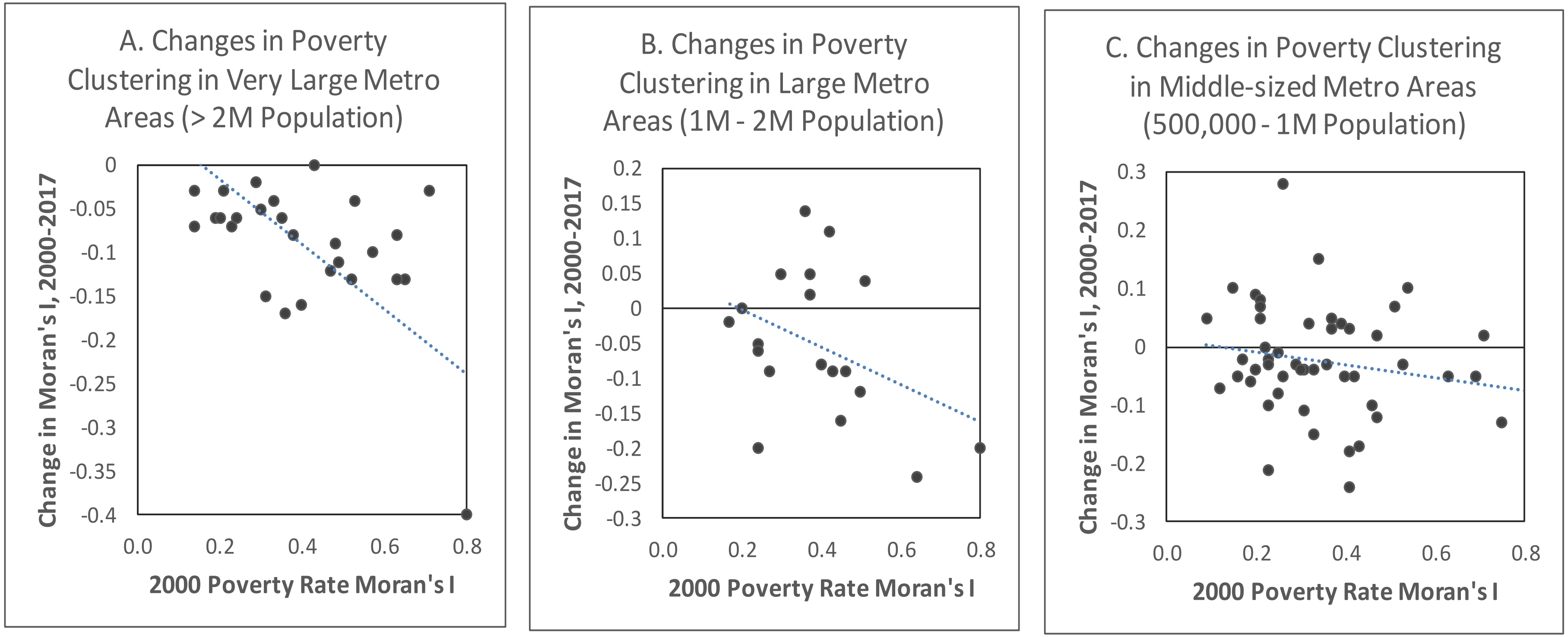


Figure 5:
2000-2017 Changes in Poverty Rate Moran's I Values (y-axis) vs. 2000 Values (x-axis), by Metro Area Size Category



rate MI values with thirteen other metropolitan-level socio-economic status variables. These coefficients vary from a high of .84 (for 2000 MI values as compared to 2017 MI values) to a low of just .03 (for comparisons between 2017 MI values and the 2016 Black population share).

<u>Correlations between clustered poverty and other measures of income</u>. The strong correlation between 2000 and 2017 poverty rate Moran's I values is not unexpected. More surprising is the strong correlation between poverty clustering and income clustering. This suggests that the same exclusionary land use and housing market processes drive both poverty and income sorting. Just as the non-poor try to avoid living near the poor, the wealthy mostly avoid living near the less wealthy. A similar sorting dynamic applies to middle-income households.

Recalling the scatterplots depicted in Figure 3, the low correlation coefficient values between clustered poverty and poverty rates are also not surprising.

Somewhat more surprising is the low correlation coefficient (e.g., 0.02) between poverty clustering and income inequality, as measured by comparing the top 95th percentile of the income distribution with the bottom 20th percentile.

<u>Correlations between clustered poverty and racial segregation</u>. Much has been made of the reinforcing nature of spatially-concentrated poverty and racial segregation, especially among African-Americans. It is therefore a little surprising to find that the correlations between spatially-concentrated poverty and racial and ethnic segregation[10] are not stronger when measured at the metropolitan scale. As Table 3 reveals, the correlation coefficient between poverty clustering and the 2016 Black-White Dissimilarity Index is a relatively modest .43. At .11, the correlation coefficient between spatially-concentrated poverty and the 2016 Dissimilarity Index for Latinos (versus non-Latinos) is even lower.

Table 4: Correlation Coefficients Comparing 2017 Poverty Clustering Using Moran's I and Other Metropolitan-scale Socio-economic Measures

Comparisons of **2017 Poverty Rate Moran's I Values** With:		Pearson's Correlation Coefficient
Income and Poverty-based Measures	Year 2000 Poverty Rate Moran's I	0.84**
	2017 Median Household Income Moran's I	0.84**
	Year 2000 Median Household Income Moran's I	0.79**
	2017 Poverty Rate	-0.28*
	2017 Median Household Income	0.13
	95th-to-20th Income Percentile Ratio (2012)	0.02
Race and Ethnicity-based Measures	2016 Black-White Dissimilarity Index	0.43**
	2016 Latino Share of Population	-0.41**
	2017 Poverty Rate Moran's I (Latino population only)	0.32*
	2016 Latino/non-Latino Dissimilarity Index	0.11
	2016 Black Population Share	0.03
Other Demographic Measures	Percent Foreign-born in 2010	-0.32*
	Median Age in 2010	0.21
	Population in 2017	-0.07

** indicates statistical significance at the .01 level; * indicates statistical significance at the .05 level

II. SPATIALLY-CONCENTRATED POVERTY AND METROPOLITAN ECONOMIC PERFORMANCE

Do higher levels of spatially-concentrated poverty adversely affect metropolitan scale economic outcomes? To find out, we developed a series of five regression models comparing Year 2000 poverty rate Moran's I (MI) values to subsequent changes in overall poverty rates, Black poverty rates, household income levels, employment levels, and Black-White segregation levels. The results of these regression models are presented in Table 5.

The dependent variable in each regression model is a measure of change.[11] In the case of poverty (Model A), it is the change in the metropolitan area poverty rate between 2005 and 2017. In the case of Black poverty (Model B), it is the change in African-American poverty rates between 2009 and 2017. In the case of median household income (Model C), the dependent variable is the nominal change in median household income between 2009 and 2017. For employment (Model D), we count changes in the number of employed residents between 2009 and 2017. Finally, in a slightly different vein, in Model E we compare poverty rate and income clustering to changes in Black-White segregation levels between 2000 and 2016.

To account for the many factors that might explain metropolitan-scale economic performance in addition to spatially-concentrated poverty, we include numerous independent variables in the regression models beyond just poverty rate MI values. These include: (i) initial poverty rates (for 2005) and median household income levels (in 2009); (ii) population size (as of 2005); (iii) separate fixed effect variables indicating whether a particular metro area is located in the Midwest, South, or West; (iv) separate variables measuring the share of the population that was African-American, Latino, or foreign-born as of 2000; (v) Black-White and Latino/non-Latino Dissimilarity Index values as of 2000; and, (vi) the 95th-to-20th Percentile Income Ratio in 2012. To account for the potential biasing effects of multi-collinearity, we used forward stepwise regression to enter the independent variables in order of their incremental contribution to explaining any of the remaining unexplained variance in the values of the dependent variable. If an independent variable does not enter a stepwise regression model, it can be said to have no statistically significant effect on the value of the dependent variable. Turning to the individual regression model results:

- Model A: Changes in 2005-2017 Poverty Rates: Among the metropolitan areas included in this study, the average 2017 poverty rate stood at 12.8 percent, just 0.16 percent higher than in 2005. There was much more change among individual metro areas. At one extreme, McAllen (Texas) saw its poverty rate fall by eleven percent between 2005 and 2017; at the other extreme, and over the same period, the poverty rate in Youngstown (Ohio) rose by four percent.

  As the regression results presented in in Table 4 indicate, poverty rates declined most between 2005 and 2017 in those metro areas with higher initial poverty rates and income levels. They declined more modestly among metro areas in the South and among larger metro areas; and increased modestly among those with more foreign-born residents, those with a higher share of African-American residents, and those with a more unequal equal income

Table 5: Regression Models of Metropolitan Economic Performance Incorporating Measures of the Spatial Concentrations of Poverty and Median Household Income

Model A: Change in Metro Area Poverty Rate between 2005 and 2017

Independent Variable	Coefficient	Beta	t-stat
2005 Poverty Rate	-0.57	-1.24	-13.05
2009 Median Income	0.00	-0.89	-8.08
95%/20% Income Ratio	0.27	0.16	2.13
Pct. Foreign-born in 2000	10.50	0.42	4.32
Southeast Region Fixed Effect	-1.78	-0.30	-3.93
Pct. African-American Population in 2000	5.73	0.28	3.74
Metro Area Population in 2005	0.00	-0.18	-2.45
2000 Poverty Rate and Median Household Income MI Values do not enter			
Constant	14.06		8.59
r-squared	0.68		
Observations	97		

Model B: Change in Black Poverty Rate between 2009 and 2017

Independent Variable	Coefficient	Beta	t-stat
Black Poverty Rate in 2000	-0.12	-0.21	-2.10
2000 Poverty Rate and Median Household Income MI Values do not enter			
Constant	3.25		2.27
r-squared	0.03		
Observations	97		

Model C: 2009-2017 Change in Metro Area Median Household Income

Independent Variable	Coefficient	Beta	t-stat
2009 Median Household Income	0.38	1.04	7.24
2005 Poverty Rate	369.42	0.47	3.77
Pct. Foreign-born in 2000	-16,542	-0.39	3.21
2000 Median Household Income MI Value	-7,219	-0.24	-2.68
Constant	-15,253		-4.45
r-squared	0.60		
Observations	97		

Model D: 2009-2017 Change in Employed Residents

Independent Variable	Coefficient	Beta	t-stat
Employed Residents in 2009	0.46	4.65	5.15
2000 Black-White Dissimilarity Index	-149,931	-0.13	-2.32
Metro Area Population in 2005	-0.21	-3.84	-4.31
Southeast Region Fixed Effect	52,331	0.19	3.68
Pct. Foreign-born in 2000	399,345	0.23	3.61
2000 Poverty Rate and Median Household Income MI Values do not enter			
Constant	30269		0.71
r-squared	0.76		
Observations	97		

Model E: 2000-2016 Change in Black-White Dissimilarity Index

Independent Variable	Coefficient	Beta	t-stat
2000 Black-White Dissimilarity Index	-0.36	-0.84	-9.02
Median Age in 2000	0.00	0.21	2.64
Pct. African-American in 2000	0.20	0.37	4.15
Southeast Region Fixed Effect	-0.05	-0.46	-4.71
West Region Fixed Effect	-0.03	-0.27	-2.55
2000 Poverty Rate and Median Household Income MI Values do not enter			
Constant	0.04		0.83
r-squared	0.47		
Observations	97		

distribution. The Year 2000 poverty rate MI value did not enter the regression model. Nor did the comparable Year 2000 MI value for median household income.

These results lead us to conclude that the degree to which poverty and income were spatially concentrated (as of the Year 2000) had no effect on poverty rate changes between 2005 and 2017. Altogether, the seven variables that entered the stepwise model accounted for a robust 68 percent of the variation in poverty rate change between 2005 and 2017.

- Model B: Changes in African-American Poverty Rates between 2009 and 2017. African-American incomes are much lower than White incomes, and African-American poverty rates are much higher. Nationally, the African-American poverty rate declined very slightly between 2009 and 2017, from 26.5% to 25.2%. Among the metropolitan areas included in this study, the degree to which poverty (and income) was spatially concentrated played no role in explaining changes in the African-American poverty rates between 2009 and 2017.

- Model C: Changes in Median Household Income Between 2009 and 2017: Measured in current dollars, the median household income among all the metro areas included in this study rose by twelve percent between 2009 and 2017, from $53,431 to $59,805. Some metro areas (e.g., San Jose and San Francisco-Oakland) saw their income levels rise at a much faster rate than this average, while income levels in other metro areas (e.g., Winston-Salem) rose more slowly, or even declined (e.g., Las Vegas). As the regression model results presented in Table 5 indicate, median household income levels rose most sharply between 2009 and 2017 among metro areas with higher initial income levels, among those with higher poverty rates in 2005, and among those with fewer foreign-born residents in 2000. The 2000 poverty MI value had no effect on the rate of 2009-2017 income growth, however the 2000 median household income MI value did: Among the metro areas included in this study, household incomes rose noticeably faster in the places where households were not segregated by income. Altogether, the four variables that entered Model C accounted for 42 percent of the variation in median household income growth among large metro areas between 2009 and 2017.

- Model D: Employment Change between 2009 and 2017: The U.S. economy lost 8.7 million jobs to the Great Recession between 2007 and 2010, and it would take another six years to get back 2007 employment levels. Even so, by 2017, the number of jobs in in the U.S. economy was 12 percent higher than it was in 2009. Among the metropolitan areas included in this study, the number of jobs (measured as a count of employed residents) rose by an average of 9.4 percent between 2009 and 2017. Four metro areas (Charlotte, Greenville, Winston-Salem, and Grand Rapids) recorded employment growth in excess of thirty percent during this period. On a less optimistic note, the Detroit, Youngstown, Dayton, Springfield, and Toledo metro areas all finished 2017 with fewer jobs than in 2009.

  As the stepwise regression model results presented in Table 5 indicate, metro areas in the South and those with more foreign-born residents added more new jobs between 2009 and 2017 than did other metropolitan areas. Metro area size played a mixed role: Controlling for other factors, metros with more jobs in 2009 added jobs at a faster rate between 2009 and 2017, while those with more residents did not. Metro areas in which racial segregation was more pronounced lost jobs. Measured using Moran's I, the degree to which poverty was spatially concentrated had no apparent effect on the number of jobs added between 2009 and 2017. Nor did the MI value for median household income. Altogether, the four variables that entered Model D accounted for 76 percent of the variation in change in the number of employed residents between 2009 and 2017.

- <u>Model E: Changes in Black-White Segregation Levels between 2000 and 2016</u>: As noted in this paper's introduction, Black-White segregation levels across the United States have declined significantly since the late 1980s. Nationally, the Black-White Dissimilarity Index (BWDI) fell from 0.67 in 1990 to 0.59 in 2010 (Logan and Stults, 2011). Among the metro areas included in this study, the average BWDI fell from .58 in 2000 to .53 in 2016. Growing metros in the South and West experienced the sharpest BWDI declines, while shrinking and stable metros in the Midwest and Northeast experienced more modest declines. As the regression model results presented in Table 5 reveal, the higher a metro area's BWDI value in the year 2000, the greater its subsequent BWDI decline. Other factors that affected metro-level rates of BWDI decline between 2000 and 2016 were median age (metros with younger populations saw greater BWDI declines) and the share of African-Americans in the population (metros with larger shares experienced lower declines). As measured using Moran's I, the degree to which poverty and income were spatially clustered as of the Year 2000 had no apparent effect on the rate of BWDI change over the next sixteen years. Among the metro areas included in this study, the five variables that entered Model E accounted for 47 percent of the variation the rate of BWDI change between 2000 and 2016.

In sum, these results do not find any systematic connection between the degree to which poverty was spatially concentrated in a metropolitan area in the Year 2000 and its subsequent economic performance. Those metropolitan areas in which poverty was clustered in one or a few neighborhoods did not see their overall or Black poverty rates fall less between 2005 and 2017. Nor did they record systematically lower rates of income or employment growth. Nor did levels of Black-White segregation decline more (or less) between 2000 and 2016 in metros in which poverty or income were more spatially clustered. The one connection between economic segregation and metro-level economic performance revolves around changes in household income: those metro areas in which households with varying incomes were spatially mixed saw their median household income levels rise faster than metro areas in which households were segregated by income level.

III. SPATIALLY-CONCENTRATED POVERTY AND INDIVIDUAL OUTCOMES

Having been unable to detect a connection between spatially-concentrated poverty and metropolitan economic performance, we now switch scales to investigate possible connections between locally clustered poverty and individual economic outcomes. Because most anti-poverty programs are oriented toward individuals rather than metropolitan areas, this is a much more relevant issue. It is also a more difficult inquiry given the lack of data connecting place-based attributes with individual outcomes. The only national dataset that couples place characteristics with people-based outcomes is the Michigan Panel Study on Income Dynamics (PSID), which, since 1968, has annually collected the income histories of more than 18,000 people living in 5,000 families. Yet even with this impressive number of observations, the PSID's coverage is too sparse to investigate the effects of locally concentrated poverty.

To fill this gap, a research team led by Raj Chetty and Nathaniel Hendren at Harvard University's Opportunity Insights project obtained the 1996-2012 income tax records of a huge and representative sample of income tax filers born between 1980 and 1986. Using social security numbers and/or taxpayer identification numbers, Chetty and Hendren and their colleagues determined where each tax filer was born and raised, and the economic circumstances of their parents. Each tax filer was then assigned to a cohort based on their age, gender, race, and household composition when they were growing up.

Chetty and Hendren then developed a series of statistical models which predicted the likelihood that a given filer would earn a systematically higher or lower income than their cohort average based on the make-up of their households *and the socio-economic characteristics of their childhood census tract or county of residence.* This enabled them to isolate the place-based attributes that most contributed to a child's economic mobility and success as they aged into adulthood (Chetty et al., 2014a, 2014b, 2016). Because of the huge size of their sample, Chetty and Hendren were able to generate economic mobility probabilities for almost every combination of census tract and demographic group.

The result is a database which is organized by census tract and lists the probabilities that different combinations of racial, gender and parental household characteristics will generate better and worse economic mobility outcomes. These probabilities can then be combined across gender and racial categories to identify which census tracts and counties are associated with higher or lower levels of economic mobility.

Having downloaded this database, we then identified 16,232 census tracts (out of 75,000) in which young Blacks and Hispanics had a 50% or higher probability of making an adult income that was in the 75th percentile (or higher) of their race-gender-household-type cohort when calculated at a national scale. These tracts were subsequently identified as "opportunity tracts."

We next compared the set of opportunity tracts to a different listing of census tracts distinguished by their degree and type of clustered poverty. This second listing was identified using a statistic known as Anselin's

Local Moran's I, or ALMI for short. ALMI values can be calculated for individual spatial observations (such as census tracts) by comparing the difference between their individual attribute values (e.g., poverty rates) and the mean attribute value (for all observations) as weighted by the distance between each observation and its neighbors, and as further normalized by a measure of the attribute variance. Each observation's ALMI value is accompanied by a Z-score which indicates whether that observation is surrounded by other observations with similarly high values (i.e., "High-high") or similarly low values ("Low-low"), or whether high values are surrounded by low values ("High-low") or whether low values are surrounded by high values ("Low-high"). Not all spatial observations are so classified; many exhibit no evidence of spatial clustering of any kind.

Having identified the number and proportion of opportunity tracts within each poverty cluster type, we next divided that proportion by the share of cluster types within each metro area. This type of ratio is known as a location quotient and can be robustly used to assess the extent to which an attribute is locally over- or under-concentrated. Location quotient values above 1.0 Indicate that a given characteristic is more highly concentrated, while location quotient values less than 1.0 indicate under-concentration. In the current case, a location quotient value above 1.0 means that a local poverty cluster has a greater proportion of opportunity tracts than its metropolitan area as a whole. Conversely, a location quotient value less than 1.0 means that opportunity tracts are under-represented in a poverty cluster type. Appendix B lists estimated opportunity location quotients (OLQ) values for each metropolitan area and poverty cluster type.

Table 6 summarizes these OLQs by poverty cluster type. To the degree that spatially-concentrated poverty reduces individual opportunities, especially for young African-Americans and Latinos, we would expect average and median OLQ values in low-poverty clusters to be much higher than in high-poverty clusters. In other words, after controlling for their race, gender, and household type, children who grow up in areas of spatially-concentrated poverty are thought to be less likely to achieve economic success as adults than otherwise similar children who grow up in areas of low poverty. Likewise, to the degree than children who grow up in mixed-poverty clusters—either high-poverty tracts surrounded by low-poverty tracts, or low-poverty tracts surrounded by high-poverty tracts—are also likely to have fewer economic opportunities, we would expect to observe lower OLQ values for those poverty cluster types than for low-poverty clusters.

Table 6 mostly confirms these expectations. For low-poverty clusters (low poverty tracts surrounded by other low-poverty tracts), the average OLQ value among the 104 largest metro areas is 1.24. This means that the proportion of opportunity tracts in low-poverty clusters is 24% higher, on average, than the proportion of opportunity tracts overall. At the other extreme, the average OLQ for high-poverty tracts is .78, meaning that the proportion of opportunity tracts in high-poverty clusters is 22% lower than the proportion of opportunity tracts overall. The average OLQ for low-high clusters (low poverty tracts surrounded by higher poverty tracts) is .99, while the mean OLQ for high-low clusters (high poverty tracts surrounded by low-poverty ones) is 1.04. Neither of these latter two values is notably different from 1.0, meaning that

Table 6: Opportunity Location Quotient Statistics by Poverty Cluster Type				
Poverty Cluster Type ► / Location Quotient-based Opportunity Measure ▼	Low Poverty surrounded by Low Poverty	Low Poverty surrounded by High Poverty	High Poverty surrounded by Low Poverty	High Poverty surrounded by High Poverty
Mean Opportunity Location Quotient (OLQ)	1.24	0.99	1.04	0.78
Median Opportunity Location Quotient (OLQ)	1.32	0.88	0.78	0.73
Percentage of Metro Areas with OLQ > 1.2	58%	28%	31%	15%
Percentage of Metro Areas with LQ < 0.8	20%	42%	53%	59%
Number of Metro Areas in Sample	104	102	77	104

opportunity tracts are neither under-represented nor over-represented in these two types of mixed poverty clusters.

When, as in the current case, the distribution of underlying values is skewed, median values for more robust comparisons than mean values. Among low-poverty clusters, the median OLQ is 1.32, while for high-poverty clusters, it is just .73. Among low-high poverty clusters, the median OLQ value is .88, while among high-low clusters, it is .78. Taken in aggregate, these values indicate that opportunity tracts are significantly more likely to overlap with low-poverty tract clusters than with high-poverty clusters or mixed-poverty clusters. Or, to put it more succinctly, minority children are much more likely to succeed as adults if they come from a low-poverty tract located amidst other low-poverty tracts, and far less likely to succeed if they come from a neighbourhood in which poverty is spatially concentrated.

These results present tendencies, not certainties. America's metropolitan areas are as spatially diverse spatially as they are demographically diverse. Fully twenty percent of metro areas had a low-poverty OLQ less than 0.8, meaning that opportunity tracts were under-represented by at least 20% among their low-poverty clusters. Conversely, fifteen percent of metro areas had a high-poverty OLQ value above 1.2, meaning that opportunity tracts were over-represented in their high-poverty tract clusters.

These results apply to individuals based solely on their presence in a particular demographic and/or socioeconomic group. They do not apply to people based on their unique and individual characteristics. As Chetty and Hendren and their colleagues take great pains to make clear, they are based on statistical probabilities which are accompanied by significant margins of error. Still, overall, the means and medians presented in Table 5 tell a convincing story of the connection between concentrated poverty and individual opportunity. Children who grow up in neighborhoods of concentrated poverty are significantly less likely to earn comparable incomes as adults than children who grow up in neighborhoods in which poverty is not so embedded. This is especially true for African-Americans and Latinos.

IV. SUMMARY OBSERVATIONS AND POLICY IMPLICATIONS

When it comes to the composition of America's urban neighborhoods, social scientists have long expressed a bias toward heterogeneity and mixing. Racially-integrated neighborhoods are regarded as preferable to racially-segregated neighborhoods, mixed-use communities are considered preferable to narrowly-zoned communities, and mixed-income neighborhoods and housing developments are thought to be preferable to neighborhoods and housing projects sorted by income. While there is ample and convincing evidence supporting the economic, social, and political benefits of racial integration, the evidence regarding the desirability of mixed-income communities is not quite so compelling.

This working paper uses two measures of spatial autocorrelation—the extent to which similar observations are clustered in space—to explore the macro-level and micro-level costs associated with the most extreme form of income segregation: spatially-concentrated poverty. At the macro-level, we explore the extent to which spatially-clustered poverty is associated with adverse economic and racial segregation outcomes. At the micro-level, we consider the degree to which individuals who grow up in concentrated poverty neighborhoods suffer from reduced economic mobility.

We do not explore the meso-level effects of spatially-clustered poverty; that is, the effects of spatially concentrated poverty on individual neighborhoods. There is already considerable evidence documenting the extent to which concentrated-poverty neighborhoods suffer from a lack of economic opportunities and private investment, higher crime rates, worse education outcomes, and lower levels of political engagement.

At the macro-level, we find no evidence that metropolitan areas in which poverty was more spatially concentrated in the Year 2000 suffered from higher (subsequent) rates of poverty growth, from lower rates of employment growth, or from higher (or lower) rates of Black-White segregation. This suggests that the adverse effects of spatially-concentrated poverty are mostly localized and do not necessarily spill over to the larger metropolitan area.

We did find a relationship between the incidence of spatially-concentrated income and median household income growth. Evaluated at the mean, those metro areas in which incomes were more spatially concentrated saw their median household income grow by $7,200 less between 2009 and 2017 than those in which poverty was much less concentrated. This is a significant amount, and it suggests that the principal regional effect of local clustering by income groups is to act as a drag on household income growth.

We can think of several reasons for this finding, most notably that higher-wage employers may be reluctant to invest in metropolitan areas in which public policies have failed to reduce the incidence of concentrated poverty. A deeper understanding of this connection will have to await further empirical study.

The effects of spatially-concentrated poverty are much more severe and pernicious when evaluated at the micro- or individual level. By comparing the extent to which young Black and Latino residents of high-poverty neighborhoods *surrounded by other high-poverty neighborhoods* suffer have lower adult incomes (as compared with otherwise similar residents of low-poverty and mixed-poverty neighbourhood clusters), we can say that the principal societal cost associated with spatially-concentrated poverty is to reduce individual economic opportunities. This effect compounds over time, resulting in huge welfare losses to current and future generations.

One caveat: this finding is based in a methodology that combines our identification of census tracts in which poverty is spatially-concentrated with a roster of low (economic) opportunity census tracts generated by researchers at Harvard University. It is not based on first-hand observations of the economic trajectories of individual residents of neighborhoods in which poverty is spatially-concentrated vs. neighborhoods in which poverty is more dispersed.

These findings have significant implications for local economic and community development practice. First and most important, they suggest that the costs associated with spatially-concentrated poverty [and income ranges] accrue at the metropolitan as well as the neighbourhood level. This means that state and metropolitan-level institutions such as state economic development and housing agencies, metropolitan planning organizations (MPOs), regional councils-of-government (COGs) and regional economic development bodies all have a stake in reducing the incidence of spatially-concentrated poverty.

Second, among cities and metropolitan areas in which poverty is hyper-spatially-concentrated (i.e., have a poverty rate Moran's I value greater than .4), even small reductions in spatially-concentrated poverty can have significant payoffs.

Third, in terms of ameliorating the adverse individual effects of spatially concentrated poverty, particularly as they reduce young people's economic mobility, policymakers and program officials should focus on strategies that reduce that geographic extent of local poverty clusters. As the results presented in Table 6 suggest, among Black and Latino children, living in a high-poverty tract surrounded by other high-poverty tracts more adversely affects their adult economic mobility prospects than living in a neighbourhood that is less uniformly poor. This suggests that local anti-poverty efforts that try to reduce the incidence of poverty within disadvantaged neighborhoods may work better when accompanied by initiatives that also seek to shrink their physical size or breakup their geographic contiguity.

This suggestion should not be regarded as endorsing the market-led gentrification of poor neighborhoods or other initiatives that too often displace existing residents. Instead, it should be regarded as favoring the locally-engaged addition of mixed-income housing projects and job-generating commercial projects in a manner that most benefits current neighbourhood residents, especially those with families.

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Appendix A: 2000 and 2017 Poverty Rate Moran's I Values for U.S. Metropolitan Areas with more than 500 000 Residents

Metropolitan Area	Poverty Rate Moran's I		2017 Poverty Rate Moran's I by Demographic Group		
	2000	2017	Whites	Blacks	Latinos
Akron OH	0.71 *	0.73 *	0.67 *	0.19 *	0.06 *
Albany NY	0.41 *	0.44 *	0.36 *	0.04 *	0.22 *
Albuquerque NM	0.16 *	0.11 *	0.12 *	0.01	0.10 *
Allentow n PA	0.54 *	0.64 *	0.64 *	0.08 *	0.15 *
Atlanta GA	1.00 *	0.40 *	0.12 *	0.26 *	0.04 *
Augusta GA	0.41 *	0.23 *	0.18 *	0.11 *	-0.01
Austin TX	0.35 *	0.29 *	0.27 *	0.11 *	0.24 *
Bakersfield CA	0.23 *	0.20 *	0.19 *	0.03 *	0.13 *
Baltimore MD	0.71 *	0.68 *	0.38 *	0.27 *	0.06 *
Baton Rouge LA	0.23 *	0.02 0	0.34 *	0.14 *	-0.01
Birmingham AL	0.30 *	0.35 *	0.20 *	0.10 *	0.01
Boise ID	0.09 *	0.14 *	0.15 *	-0.03	0.00
Boston MA	0.65 *	0.52 *	0.45 *	0.06 *	0.22 *
Bridgeportk CT	0.69 *	0.64 *	0.56 *	0.03 0	0.37 *
Buffalo NY	0.45 *	0.29 *	0.19 *	0.02 0	0.08 *
Charleston SC	0.31 *	0.20 *	0.20 *	0.07 *	0.01
Charlottea NC	0.40 *	0.24 *	0.17 *	0.18 *	0.05 *
Chattanooga TN	0.39 *	0.43 *	0.31 *	0.08 *	0.01
Chicago IL	0.47 *	0.35 *	0.16 *	0.06 *	0.08 *
Cincinnati OH	0.53 *	0.49 *	0.32 *	0.19 *	0.06 *
Cleveland OH	0.80 *	0.40 *	0.27 *	0.07 *	0.06 *
Colorado Springs CO	0.22 *	0.22 *	0.19 *	0.06 *	0.13 *
Columbia SC	0.33 *	0.18 *	0.12 *	0.06 *	-0.01
Columbus OH	0.43 *	0.43 *	0.37 *	0.15 *	0.12 *
Dallas-Fort Worth TX	0.38 *	0.30 *	0.28 *	0.13 *	0.16 *
Dayton OH	0.51 *	0.58 *	0.44 *	0.09 *	0.04 *
Daytona Beach FL	0.47 *	0.35 *	0.26 *	0.03	0.04
Denver CO	0.20 *	0.14 *	0.12 *	0.04 *	0.07 *
Des Moines IA	0.29 *	0.26 *	0.23 *	0.06 *	0.01
Detroit MI	0.85 *	0.73 *	0.46 *	0.20 *	0.09 *
Durham-Chapel Hill NC	0.19 *	0.13 *	0.10 *	0.06 *	0.01
El Paso TX	0.25 *	0.24 *	0.23 *	0.04 *	0.23 *
Fayetteville AR	0.30 *	0.26 *	0.19 *	0.01	0.10 *
Fort Myers FL	0.41 *	0.17 *	0.15 *	0.10 *	0.01
Fresno CA	0.26 *	0.21 *	0.19 *	0.12 *	0.20 *
Grand Rapids MI	0.43 *	0.34 *	0.28 *	0.04 *	0.07 *
Greensboro NC	0.21 *	0.29 *	0.24 *	0.16 *	0.14 *
Greenvillen SC	0.33 *	0.29 *	0.24 *	0.13 *	0.08 *
Harrisburg PA	0.31 *	0.27 *	0.19 *	0.03	0.04
Hartfordd CT	0.80 *	0.60 *	0.63 *	0.04 *	0.30 *
Honolulu HI					
Houston TX	0.36 *	0.19 *	0.16 *	0.07 *	0.09 *
Indianapolis IN	0.63 *	0.50 *	0.39 *	0.14 *	0.13 *
Jackson MS	0.40 *	0.35 *	0.08 *	0.25 *	-0.02
Jacksonville FL	0.42 *	0.53 *	0.31 *	0.17 *	0.16 *
Kansas City MO	0.48 *	0.39 *	0.33 *	0.11 *	0.07 *
Knoxville TN	0.75 *	0.62 *	0.54 *	0.21 *	0.11 *
Lakeland FL	0.25 *	0.17 *	0.16 *	0.03	0.04
Lancaster PA	1.10 *	0.87 *	0.65 *	0.06	0.07
Las Vegase NV	0.18 *	0.20 *	0.18 *	0.09 *	0.10 *
Little Rock AR	0.43 *	0.26 *	0.16 *	0.06 *	-0.01
Los Angeles-Long Beach CA	0.24 *	0.18 *	0.16 *	0.03 *	0.13 *
Louisville–Jefferson Cnty KY	0.37 *	0.42 *	0.31 *	0.14 *	0.03 *

Metropolitan Area	Poverty Rate Moran's I		2017 Poverty Rate Moran's I by Demographic Group		
	2000	2017	Whites	Blacks	Latinos
Madison WI	0.34 *	0.49 *	0.51 *	0.09 *	0.09 *
McAllen TX	0.12 *	0.05 *	0.05 *	-0.02	0.04 *
Memphis TN	0.50 *	0.38 *	0.24 *	0.29 *	0.02 *
Miami-Ft. Lauderdale FL	0.31 *	0.16 *	0.16 *	0.06 *	0.09 *
Milwaukee WI	0.64 *	0.40 *	0.29 *	0.12 *	0.10 *
Minneapolis-St. Pau MN	0.57 *	0.47 *	0.35 *	0.09 *	0.05 *
Modesto CA	0.16 *	0.11 *	0.10 *	0.00	0.04
Nashville TN	0.46 *	0.37 *	0.19 *	0.16 *	0.05 *
New Haven CT	0.63 *	0.58 *	0.55 *	0.07 *	0.38 *
New Orleans LA	0.24 *	0.04 *	0.16 *	0.09 *	0.01 *
New York-Newark NY-NJ	0.33 *	0.29 *	0.18 *	0.05 *	0.15 *
Norfolk VA	0.24 *	0.19 *	0.11 *	0.13 *	0.03 *
Ogden UT	0.20 *	0.29 *	0.30 *	-0.02	0.08 *
Oklahoma City OK	0.24 *	0.18 *	0.16 *	0.08 *	0.03 *
Omaha NE	0.37 *	0.40 *	0.37 *	0.09 *	0.15 *
Orlando FL	0.10 *	0.11 *	0.10 *	0.02 *	0.05 *
Palm Bay FL	0.23 *	0.13 *	0.09 *	0.01	0.03
Philadelphia PA	0.85 *	0.59 *	0.52 *	0.21 *	0.19 *
Phoenix AZ	0.16 *	0.19 *	0.17 *	0.05 *	0.13 *
Pittsburgh PA	0.29 *	0.27 *	0.18 *	0.03 *	0.04 *
Portland ME	0.83 *	0.90 *	0.63 *	0.32 *	0.09
Portland OR	0.14 *	0.07 *	0.07 *	0.02 *	0.01 *
Providence RI	0.36 *	0.50 *	0.46 *	0.03	0.20 *
Provo-Orem UT	0.42 *	0.37 *	0.37 *	0.01	0.10 *
Raleigh NC	0.37 *	0.39 *	0.30 *	0.34 *	0.11 *
Richmond VA	0.40 *	0.32 *	0.23 *	0.24 *	0.13 *
Riverside-San Bernardinoo CA	0.14 *	0.11 *	0.11 *	0.02 *	0.08 *
Rochester NY	0.51 *	0.55 *	0.50 *	0.06 *	0.14 *
Sacramento CA	0.18 *	0.22 *	0.19 *	0.04 *	0.08 *
Salt Lake City UT	0.27 *	0.18 *	0.17 *	0.03 *	0.04 *
San Antonis TX	0.30 *	0.25 *	0.25 *	0.08 *	0.17 *
San Diego CA	0.23 *	0.16 *	0.15 *	0.01 *	0.09 *
San Francisco-Oakland CA	0.21 *	0.18 *	0.08 *	0.05 *	0.05 *
San Jose CA	0.17 *	0.15 *	0.09 *	0.01	0.03 *
Sarasota FL	0.15 *	0.25 *	0.21 *	0.01	0.11 *
Scranton–Wilkes-Barre PA	0.21 *	0.28 *	0.27 *	0.00	0.03
Seattle WA	0.19 *	0.13 *	0.12 *	0.03 *	0.03 *
Spokaney WA	0.17 *	0.15 *	0.13 *	0.00	0.03 *
Springfield MA	0.37 *	0.42 *	0.42 *	0.04 *	0.22 *
St. Louis MO	0.63 *	0.55 *	0.22 *	0.10	0.04 *
Stockton CA	0.32 *	0.36 *	0.31 *	0.18 *	0.18 *
Syracuse NY	0.47 *	0.49 *	0.42 *	0.08 *	0.17 *
Tampa-St. Petersburg FL	0.49 *	0.38 *	0.30 *	0.10 *	0.15 *
Toledo OH	0.46 *	0.36 *	0.30 *	0.09 *	0.11 *
Tucson AZ	0.20 *	0.20 *	0.21 *	0.05 *	0.09 *
Tulsa OK	0.23 *	0.21 *	0.23 *	0.07 *	0.06 *
Ventura CA	0.20 *	0.16 *	0.19 *	0.00	0.09 *
Washington DC	0.52 *	0.39 *	0.10 *	0.20 *	0.08 *
Wichita KS	0.21 *	0.26 *	0.20 *	0.07 *	0.07 *
Winston-Salem NC	0.53 *	0.50 *	0.36 *	0.16 *	0.07 *
Worcester MA	0.26 *	0.54 *	0.61 *	0.01	0.09 *
Youngstown OH-PA	0.36 *	0.33 *	0.30 *	0.07 *	0.14 *

* Indicates statistical significance at the .01 level

Appendix B: Opportunity Location Quotients By Poverty Cluster Type for U.S. Metropolitan Areas with More than 500,000 Population

Metro Area	High Poverty-High Poverty OLQ	High Poverty-Low Poverty OLQ	Low Poverty-High Poverty OLQ	Low Poverty-Low Poverty OLQ
Akron OH	0.76	na	0.87	0.82
Albany NY	1.46	0.00	1.31	0.97
Albuquerque NM	0.73	0.00	0.00	1.48
Allentown PA	1.54	na	0.86	0.92
Atlanta GA	0.35	2.29	0.40	1.67
Augusta-Richmond County GA-SC	0.88	0.00	2.50	1.94
Austin TX	0.00	0.00	1.71	0.30
Bakersfield CA	0.61	1.56	0.88	1.33
Baltimore MD	0.43	1.79	0.64	1.65
Baton Rouge LA	0.21	0.86	0.00	2.07
Birmingham AL	0.22	3.67	1.03	1.71
Boise ID	0.74	0.00	0.00	2.33
Boston MA	1.62	0.79	0.99	0.42
Bridgeport-Stamford CT	0.82	na	1.15	0.81
Buffalo NY	1.52	4.73	1.18	0.72
Fort Myers FL	0.81	0.00	1.28	0.00
Charleston SC	0.47	3.90	0.30	1.49
Charlotte NC	0.54	0.00	0.70	1.85
Chattanooga TN	0.65	na	1.63	1.17
Chicago IL	0.32	0.00	0.61	1.62
Cincinnati OH	0.54	1.68	0.28	2.01
Cleveland OH	0.73	0.00	2.14	0.85
Colorado Springs CO	0.68	na	1.03	1.54
Columbia SC	1.02	na	0.96	1.60
Columbus OH	0.93	1.60	0.58	1.62
Dallas-Fort Worth TX	0.60	1.49	0.87	1.42
Dayton OH	0.95	na	0.00	1.10
Daytona Beach- FL	0.92	na	0.00	0.69
Denve CO	0.76	0.00	0.39	1.53
Des Moines IA	1.03	na	1.98	1.27
Detroit MI	0.62	0.64	1.26	1.21
Durham-Chapel Hill NC	0.74	na	0.49	0.00
El Paso TX	0.94	0.75	0.00	1.74
Fayetteville AR	1.02	3.58	1.43	1.19
Fresno CA	0.77	0.94	2.15	1.43
Grand Rapids MI	1.59	7.95	1.33	0.44
Greensboro-High Point NC	0.81	na	0.56	2.40
Greenville SC	1.07	na	1.02	1.56
Harrisburg PA	1.47	na	2.80	0.37
Hartford CT	1.22	2.02	1.13	0.48
Houston TX	0.52	1.01	0.89	1.35
Indianapolis IN	0.46	0.00	1.00	1.48
Jackson MS	0.00	na	0.00	2.25
Jacksonville FL	0.20	0.92	1.23	1.64
Kansas City MO-KS	0.51	2.07	0.67	1.47
Knoxville TN	0.80	na	2.57	1.83
Lakeland FL	0.56	3.67	0.00	1.83
Lancaster PA	1.65	na	0.78	1.42
Las Vegas- NV	0.61	1.14	0.69	1.56
Little Rock AR	0.91	0.00	1.34	0.73
Los Angeles CA	0.55	0.49	0.82	1.49
Louisville–Jefferson County KY	0.57	0.00	1.62	1.80

Metro Area	High Poverty-High Poverty OLQ	High Poverty-Low Poverty OLQ	Low Poverty-High Poverty OLQ	Low Poverty-Low Poverty OLQ
Madison WI	1.25	na	na	0.00
McAllen TX	1.11	0.67	na	1.19
Memphis TN	0.29	na	0.91	1.55
Miami-Ft. Lauderdale-W. Palm Beach FL	0.59	0.81	0.83	1.23
Milwaukee WI	0.73	0.00	0.53	1.32
Minneapolis-St. Paul MN	0.21	1.38	1.42	0.71
Modesto CA	0.26	0.00	3.71	2.47
Nashville TN	0.25	0.00	0.35	1.85
New Haven CT	1.02	0.00	1.12	0.91
New Orleans LA	0.61	0.29	0.73	1.45
New York-Newark NY-NJ	0.69	0.59	0.95	1.18
Sarasota FL	0.81	na	0.62	0.48
Ogden UT	0.89	0.00	2.21	0.32
Oklahoma City OK	0.97	0.93	0.86	1.13
Omaha- NE-IA	0.75	2.82	0.59	1.16
Orlando FL	0.34	0.45	1.42	1.72
Oxnard CA	0.10	1.13	0.50	1.25
Palm Bay FL	0.49	na	1.62	1.62
Philadelphia PA-NJ-DE	0.59	0.78	0.61	1.15
Phoenix AZ	0.70	0.42	1.11	1.30
Pittsburgh PA	1.78	0.00	1.52	0.92
Portland ME	2.67	na	0.00	0.00
Portland OR-WA	0.82	0.00	1.35	1.66
Providence RI	1.84	1.57	1.31	0.50
Provo-Orem UT	1.09	0.00	2.32	0.70
Raleigh NC	0.31	1.23	0.70	1.35
Richmond VA	0.60	0.00	0.74	1.42
Riverside-San Bernardino CA	0.62	0.56	0.59	1.28
Rochester NY	0.55	0.36	0.97	1.54
Sacramento CA	0.82	1.24	0.97	1.30
Salt Lake City UT	0.67	0.00	0.51	1.63
San Antonio TX	0.33	0.44	0.59	1.93
San Diego CA	0.80	0.94	1.05	1.18
San Francisco-Oakland CA	0.51	1.17	0.88	1.44
San Jose CA	0.72	0.98	1.04	1.13
Scranton–Wilkes-Barre PA	4.00	0.00	0.00	0.00
Seattle WA	1.11	1.30	0.63	0.84
Spokane WA	0.89	3.57	1.19	0.79
Springfield MA	1.85	na	2.59	1.73
St. Louis MO	0.38	1.30	0.34	1.69
Stockton-Lodi CA	0.67	0.00	1.22	1.02
Syracuse NY	1.95	0.00	1.52	0.83
Tampa-St. Petersburg FL	0.45	0.34	0.98	1.32
Toledo OH	0.66	na	0.68	1.04
Tucson AZ	0.27	1.32	0.44	1.21
Tulsa OK	0.90	0.70	0.35	1.19
Norfolk-Virginia Beach VA	0.44	0.97	0.59	1.54
Washington DC-VA	0.55	1.43	0.81	1.29
Wichita KS	0.61	na	0.68	1.61
Winston-Salem NC	0.19	na	0.55	1.68
Worcester MA	1.40	na	1.94	0.38
Youngstown OH	1.18	na	1.02	0.00

ENDNOTES

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[1] The Census Bureau reports that the 2018 poverty rate in the United States stood at 12.3 percent. This was 0.3 percentage points higher than in 1980.

[2] The formula for Moran's I is as follows:

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

Where *N* is the number of spatial units indexed by *i* and *j*; *x* is the variable of interest; *x* is the mean value of x; w_{ij} is a matrix of spatial weights with 0 on the diagonal; and W is the sum of all W_{ij}s.

[3] The hotspot maps presented in Figures 1b and 2b are constructed using the Getis-Ord Gi* statistic which is calculated as follows:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}, \ \forall j \neq i$$

To be a statistically significant hot spot, a feature will have a high attribute value and be surrounded by other features with high values. The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance, a statistically significant z-score results.

[4] Following the Office of Management and Budget's (OMB) Statistical Policy Directive 14, the Census Bureau uses a set of money income thresholds that vary by family size and composition to determine who is in poverty. If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically. The official poverty definition uses money income before taxes and does not include capital gains or noncash benefits (such as public housing, Medicaid, and food stamps). Individual and household poverty rates are updated annually using data from the American Community Survey.

[5] Census tracts generally encompass a population between 2,500 to 8,000 people. Bureau of Census describes them as "relatively permanent", but they do change over time as new census tracts are added in growing communities. The 2000 Decennial Census included 65,132 separate census tracts (excluding Alaska and Hawaii). The 2010 Census included 72,526 tracts.

[6] While the Decennial Census is a true census that surveys all residents, the ACS is a sample survey that reaches roughly 2.4 percent of U.S. households. As with any sample survey, this means that its results include some amount of sampling error. Fortunately, all ACS estimates are accompanied by calculations of margins-of-error, making it possible to reliably compare ACS estimates across time and space.

[7] Moran's I is sensitive to the number of observations and to the distance threshold for which adjacent observations are considered. Both of these parameters are smaller for smaller metropolitan areas, resulting in lower Moran's I values for a given amount of spatial clustering.

[8] The Moran's I values presented in Figure 4 and Table 3 were calculated differently than those presented elsewhere in this working paper. Those MI values were calculated with unweighted distances using poverty rates for all census tracts in each metropolitan area. Recognizing that Whites, Blacks, and Latinos are distributed differently across each metro area, and that depending on the metro area, some census tracts may not have any Black or Latino residents, comparing population counts by race across all using unweighted distances would serve to reduce MI values below their true levels. When calculating Black and Latino poverty MI values, we included only those tracts in which the proportion of Black and Hispanic residents was double the metropolitan area percentage; and in which there were at least 200 Black or Hispanic residents. For Whites, we considered only those tracts in which at least 2/3 of the population was White. To lessen the distorting effects of minor satellite clusters, we weighted the poverty rates of nearby census tracts

by the inverse of the squared distances between them. These procedures have the effect of identifying true spatial clusters—that is those with sizeable populations of the characteristics of interest, making the resulting clustering comparisons more robust.

[9] Moran's I values calculated using an inverse-distance-squared threshold can have an absolute value larger than 1.0.

[10] The Dissimilarity Index calculates the share of any two groups that would have to move in order to achieve complete integration. It is calculated as follows:

$$\frac{1}{2}\sum_{i=1}^{N}\left|\frac{a_i}{A}-\frac{b_i}{B}\right|$$

Where: a_i = the population of group A in the i^{th} area, e.g. census tract; A = the total population in group A; b_i = the population of group B in the i^{th} area, and B = the total population in group B.

Among U.S. metro areas with more than a half million residents, the Black-White Dissimilarity Index in 2016 ranged from a low of .28 in Columbia, South Carolina to a high of .78 in Milwaukee; the average value stood at .53.

[11] The use of different starting dates (e.g., 2005 vs. 2009) reflects changes in metro area boundary definitions and ACS reporting practices.