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Good and Bad News About Income Inequality in Urban America

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Photo by David Rosenberg

The U.S. is heralded globally as a land of economic opportunity and justly so. American print and social media are full of testimonials from immigrants and native-borns alike who have pulled themselves up by their bootstraps to join the ranks of the wealthy and well-off. Yet the U.S. is also a land of deepening inequality. Based on Census Bureau income tabulations, the Gini coefficient for the U.S. currently stands at 48, up from 39 in 1968[1] (Kitov & Kitov 2013).[2] Of the world's 10 wealthiest countries with at least ten million inhabitants, the U.S.'s Gini coefficient is a full five points higher than second-place Italy's.[3] Incomes in the U.S. are especially unequal when compared by race and ethnicity, with the median income among Black households in 2021 standing at just 65% of that of white households.[4] These same race and ethnicity-based disparities extend to wealth, homeownership, health care delivery, and school spending (Federal Reserve 2021 (wealth); Choi et al. 2019 (homeownership); Williams & Rucker 2000 (health care); Weathers et al. 2022 (school spending)).

Within the U.S., income inequality is surprisingly consistent among states. At .498, the average Gini coefficient for the five most unequal states (New York, Connecticut, Louisiana, Mississippi, and California) in 2019 was just five decimal points higher than the average for the five least unequal states (Utah, Idaho, Wyoming, South Dakota, and Alaska).[5] Compared by region, inequality is slightly greater among states in the Southeast, Southwest, New England, and Mid-Atlantic regions than among states in the Pacific, Mountain, and Midwest regions. Compared by state, income inequality is largely invariant concerning population size, population growth and growth rate, GDP per capita, urbanization share, and educational attainment (Appendix A).

What about inequality as measured at the metropolitan, county, or city scale—the places where people actually live? Different studies produce different results depending on the choice of geography, study period, and inequality indicator. Comparing changes in Gini coefficient values between 2006 and 2012, Florida (2017) found income inequality to have increased in 226 out of 356 U.S. metro areas. Leading Florida's list of the most unequal U.S. metro areas in 2012 were New York City-Newark-Long Island (with a 2012 Gini coefficient of .504), Miami-Ft. Lauderdale-Pompano Beach (.496), Los Angeles-Long Beach-Santa Ana (.485), Memphis (.482) and Houston (.479).

Using a different inequality measure, the 95/20 percentile ratio (the ratio of the 95th percentile income to the 20th percentile income), a 2016 Brookings study found income nominal income inequality to have increased significantly between 2007 and 2014 in 57 of the nation's 100 largest

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[1] Depending on the publication, the Census Bureau reports Gini coefficients on both a 0-to-100 scale and a 0-to-1 scale. (https://equitablegrowth.org/u-s-income-and-wealth-inequality-are-no-longer-increasing-but-a-return-to-the-equitable-levels-of-the-mid-20th-century-isnt-likely-anytime-soon/)

[2] Studies using inequality yardsticks other than Gini coefficient report similarly widening income disparities. A 2020 study by the Pew Research Center (Horowitz et al. 2020) comparing changes in the share of total income going to different income groups found that among upper-income households, the aggregate income share had increased from 29% in 1970 to 48% in 2018; while among lower-income households over the same period, it fell from 10% to 9%. The biggest change was among middle-income households, who saw their share of national income fall from 62% in 1970 to just 43% in 2018.

[3] https://data.worldbank.org/indicator/SI.POV.GINI

[4] https://www.census.gov/content/dam/Census/library/visualizations/2021/demo/p60-273/figure2.pdf

[5] As reported on the Census Bureau data website, https://data.census.gov/table/ACSDT5Y2019.B19083 (retrieved November 2023).

U.S. areas (Berube & Holmes 2016). The Brooking study found upsurges in inequality to be especially pronounced among central cities of the largest metro areas, with the largest significant increases occurring in mid-sized cities such as New Haven, New Orleans, Boise, Knoxville, Stockton, and Cincinnati. As with metro areas, city-level increases in numerical income inequality were driven more by those at the bottom end of the income distribution becoming poorer than by those at the top becoming richer.

Because households of similar incomes tend to group themselves spatially, researchers have focused as much on income segregation—the degree to which rich and poor households live apart from one another--as on numerical inequality. Among U.S. metropolitan areas, Jargowsky (1996) found income segregation as measured at the census tract level to have increased between 1970 and 1990 for both Black people and whites. Using a slightly different indicator, Mayer (2001) found census tract-level income segregation to have decreased during the 1970s but then to have jumped sharply upward during the 1980s. Focusing on poverty rather than income, Massey and Fischer (2003) found the spatial incidence of poverty within U.S. metro areas to have increased during the 1980s, but then to have declined during the 1990s. Studying families rather than households, Watson (2006a) found income segregation among U.S. metro areas to have increased steadily between 1970 and 1990, but then moderated between 1990 and 2000. In a separate paper, Watson (2006b) observed a positive relationship between rising numerical income inequality and rising income segregation; that inequality at the top of the income distribution had a bigger effect on income segregation in rapidly growing metro areas than in slowly growing ones; and that among slowly-growing metro areas, large increases in income segregation were coupled with higher-than-expected rates of new home construction.

Covering the same 1980-2000 period and using a more robust measure of income segregation but limiting their analysis to the 100 largest U.S. metro areas, Reardon and Bischoff (2011) found there to be a strong and robust relationship between within-race income inequality and within-race income segregation; and that increased income segregation was primarily driven by the housing choices of upper rather than lower-income households. In a later paper updating their analysis through 2009, Bischoff and Reardon (2014) found income segregation to be strongly and positively associated with income inequality, metro area population size, the proportion of children in the population, and average educational attainment, but to have no relationship with unemployment or the share of manufacturing jobs.

Florida (2017) provides more recent estimates of income segregation. Using dissimilarity indices to compare the spatial distributions of poor and rich residents (based on the number of households in census tracts in which the 2010 median household income either fell below the poverty line or exceeded $200,000) Florida identified Cleveland, Detroit, Memphis, Milwaukee and Columbus (Ohio), Philadelphia, Phoenix, Buffalo, Kansas City and Nashville as the ten most income segregated U.S. metro areas. Overall, Florida found income segregation levels to be strongly associated with metro area location (higher in the Rustbelt), population size and density (increasing with both), as well as the presence of high technology industries and a well-educated workforce. Confirming Watson's and Bischoff and Reardon's earlier findings, Florida found overall patterns of income segregation to be driven by the exclusionary housing preferences of the wealthy and near wealthy rather than by the lack of housing choices available to the poor. Coupling his income inequality and segregation findings with the place-based economic mobility findings produced by Chetty et al. (2014), Florida observed an inverse relationship between the two, noting that many of the metros with the highest rates of upward economic mobility are also the metros with the highest levels of income inequality and segregation. The results of these and other key income inequality and segregation studies are summarized in Table 1. For a fuller discussion of the biases and limitations of the various income segregation measures, see Reardon et al. (2018).

This working paper draws on recent U.S. Census data to update and clarify the local income inequality story. First, using census tract and block group-level medians, it generates two complementary income inequality indicators for the nation's seventy-three largest urban counties for the years 2000 and 2020. The first is based on 90/10 percentile ratios and provides a summary measure of county-level income inequality regardless of census tract or block group location. The second makes use of Moran's I, a statistical measure of spatial autocorrelation, to measure the level of income segregation; that is, the degree to which wealthy neighborhoods cluster far away from poor ones. Next, it builds a series of regression models that explain changes in county-level income inequality and income segregation during the 2000-2020 period. Third, using a series of scatterplots and trendlines, it takes on the "so what" question of whether changes in income inequality and segregation when measured at the county level are associated with widening racial income, poverty, and homeownership gaps. A fourth section looks at the relationships between local income inequality and sprawl, gentrification, and local land use regulations. Reflecting on these empirical findings, a final section reviews the usefulness of local income inequality measures to policymakers considering local economic development and anti-poverty policies.

The upshot of these county-level comparisons is that: (i) while nominal income inequality worsened between 2000 and 2020, the level of income segregation declined; (ii) nominal income inequality worsened more in counties with more productive economies (as measured by GDP per worker) while income segregation declined more in counties with rising median incomes; (iii) when measured at the county level, worsening residential segregation and widening racialized income, poverty, and homeownership gaps are largely unrelated to changes in nominal or spatial income inequality; and (iv) except for increased gentrification activity, which is associated with an decrease in income segregation, recent changes in county-level income inequality are unrelated to where population growth occurs and to whether it is overly impacted by restrictive land use regulations.

It is important when reviewing these findings to continually remind oneself of three things. The first is they are based on county-level aggregations of census tract and census block group data and not on individual or household observations. The fact that income inequality may not be associated with economic and racial disparities when measured at the county level in no way means that residents of poor and minority neighborhoods have economic and housing opportunities comparable to those available to residents of wealthy and majority neighborhoods. The second is that they refer to income inequality and not wealth inequality. Whereas income counts economic gains realized in a single year, wealth is cumulative across years and generations. This is one reason the incidence of wealth inequality is greater than the incidence of income inequality (Horowitz et al., Pew Research Center 2020). Finally, and in a related vein, although they are related, income inequality is not the same thing as poverty. Poverty is about absolute economic hardship whereas income inequality is about comparative access to economic resources. Even when they live in middle-income and wealthy neighborhoods, poor Americans

Table 1: Summary Results of Selected Metropolitan Area and City Income Inequality Studies

Authors & Study Year	Key Findings	Study Period	Inequality Metric	Reporting Geography	Data Geography
Nominal Income Inequality					
Berube & Holmes (Brookings Institution) 2016	In 2014, the 95/20 ratio for the 100 largest U.S. metro areas was 9.7, and for big cities in those metro areas, it was 11.8. These compare to 9.3 for the nation as a whole. Inequality tends to be greatert in larger metro areas, while for cities, the relationship between inequality and city size is weaker.	2014	95/20 Median income percentile ratios	100 largest US metro areas and their core cities	Census tracts
Florida 2017	Income inequality increased in 2/3 of U.S. metro areas between 2006 and 2012; running higher in core cities than in their metro areas.	2006-2012	Gini coefficients	U.S. metro areas	Census tracts
Spatial Income Inequality (Income Segregation)					
Jargowsky 1996	Income segregation steadily worsened for Whites, Blacks, and Hispanics throughout the 1970s and 1980s, increasing most for Blacks and Hispanics during the 1980s.	1970-1990	Neighborhood Segregation Index	U.S. metro areas	Census tracts
Massey & Fischer 2000	Increases in concentrated poverty before 1970 are best explained by changes in average income and the share of foreigners. Between 1970 and 1990, they are best explained by the interaction between racial/ethnic segregation and broadly rising income inequality.	1970-1990	Poverty Isolation Index	60 largest metro areas	Census tracts
Watson 2006	Changes in income and racial segregation patterns occur more quickly in fast-growing metro areas than in slower-growing or shrinking ones.	1970-2000	Centile Gap Index	216 metro areas	Census tracts
Reardon & Bischoff 2011	There is a strong and positive relationship between nominal income inequality and income segregation, an effect that is larger for black families than for white families. This relationship occurs primarily through the housing locational choices and segregation effects of higher-income households.	1970-2000	Rank-Order Information Theory Index	100 largest metro areas	Census tracts
Bischoff & Reardon 2014	Income segregation among metro areas has grown rapidly since 1970, particularly among Black and Hispanic families. Among individual metro areas, variations in income segregation are systematically related to size, level of income inequality, age composition, and average educational levels.	1970-2011	Multiple measures	117 largest metro areas	Census tracts
Florida 2017	Income segregation among large U.S. metro areas is closely correlated with size and density along with their concentrations of high-tech industries and creative-class workers.	2010	High vs. low-income Dissimilarity Index	All U.S. metro areas	Census tracts

still face systemic shortages of jobs, housing, health care, and schooling opportunities compared to their wealthier neighbors. If the goal is to reduce the incidence and burdens of poverty, policies designed to reduce income inequality can help but they will be far from sufficient.

I. MEASURING AND COMPARING COUNTY-LEVEL INCOME INEQUALITY

Gini coefficients have long been the metric of choice when comparing income inequality across nations and states, but because of the way the Census Bureau keeps track of survey respondent locations, they are harder to construct at the local level.[6] In their place, most local inequality studies make use of percentile ratios, which compare average or median incomes among census tracts in the upper-most percentile of the local income distribution to those in the bottom-most. The Brookings study referenced above compared average incomes in the 95th percentile of census tracts (in each metropolitan area) to those in the 20th percentile. A different state-level inequality study by the Economic Policy Institute (Sommeiller et al. 2016) was more extreme in its approach to measuring percentile income inequality. It compared incomes in the 99th percentile of the census tract income distribution to those in the first percentile.

One limitation of percentile ratios is that they are indifferent to questions of space and location. That is, they do not measure the level of spatial separation between high- and low-income households. This type of spatial income inequality, also known as income segregation, can be easily measured using the spatial autocorrelation statistic known as Moran's I. Spatial autocorrelation refers to the fact that there are many characteristics, for example, household income, for which we observe adjacent or nearby observations to have similar values, and those further away to have different values. Moran's I values vary between 0 and 1, with higher values indicating a high level of spatial autocorrelation or clustering, and lower values indicating spatial autocorrelation or dispersion. When used to compare income segregation levels among places like cities or counties, higher values of Moran's I (e.g., values above 0.4) indicate that upper and lower-income residents each cluster among themselves in far-apart locations. Lower Moran's I values (e.g., values below 0.20) indicate that upper and lower-income households are spatially intermixed. Unlike other segregation measures such as dissimilarity or the entropy indices, Moran's I is non-linear, meaning that a Moran's I value of 0.5 indicates a clustering level that is more than twice the level associated with a Moran's I value of .25.

For this analysis, I use 90/10 median income percentile ratios to measure non-spatial income inequality and Moran's I values to measure income segregation among the nation's seventy-three largest urban counties. To explore the effects of geographic resolution on the two measures, I did so at two spatial scales, census tracts and census block groups. Census tracts are small, relatively permanent county subdivisions typically ranging in size from 1,200 to 8,000 inhabitants. Census block groups are statistical divisions of census tracts containing between 600 and 3,000 residents and are the smallest spatial scale at which median income data is available. The typical census tract contains between three and five block groups.

When calculating percentile ratios, I sorted the census tracts and block groups within each county from low to high based on their median household income and then calculated the ratio of the 90th percentile tract (or block group) median income to the 10th percentile tract (or block group) median income. Provided that there are enough census tracts to form a meaningful

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[6] Census respondent data in the U.S. is geocoded to districts known as PUMAs (Public Use Microsample Areas) which are larger than census tracts and do not aggregate smoothly to cities and counties. Further problems arise from the Census Bureau's use of "top-coded" categories. The top income category in 2000 was set at $200,000; for 2020, it was increased to $250,000.

distribution—fifty is an appropriate minimum—the 90/10 percentile ratio hits the sweet spot between being overly sensitive to extreme median income values and not sensitive enough. I also used tract- and block group-level median household incomes to calculate Moran's I values.[7] For the sake of brevity, I will henceforth refer to tract-based median income Moran's I values in the text as MIMIs.

I had three reasons for using counties as my aggregation unit rather than cities or metropolitan areas. The first is that counties, unlike cities and metro areas, have permanently fixed boundaries. Cities, particularly those in the western U.S., are constantly expanding via annexation or incremental incorporation. And while metro area boundary changes occur less frequently than city ones, they do happen. Second, depending on the state, individual census tracts may include multiple municipalities. This adds unnecessary complications when trying to calculate or compare city-level percentile ratios or MIMI values. Except in Texas, and even then, only rarely, census tracts do not cross county boundaries. Lastly, when it comes to calculating income percentiles, cities with fewer than 300,000 residents typically have too few census tracts to counteract the biasing effects of extreme values. Large metro areas have the opposite problem when calculating MIMI values. To the degree that different income groups cluster in more than a handful of locations, MIMIs may understate the degree of county-level income segregation.

For all these reasons, this analysis is limited to U.S. urban counties with populations in 2020 of one million or more, or to counties with 700,000 or more inhabitants having a core city with at least 300,000 inhabitants. Applying these criteria limits the number of counties and city/county combinations included in this analysis to seventy-three and the number of states to twenty-five. Four states have four or more counties meeting the minimum size criteria: California (12 counties), New York (8 counties), Texas (7 counties) and Florida (6 counties). Ten counties are included that lack a central city with at least 300,000 inhabitants; they are Palm Beach County (Florida), Gwinnett County (Georgia), Montgomery County (Maryland), Middlesex County (Massachusetts), Oakland County (Michigan), Nassau and Suffolk Counties (New York), Collin County (Texas), and Fairfax and Arlington Counties (Virginia). Two wraparound counties, Baltimore County and St. Louis County are combined with their core cities, as are Fairfax and Arlington Counties in northern Virginia. Among the large cities not included in this analysis are Omaha, Wichita, New Orleans, Stockton, St. Paul, Greensboro, Lincoln, Durham, Madison, Toledo, and St. Petersburg. Collectively, the seventy-three counties included in this analysis accounted for 38 percent of the U.S. population in 2020.

When comparing local income inequality between places, the scale at which the data is collected matters. For the counties included in this analysis, using census block groups as the unit of observation instead of census tracts raises the average 90/10 percentile ratio in 2020 from 3.32--meaning that the average 90th percentile census tract median income in 2020 was 3.32 times the average 10th percentile median income—to 3.80 and the average MIMI value from 0.45 to 0.57.[8] These differences are partly due to some block group median income estimates being coded as

[7] Moran's I values are calculated from the formula: $I = (N/W)*\Sigma\Sigma w_{ij}(x_i–x)(x_j–x)/\Sigma(x_i–x)^2$ where N is the number of spatial observations indexed by i and j; w_{ij} is a matrix of spatial weights; x is the variable of interest; and W is the sum of all w_{ij}.

[8] The correlation coefficient between 90/10 percentile ratios for 2020 based on census tract versus block group median incomes is 0.60. For Moran's I values, it is 0.66.

"missing" for confidentiality reasons. Because of this, I will henceforth use tract-based observations for all comparisons.

As noted earlier, 90/10 percentile ratios and MIMI values measure inequality in different ways. 90/10 percentile ratios measure inequality in purely nominal terms without regard to census tract location. By contrast, MIMI values measure inequality spatially and are higher when census tracts with similar income levels are located adjacent to one another. The complementary nature of the two indicators is evident from **Figure 1**, which compares county-level 90/10 percentile ratios and MIMI values for 2000 and 2020. While both measures track together generally, the correlation coefficient between the two in 2000 was just 0.29. By 2020, it had fallen to 0.19.

Figure 1: County-level Comparisons of Nominal and Spatial Income Inequality in 2000 and 2020

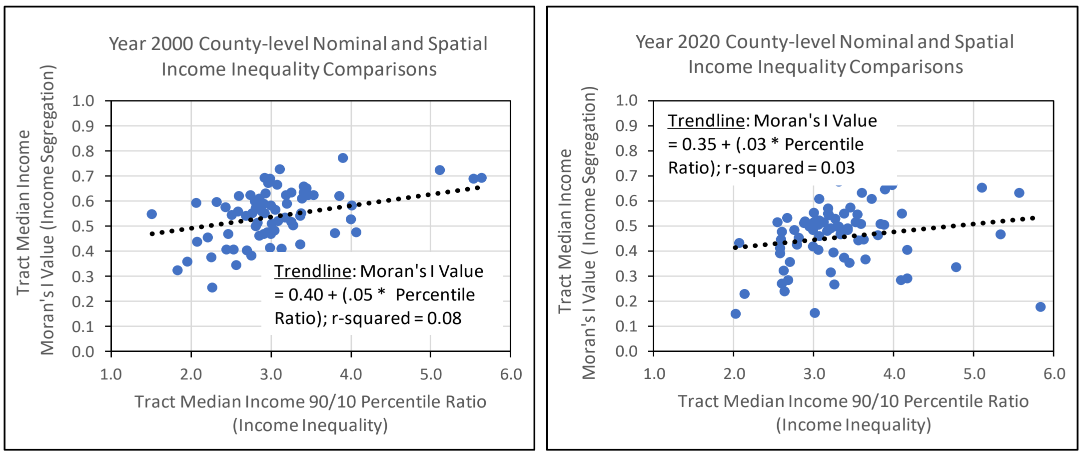
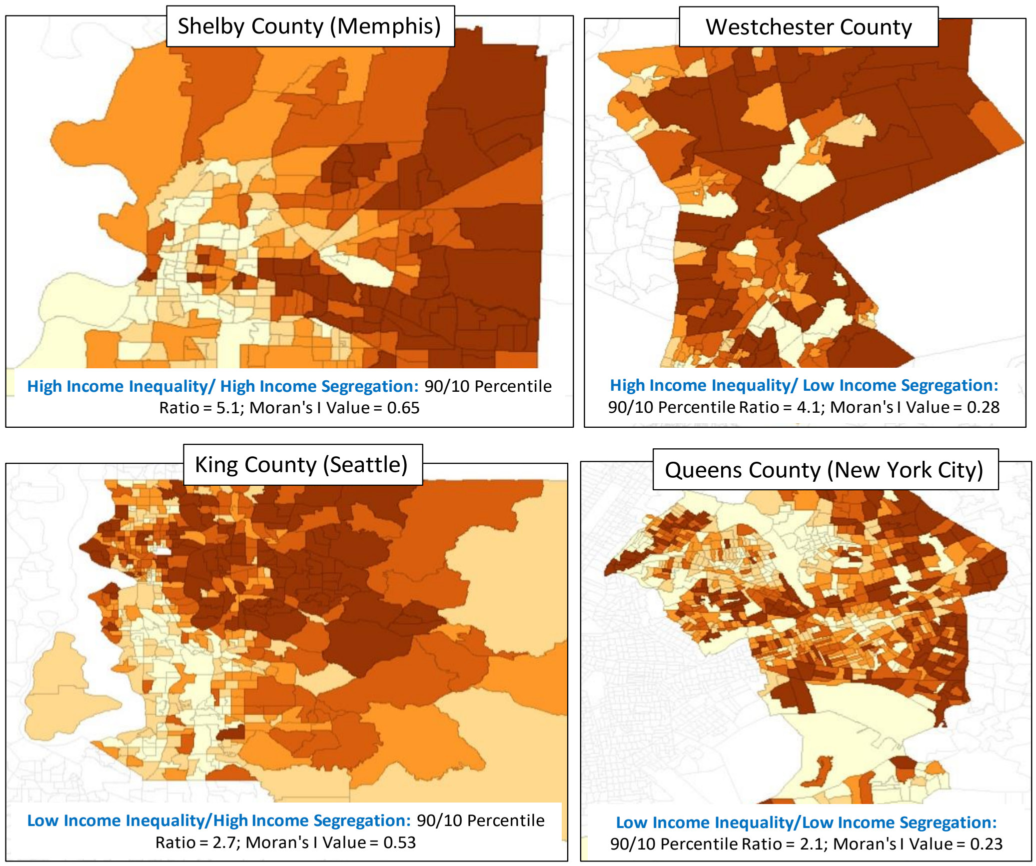


Figure 2 makes this same point in another way, by mapping 2020 median income quintiles by census tract for four different combinations of nominal and spatial income inequality. The top left panel of Figure 2 depicts 2020 median household incomes by census tract for Shelby County (Tennessee), which is the city of Memphis' home county. Note the variations in shading (which indicate different median income quintiles) and the way similarly shaded census tracts are clustered. These patterns are indicative of high levels of both nominal and spatial inequality. The top-right panel of Figure 2 presents a comparable quintile map for Westchester County (New York) in which there is a large numerical gap between high-income and low-income tracts, but the two are integrated spatially. This is indicative of places with high levels of nominal inequality but low levels of spatial inequality. The bottom-left panel of Figure 2, which is for King County in Washington (the home county to Seattle), depicts a situation in which residents of high-income and low-income tracts have not-so-dissimilar incomes but are sharply divided along spatial lines. The lower-right panel of Figure 2 is for Queens County in New York City and presents a situation in which the gap between high-income and low-income neighborhoods is relatively small and the two types of neighborhoods are spatially interspersed in checkerboard fashion. Appendix B includes the full set of tract-based and block group-based 90/10 percentile ratios and Moran's I values for 2000 and 2020 for all seventy-three counties.

Figure 2: Four Combinations of High and Low Nominal and Spatial Income Inequality



II. MIRROR, MIRROR ON THE WALL, WHO IS THE MOST UNEQUAL COUNTY OF ALL?

The most important thing to know about income inequality in America is how widely it varies between places. In terms of nominal inequality, the average 90/10 percentile ratio for the five most unequal counties in our 73-county sample was 2.3 times the ratio for the five least unequal counties. In terms of spatial inequality, the average MIMI value for the five most income-segregated counties was 3.4 times the value for the five least income-segregated counties or income segregation.

Table 2 adds further specifics to these comparisons. As listed in the left-hand panel of Table 2, among the most nominally unequal counties in 2020 were Essex (the home county of Newark with a 90/10 percentile ratio of 5.6), Fulton (Atlanta: 5.3), Shelby (Memphis: 5.1), the District of Columbia (4.8), Suffolk (Boston: 4.2), Hamilton (Cincinnati: 4.2) and Cuyahoga (Cleveland: 4.1). The sources of these inequities varied by place. In Essex and Shelby Counties, there were many more low-income tracts than high-income ones. The opposite was the case in Suffolk and the District of Columbia in which high-income neighborhoods far outnumbered low-income neighborhoods. In Fulton, Hamilton, and Cuyahoga Counties, there were numerous high-income and low-income neighborhoods but few middle-income ones. Among the counties with the lowest levels of nominal inequality in 2020 were Suffolk and Queens in New York State, Salt

Table 2: Counties with the Highest & Lowest Levels of Nominal & Spatial Income Inequality in 2020

	Counties Listed in Order of NOMINAL Income Inequality in 2020	2020 90/10 Percentile Ratio	Counties Listed in Order of Spatial Income Inequality in 2020	2020 Moran's I Value
MOST Unequal Counties	Essex, NJ (Newark)	5.56	Jefferson, KY (Louisville)	0.67
	Fulton, GA (Atlanta)	5.33	St. Louis City & County, MO	0.66
	Shelby, TN (Memphis)	5.10	Shelby, TN (Memphis)	0.65
	District of Columbia	4.77	Cook, IL (Chicago)	0.64
	Suffolk, MA (Boston)	4.17	Fresno, CA	0.63
	Hamilton, OH (Cincinnati)	4.17	Essex, NJ (Newark)	0.63
	Cuyahoga, OH (Cleveland)	4.10	Pima, AZ (Tucson)	0.61
	Westchester, NY	4.09	Jackson, MO (Kansas City)	0.61
	St. Louis City & County, MO	3.97	Baltimore City & County, MD	0.57
	Cook, IL (Chicago)	3.88	Riverside, CA	0.57
Average		3.32		0.45
LEAST Unequal Counties	Suffolk, NY	2.02	Suffolk, NY	0.15
	New York, NY (NYC)	2.07	Montgomery, MD	0.15
	Queens, NY (NYC)	2.13	Nassau, NY	0.18
	Salt Lake, UT	2.54	Queens, NY (NYC)	0.23
	Multnomah, OR (Portland)	2.57	Fairfax & Arlington, VA	0.24
	Middlesex, MA (Cambridge)	2.57	Palm Beach, FL	0.27
	Orange, CA (Santa Ana)	2.59	Collin, TX	0.27
	Gwinnett, FL	2.59	Denver, CO	0.28
	Collin, TX	2.60	Westchester, NY	0.28
	Honolulu, HI	2.61	Suffolk, MA (Boston)	0.29

Lake, Middlesex (Cambridge, MA), and Gwinnett, just north of Atlanta. What these counties have in common is that they mostly consist of middle-income census tracts.

The right-hand panel of Table 2 presents a comparable listing of most and least income-segregated counties. The counties in which rich and poor neighborhoods were the most segregated in 2020 include Jefferson County in Kentucky (with a MIMI value of 0.67), St. Louis City and County (0.66), Shelby County in Tennessee (0.65) and Cook County in Illinois (0.64). Jefferson, Shelby and Cook counties are the home counties to Louisville, Memphis, and Chicago, respectively. The counties in which high-income and low-income neighborhoods were the least segregated in 2020 include Suffolk and Nassau Counties in New York State and Montgomery County in Maryland.

Based on the simple correlation coefficients shown in **Table 3**, when compared with other county-level demographic and economic characteristics, incomes in 2020 were nominally more unequal in counties with larger shares of Black residents, higher levels of Black-white housing segregation, higher homeownership costs (relative to rents), higher poverty rates, and lower rates of population growth. In terms of spatial inequality, higher levels of income segregation in 2020

Table 3: Correlation Coefficient Comparing 2020 Inequality Measures with Other County Characteristics

County Population, Economic and Housing Characteristics, 2020 (Sources: All data is from online American Community Survey tabulations except for county GDP data, which is available from the Bureau of Economic Analysis)		Correlation Coefficient: 90/10 Percentile Ratio	Correlation Coefficient: Moran's I Value
Demographic Characteristics	Population	-0.12	0.09
	White Population Share	-0.23 *	0.03
	Black Population Share	0.55 **	0.20
	Hispanic Population Share	-0.12	-0.01
	Black-white Dissimilarity Index	0.50 **	0.03
	Latino-non-Latino Dissimilarity Index	0.29 *	0.23 *
	Foreign-born Population Share	-0.13	-0.36 **
	Married-couple Families as a Share of Households	-0.33 **	0.08
	Share of Adults with Bachelors Degrees	-0.07	-0.21
Income & Economic Characteristics	Median Household Income	-0.16	-0.51 **
	White Median Husehold Income	0.07	-0.43 **
	Black Median Household Income	-0.18	-0.56 **
	Latino Median Household Income	-0.08	-0.50 **
	Poverty Rate	0.30 **	0.39 **
	White Poverty Rate	0.02	0.27 *
	Black Poverty Rate	0.24 *	0.45 **
	Latino Poverty Rate	0.21	0.39 **
	Real GDP per worker	-0.02	-0.28 *
	Real GDP per square mile	-0.17	-0.06
	% of Workers employed in Management Occupations	-0.02	-0.10
	% of Workers employed in Information and Technical Industries	0.06	-0.14
Housing Characteristics	Homeownership Rate	-0.07	-0.05
	White Homeownership Rate	0.11	0.07
	Black Homeownership Rate	0.14	-0.23 *
	Latino Homeownership Rate	-0.02	0.06
	Median Home Value	-0.19	-0.38 **
	Median Home Value/Median Income	-0.21	-0.25 *
	Monthly Home Ownership Cost (owners with mortgages)	-0.04	-0.52 **
	Median Gross Rent	-0.24 *	-0.56 **
	Monthly Ownership Cost/Monthly Gross Rent	0.36 **	-0.08
Growth & Mobility Characteristics	Population Density	-0.10	-0.10
	2000-2020 Population growth rate	-0.31 *	-0.17
	% of HHs living in same house 1 year earlier	0.11	-0.20
	% of HHs living in a different state 1 year earlier	-0.05	-0.02

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

were associated with lower median household incomes and higher poverty rates (especially among Black people and Hispanics), lower monthly homeownership and rental housing costs, lower housing values, fewer foreign-born residents, and lower levels of economic productivity per worker. These results are consistent with those of earlier studies by Jargowsky (1996), Massey and Fischer (2000), and Bischoff and Reardon (2014). As the old saying goes, correlation is not causation, so when making causal inferences about whether inequality drives other disparities or the reverse is true, these results should be regarded with care. For that, readers should consult the next section which concerns patterns of inequality change over time.

III. PATTERNS OF COUNTY-LEVEL INEQUALITY CHANGE

As per the title of this paper, the income inequality picture among America's largest urban counties is a mixture of good and bad news. On the bad news side, since 2000, nominal income inequality mostly increased. Between 2000 and 2004, the average 90/10 percentile ratio for the counties included in this analysis increased from 3.08 to 3.32 while the average MIMI value declined from 0.53 to 0.45. As indicated in **Table 4**, among the counties in which nominal income inequality worsened most were Hudson (the home county to Jersey City whose 90/10 percentile ratio increased by 1.38), Suffolk (Boston: +1.26), King (Seattle: +1.15), and the District of Columbia (+.77). Among the counties in which nominal income inequality improved most were Davidson (Nashville: -.50), Los Angeles (-.42), Travis (Austin: -.38) and Mecklenburg (Charlotte: -.35).

The exact nature of these changes varies by place. As indicated in the left-hand panel of **Figure 3,** which tracks median incomes by census tract in 2000 and 2020 for Hudson County, in situations where nominal income inequality increased, it was generally because the incomes of the residents of upper-income tracts rose faster than those of lower-income tracts. This is evident from the fact that the cumulative share curve for 2020 is everywhere below the cumulative share curve for 2000. By contrast, in the equity-improving Los Angeles County case, the 2020 cumulative share curve is for most of its run above the 2000 cumulative share curve. This is indicative of the fact that relative income gains between 2000 and 2020 in Los Angeles' poorer neighborhoods exceeded the gains in its wealthier ones.

On the good news side of the ledger, spatial income inequality (a.k.a. income segregation) mostly declined with the average MIMI value (based on census tract median income) falling from 0.53 to 0.45. Among the counties in which income segregation was most reduced were Contra Costa County, California (whose MIMII value fell by .37), Santa Clara County (San Jose: -.24), Montgomery County, Maryland (-.23), and Fulton County (Atlanta: -.23). On the other side of the ledger, there were ten counties in which income segregation worsened between 2000 and 2020, led by Hudson County (Jersey City: +.10), San Bernardino County (+.08), and Kern County (Bakersfield: +.06). When interpreting these results, readers should recall that because Moran's I is non-linear, a change in MIMI value of +.1 is more than twice as big as a change of +.05.

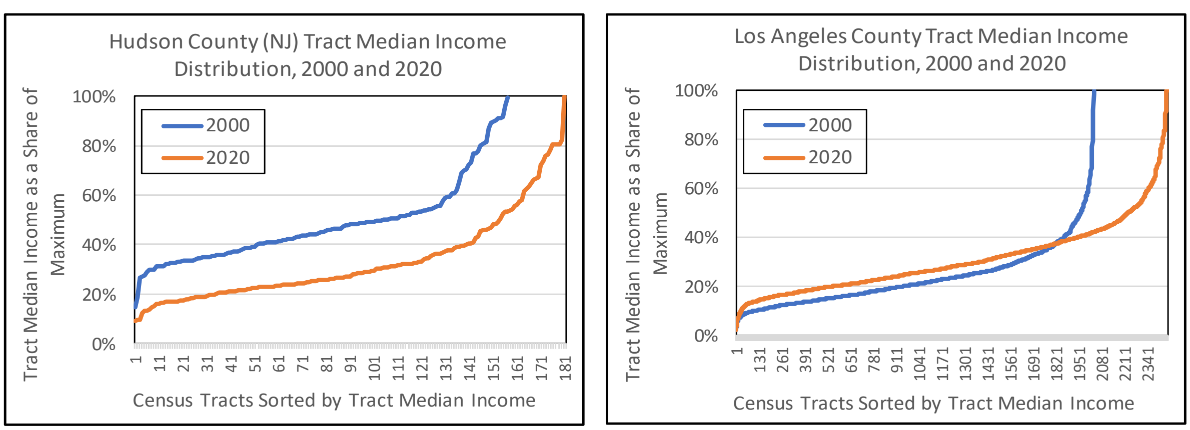
What's behind these changes? To find out, I tested three linear regression models comparing 2000-to-2020 changes in nominal and spatial income inequality with various county-based demographic, income, and housing conditions and trends. The regression results are presented in **Table 5** and identified as Model A: 2000-to-2020 changes in 90/10 median income percentile ratios; Model B: 2000-to-2020 percentage changes in 2000-to-2020 90/10 median income percentile ratios; and Model C: 2000-to-2020 changes in median income MIMI values. Because Moran's I is non-linear, there is no MIMI percentage change regression model. All the variables are measured and reported at the county level.

The independent variables in the three regression models are organized into three groups. The first group consists of the intercept term and initial (Year 2000) 90/10 percentile ratio and the 2000-to-2020 percentage changes in 2000-to-2020 90/10 median income percentile ratios; and Model C: 2000-to-2020 changes in median income MIMI values. These are meant as trending variables and are included to determine whether an acceleration or deceleration trend is

Table 4: Counties with Biggest and Smallest Improvements in Nominal and Spatial Income Inequality Between 2000-2020

	Counties Listed in order of NOMINAL Income Inequality Change	Change in 90/10 Percentile Ratio	Counties Listed in order of SPATIAL Income Inequality Change	Change in Moran's I Value
MOST Improved between 2000 and 2020	Davidson, TN (Memphis)	-0.50	Contra Costa, CA	-0.37
	Los Angeles, CA	-0.42	Santa Clara, CA (San Jose)	-0.24
	Travis, TX (Austin)	-0.38	Montgomery, MD	-0.23
	Mecklenburg, NC (Charlotte)	-0.35	Fulton, GA (Atlanta)	-0.23
	Bronx, NY (NYC)	-0.25	Dist. Of Columbia	-0.20
	San Diego, CA	-0.25	Westchester, NY	-0.19
	Fulton, GA (Atlanta)	-0.21	Middlesex, MA (Cambridge)	-0.19
	Honolulu, HI	-0.09	Hamilton, OH (Cincinnati)	-0.18
	Baltimore City & County, MD	-0.09	Suffolk, NY	-0.18
	Essex, NJ (Newark)	-0.08	Suffolk, MA	-0.18
Average		0.24		-0.09
LEAST Improved between 2000 and 2020	Hudson, NJ (Jersey City)	1.38	Hudson, NJ (Jersey City)	0.10
	Suffolk, MA (Boston)	1.26	San Bernardino, CA	0.08
	King, WA (Seattle)	1.15	Kern, CA (Bakersfield)	0.06
	District of Columbia	0.77	Oklahoma, OK (Okl. City)	0.04
	Philadelphia, PA	0.65	Clark, NV (Las Vegas)	0.03
	Jackson, MO (Kansas City)	0.63	San Francisco, CA	0.02
	Wayne, MI (Detroit)	0.62	Marion, IN (Indianapolis)	0.02
	Nassau, NY	0.58	Essex, NJ (Newark)	0.02
	Oklahoma, OK	0.57	Fresno, CA	0.01
	Bernallilo, NM (Albuquerque)	0.56	Milwaukee, WI	0.01

Figure 3: Tract-level Median Household Distributions for Hudson and Los Angeles Counties



occurring. In an acceleration trend, high and low values move further to the extremes. In a deceleration trend, high values decline faster than low values. A rising intercept value would indicate that income inequality is worsening sample wide. A falling intercept value would indicate a sample-wide improvement in income inequality.

A second group of seven independent variables consists of initial-year anchoring variables. These are included to determine whether subsequent changes in nominal or spatial income inequality follow from initial values of various demographic and economic variables of interest. Except as noted, all are based on decennial census and ACS county-level tabulations. The anchoring variables include:

- **Median household income in thousands** (MedInc): To the degree that nominal or spatial income inequality consistently worsened or improved in high-income counties, the coefficient for this variable will be positive (worsened) or negative (improved).
- **GDP per worker in thousands** (GDP/Job): County-level GDP estimates were obtained from the U.S. Bureau of Economic Analysis (BEA). To the degree that nominal or spatial income inequality consistently worsened or improved in counties producing higher value goods and services as measured on a per-worker basis, the coefficient for this variable will be positive (worsened) or negative (improved).
- **Share of jobs in information, professional services, and technology industries** (%InfoPSTJobs): To the degree that nominal or spatial income inequality consistently worsened or improved in counties with proportionately more high technology jobs, the coefficient for this variable will be positive (worsened) or negative (improved). Prior research by Florida (2017) suggests it should be positive.
- **Share of workers in management and professional occupations** (%ManageOccs): To the degree that nominal or spatial income inequality consistently worsened or improved in counties in which managers and professionals made up a larger proportion of the workforce, the coefficient for this variable will be positive (worsened) or negative (improved). Prior research by Florida (2017) suggests it should be positive.
- **Nonwhite household share** (%NonwhiteHHs): To the degree that nominal or spatial income inequality consistently worsened or improved in counties with higher proportions of nonwhite residents, the coefficient for this variable will be positive (worsened) or negative (improved).
- **Extent of Black-white residential segregation as measured by the Black-white Dissimilarity Index** (Blk-whiteDI). To the degree that nominal or spatial income inequality consistently worsened or improved in counties that are more segregated along Black-white lines, the coefficient for this variable will be positive (worsened) or negative (improved). Research into prior periods (Jargowsky 1996, Massey & Fischer 2000, Watson 2006) found it to be positive.
- **Median home values relative to median incomes** (MedHmeValu/MedInc): Note that housing values are self-reported, and do not necessarily reflect actual housing prices. To the degree that nominal or spatial income inequality consistently worsened or improved in counties in which housing was less affordable, the coefficient for this variable will be positive (worsened) or negative (improved). This coefficient could go either way. To the extent that high housing

values worsen housing affordability, it should be positive. To the extent that existing homeowners have greater equity in their homes, making moving easier, it could be negative.

A third set of six independent variables consists of potential change drivers. These are included to identify the effects of county-level demographic and economic trends on concomitant changes in nominal and spatial income inequality. They include:

- **Percent change in median household income** (%ch-MedInc): To the degree that faster-rising incomes are driving greater income inequality, the coefficient for this variable should be positive.
- **Percent change in county GDP per worker** (%ch-GDP/Job): To the degree that increasing business and worker productivity is driving greater income inequality, the coefficient for this variable should also be positive.
- **Percent change in employment in information and professional, scientific, and technical industries** (%ch-InfoPSTJobs): Workers in these industries are well-paid. To the degree that employment growth in these industries is driving greater income inequality, the coefficient for this variable should also be positive.
- **Percent change in management and professional occupations** (%ch-ManageOccs): Wages for these occupations have been rising faster than wages in service, sales, and production occupations. To the degree that employment growth in these occupations is driving greater income inequality, the coefficient for this variable should be positive.
- **Percent change in college graduates** (%ch-CollegeGrads): The lifetime earnings differential between high school graduates and those with bachelor's degrees is currently estimated to be about $1.2 million.[9] To the degree that local businesses are employing increasing numbers of college graduates resulting in rising income inequality, the coefficient for this variable should be positive.
- **Percent change in monthly homeownership costs** (%ch-MonthOwnCost): To the degree that rising housing costs are driving would-be homeowners to less expensive markets, the coefficient for this variable should be positive.

Finally, to determine whether rising nominal inequality is contributing to increased spatial inequality, I also included the change in the 90/10 percentile ratio as a change driver variable, but only in Model C, the spatial inequality change regression model. Except where noted, each independent variable is included in all three regression models. That said, I expect some to be more strongly associated with changes in nominal income inequality and others to be more strongly associated with changes in income segregation.

As with any statistical model that purports to explain change over time, one must be wary of potential endogeneity effects. By this, I mean the possibility that the dependent variable exerts a direct or feedback effect on one or more independent variables. This is unlikely to be an issue in this case. Both the 90/10 percentile ratio and MIMI change variables are statistical constructs, meaning that they do not exist outside of the analysis and thus cannot directly influence the decisions or

[9] National Association of Public and Land Grant Universities: https://www.aplu.org/our-work/4-policy-and-advocacy/publicuvalues/employment-earnings/ retrieved November 2023.

behavior of Census Bureau respondents. Both are also summary measures describing the aggregate behaviors of hundreds of thousands of individual actors who are unlikely to have prior knowledge of their magnitudes or effects. Finally, in no case is there any behavioral conduit through which potential feedback effects might occur. Descriptive statistics and source documentation for the full set of dependent and independent variables are included in Appendix C.

Regression Results

In terms of how well the regression models explain the data, the results are so-so, with r-squared values of 0.50 for all three models. These values are acceptable for this type of cross-sectional change model, but they also suggest that there is still much about recent county-level changes in income inequality left to be explained. The intercept estimates are positive and significant in the two nominal inequality change models (Models A and B), indicating that there was a sample-wide increase in nominal income inequality between 2000 and 2020 equivalent to a 69 percent rise in the 90/10 percentile ratio. In the case of the spatial inequality change model (Model C), the intercept value is not statistically significant.

The coefficients of the two trending variables, *90/10_PR* and *MI-Value* are negative and statistically significant in all three models. What this means is that income inequality declined more among counties where it was initially higher. For every unit difference between counties in 90/10 percentile ratios in 2000, there was an additional 0.29 ratio point decline and a 13-percentage point decline in 90/10 percentile ratios by 2020. This is a significant decline, but in most counties, it was not large enough to overcome the sample-wide increase in nominal income inequality indicated by the constant term. For every unit difference among counties in 2000 MIMI values, there was a 0.3 decline in MIMI values by 2020.

Of the anchoring and change driver variables, only a few are statistically significant. Whether a particular county initially had a higher proportion of Black people, was more segregated, was home to more forward-looking industries, or had a higher-status workforce made no difference in terms of income inequality rising or falling between 2000 and 2020. Nor did changes in demographic or workforce composition. These results differ from Richard Florida's (2017), who argued that there was a strong correlation between an increasingly bifurcated workforce and rising income inequality.

The exceptions to this no-difference finding are for GDP per worker (GDP/job) and housing affordability (MedValu/MedInc) in the two nominal inequality change models (Models A & B) and for initial median household income (Medinc) in the income segregation change model (Model C). Holding other factors constant, nominal income inequality increased more between 2000 and 2020 in counties that produced more high-value-added goods and services. For every $10,000 difference among counties in GDP per employee in 2000, the 90/10 percentile ratio increased by an additional .09 ratio points (Model A) and four percentage points (Model B) by 2020. By contrast, spatial income inequality (Model C) declined more in counties that were initially wealthier. For every $1,000 difference in county median household income in 2000, the MIMI value fell by .003 by 2020. All three differences are small. Nominal income inequality also declined more in counties in which housing was initially less affordable as measured by the ratio of median home value to median household income in 2020. This last finding is a bit of a surprise

Table 5: Regression Results Comparing Changes in County-level Nominal and Spatial Income Inequality Between 2000 and 2020

				MODEL A: Change in 90/10 Tract-based Median Income Percentile Ratio, 2000-2020		MODEL B: Pct. Change in 90/10 Tract-based Median Income Percentile Ratio, 2000-2020		MODEL C: Change in Tract-based Median Income Moran's I Value, 2000-2020	
Variable Type	Variable Name	Description	Year or Period	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Trending	Intercept	Constant term		**1.29**	**0.03**	**0.690**	**0.00**	0.17	0.32
Trending	90/10_PR	90/10 tract median income percentile ratio	2000	**-0.29**	**0.00**	**-0.128**	**0.00**	intentionally omitted	
Trending	MI-Value	Tract median income Moran's I value	2000	intentionally omitted		intentionally omitted		**-0.30**	**0.00**
Anchoring	Medinc	Median household income (in 000s)	2000	-0.006	0.35	-0.004	0.15	**-0.003**	**0.05**
Anchoring	GDP/Job	GDP per Worker (in 000)	2000	**0.009**	**0.00**	**0.004**	**0.00**	-0.001	0.44
Anchoring	%InfoPSTJobs	Share of jobs in information, professional & technology industries	2000	3.174	0.23	1.236	0.26	-0.720	0.28
Anchoring	%ManageOccs	Share of workers in management & professional occupations	2000	-2.529	0.15	-1.160	0.11	0.327	0.45
Anchoring	%NonwhiteHHs	Nonwhite household share	2000	0.187	0.61	-0.012	0.94	-0.051	0.57
Anchoring	BlkwhiteDIs	Black-white Dissimilarity Index	2000	0.322	0.33	0.079	0.57	0.046	0.57
Anchoring	MedValu/MedInc	Median home value/Median income	2000	**-0.138**	**0.01**	-0.036	0.07	0.011	0.35
Change Driver	%ch-Medinc	Pct. change in median household income	2000-2020	0.142	0.77	-0.080	0.69	-0.151	0.21
Change Driver	%ch-GDP/job	Pct. change in GDP per job	2000-2020	0.021	0.94	0.017	0.89	0.118	0.11
Change Driver	%ch-InfoPSTJobs	Pct. change in Info & PST jobs	2000-2020	0.144	0.66	0.176	0.19	0.013	0.88
Change Driver	%ch-ManageOccs	Pct. change in managerial & professional occupations	2000-2020	0.214	0.74	0.224	0.39	-0.067	0.67
Change Driver	%ch-CollegeGrads	Pct. change in college graduates	2000-2020	-0.395	0.42	-0.347	0.09	0.135	0.28
Change Driver	%ch-MonthOwnCost	Pct. Change in homeowner's monthly housing cost	2000-2020	-0.017	0.97	0.001	1.00	0.016	0.87
Change Driver	ch-90/10_PR	Change in 90/10 percentile ratio	2000-2020	intentionally omitted		intentionally omitted		0.033	0.06
r-squared				0.50		0.50		0.50	
Observations (number of counties)				73		73		73	

in that it suggests that the initial presence of more high-value homes contributes to rather than detracts from increasing income equality. There are several mechanisms through which this effect could occur, including the home mortgage interest deduction (which disproportionately benefits wealthier homeowners) as well as the fact that wealthier homeowners generally find it easier to extract equity from their homes.

It is also worth noting that a couple of variables, *MedValu/Medinc* in Model B and *ch-90/10_PR* in Model C, are just on the cusp of statistical significance. When more compact versions of these models were estimated by removing variables that were not statistically significant to increase the available degrees of freedom, the *MedValu/MedInc* variable became significant in a more compact version of Model B but the *ch-90/10_PR* variable did not become significant in a compact version of Model C.

Taken together, the regression results tell four stories about the changing incidence of income inequality in America's largest urban counties. The first is that there has been a broad scale increase in nominal income inequality since 2000 but no comparable increase in spatial income inequality. The second is that in counties in which income inequality was most severe in 2000, it has since trended downward. A third story is that the principal factor driving increased inequality is differences in economic productivity, with nominal income inequality having increased more since 2000 in counties whose economies are dominated by high-value-added producers. A final story concerns the things that, contrary to conventional wisdom, do not seem to be important explainers of recently rising or falling income inequality. The first of these is race and the second is employment status. Despite higher levels of spatial inequality being associated with higher levels of racial segregation as measured in single years (i.e., 2000 and 2020), as a group, counties in which Black-white segregation was more severe in 2000 did not experience either a subsequent improvement or worsening in nominal or spatial income inequality. Nor did income inequality consistently rise or fall among counties with rising numbers of college graduates or high-status jobs and occupations.

These findings are subject to several caveats, the first being that the county-level inequality indicators that serve as dependent variables in the regressions are all calculated from census all the variables are based on county-level aggregates, the regressions cannot identify significant sub-county or sub-population associations. To see why this could be important, consider the case in which a county enacts a basic income subsidy program targeted toward households with annual incomes less than $30,000. While such a program would have clear equity benefits in aggregate, to the extent that the program recipients are randomly or uniformly distributed spatially, those benefits are likely to be undercounted by tract-based measures like the ones used in this analysis. Third, some of the effects I treat as continuous (such as population growth rate and segregation level) might better be treated as categorical and included in the regressions as either fixed effects or stratifying variables. Finally, I note that these findings are limited to trends occurring in large urban counties and may not apply in the same manner to smaller counties or cities and towns.

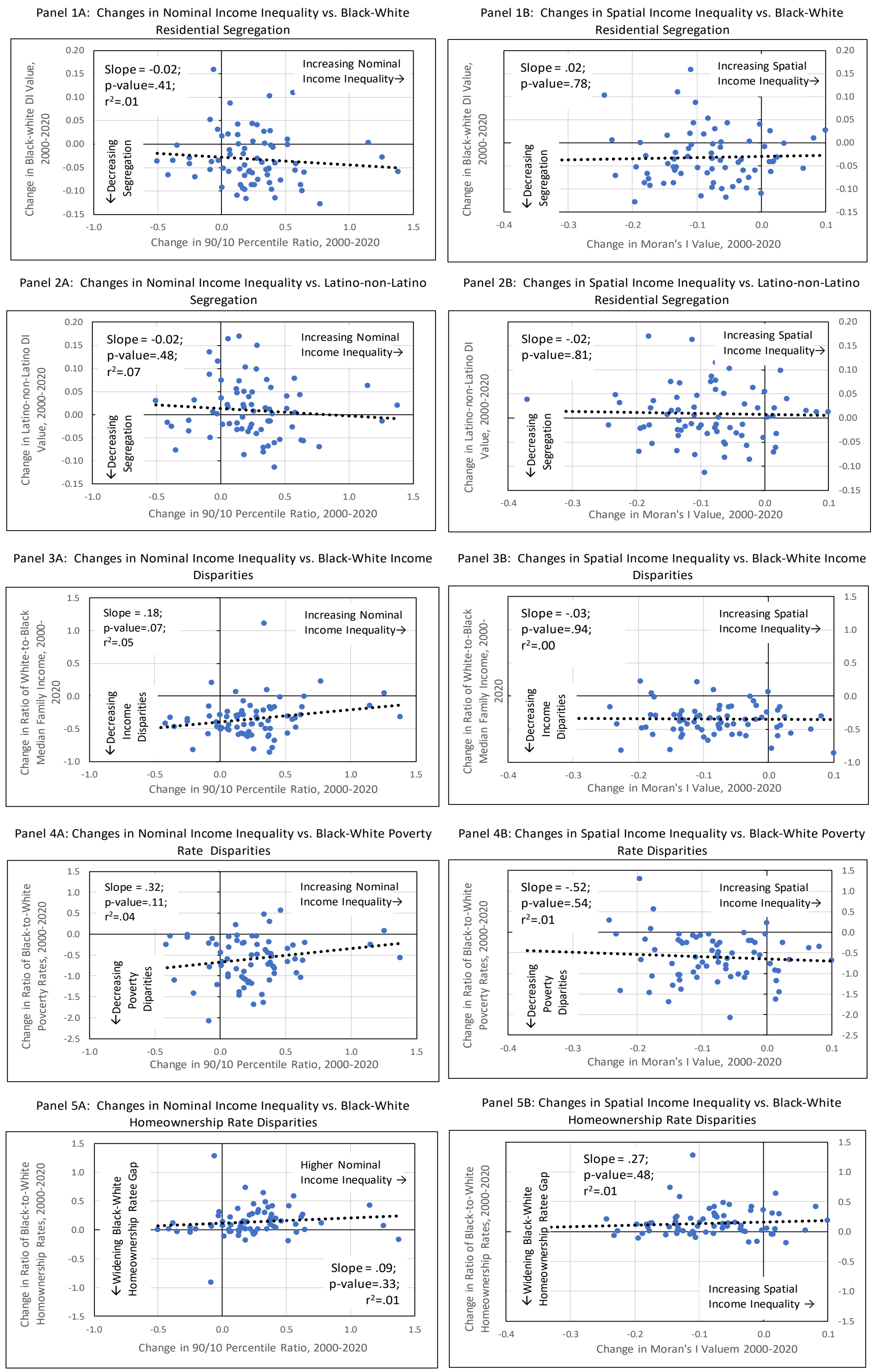
IV. FELLOW TRAVELERS IN INEQUALITY?

Is income inequality automatically a bad thing? Whereas there is some evidence connecting wealth and income inequality to reduced economic and social mobility when compared at the national level, support for the view that income inequality (as distinct from poverty) is associated with negative outcomes when measured at the local level is a good deal weaker. To bring more clarity to this issue, I compared county-level changes in nominal and spatial income inequality between 2000 and 2020 to simultaneous county-level changes in residential segregation levels and to racialized poverty, income, and homeownership disparities. These comparisons are presented in graphic form in **Figure 4**. To the extent that rising or falling nominal or spatial income inequality is associated with rising or falling segregation or racialized economic disparities, then the points indicating counties should cluster along trendlines with rising or falling slopes.

Before getting to the results, several cautions are in order. The first is that the comparisons presented in Figure 4 apply only to counties and not necessarily to smaller spatial units such as neighborhoods or census tracts. Indeed, it is not only possible but likely that the residents of neighborhoods in which incomes are unequally distributed will face vastly different education, housing, health, and economic opportunities than the inhabitants of neighborhoods comprised of uniformly rich or poor residents. Second, I do not expect any observed associations to necessarily be causal. The conditions required to establish causality require a much more robust and disaggregated series of comparisons than the one presented here. Third, as with the regression results presented previously, I do not automatically expect to observe comparable segregation and disparity associations for nominal income inequality which are presented on the left-hand side of Figure 4, as for spatial inequality, which are presented on the right-hand side. For an association to be considered statistically significant, the probability value associated with the slope estimate must be less than 0.10.

- **Black-White Residential Segregation Trends**: Among the 73 urban counties included in this analysis, the average Black-White Dissimilarity Index fell from .58 in 2000 to .55 in 2020, a small but welcome decline. As evident from the decreasing slope of the trendline in Panel 1A, and although the results are not statistically significant, Black-White residential segregation declined more in counties where nominal income inequality rose than in counties where it fell. No comparable association is apparent for changes in spatial inequality (Panel 1B). Given the circumstances, we cannot say that Black-White residential segregation grew more or less severe among counties in which nominal and spatial income inequality improved or worsened.
- **Latino-non-Latino Residential Segregation Trends**: Whereas 2020 ACS tabulations differentiate between white and non-white Latinos at the census tract level, 2000 Decennial Census tabulations do not. For Latinos, this complicates distinguishing between racial and ethnic trends. In terms of residential segregation, among the counties included in this analysis, the average Dissimilarity Index value comparing Latinos (of all races) with non-Latinos (of all races) rose from .39 in 2000 to .40 in 2020. In terms of concurrent county-level changes in nominal and spatial income inequality and changes in Latino-non-Latino residential segregation levels, none are evident from the scatterplots and trendlines presented in Panels 2A and 2B. As in the case of Black-

Figure 4: Comparing 2000-2020 Changes in Income Inequality vs. Racialized Outcomes



white segregation, we cannot say whether there is an unambiguous association between changes in income inequality and changes in Latino segregation when measured at the county level.

- **Racialized Income Disparities**: Nationally, the ratio of White median family income to Black median family income rose from 1.52 in 2000 to 1.58 in 2020, an indication that the income gap between Black and white families was growing. Among the large urban counties included in this analysis, this gap widened even more, with the ratio of White-to-Black median household incomes rising from 1.35 in 2000 to 1.68 in 2020. In the case of nominal income inequality (Panel 3A), there appears to be a consistent (although not statistically significant) association between widening income inequality overall and widening Black-White income disparities, at least when measured at the county level. No comparable association is evident between changes in spatial income inequality and rising or falling Black-White income disparities (Panel 3B). Clearly--albeit with a high degree of county-to-county variation-- rising income inequality in aggregate more adversely affects Black families than it does White families. Because 2000 Census tabulations do not clearly distinguish between Latino and non-Latino families by race, I cannot make similarly reliable comparisons between changes in income inequality and Latino income disparities.
- **Racialized Poverty Disparities**: Nationally, poverty rates declined between 2000 and 2020 for all racial and ethnic groups. Among the counties included in this analysis, the ratio of Black poverty rates to White poverty rates fell from 2.78 in 2000 to 2.13 in 2020. While this decline was certainly welcome, it still left more than twice as many Black people as Whites (as a proportion of all Blacks and Whites) with incomes below the federal poverty line. Although the relationship was not statistically significant, the Black-White poverty rate gap narrowed less among counties in which incomes grew more nominally unequal between 2000 and 2020 (Panel 4A). Overall, increasing income inequality seems to have made it more difficult for Blacks to rise out of poverty than Whites. The same was not true for spatial income inequality: when measured at the county level, changes in income segregation after 2000 had little to do with changing Black-White poverty disparities (Panel 4B).
- **Racialized Homeownership Gaps**: Nationally, the ratio of white homeownership rates to Black homeownership rates was largely unchanged between 2000 and 2020, with white homeownership rates running fifty percent ahead of Black rates in both years. The story was notably worse among the counties included in this analysis, with the ratio of White homeownership rates to Black homeownership rates rising from an average of 1.57 in 2000 to 1.69 in 2020. When compared by county, this trend occurred independently of changes in nominal or spatial income inequality.

Overall, these comparisons paint a picture in which recent increases in nominal income inequality disadvantaged Black people more than Whites in terms of changes in family income and poverty but did not affect residential segregation levels or Black-White homeownership disparities. Nor was it the case that falling spatial income inequality helped close longstanding racialized income, poverty, and homeownership gaps or lessen the severity of local residential segregation.

Sprawl, Gentrification, Land Use Regulation and Local Income Inequality

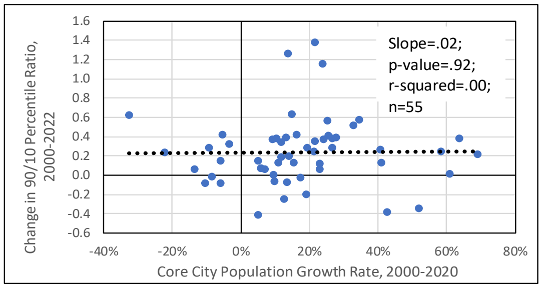
Starting in the mid-1990s, after years of losing population, America's oldest central cities began gaining them back. The trend began slowly, gradually picked up steam, and by 2010, was firmly established. America's twelve largest cities in 1970, having collectively lost 1.4 million residents between 1970 and 1990, managed to gain back 1.1 million new inhabitants by 2010. Known colloquially as gentrification, in some places, central city population growth occurred alongside suburban population growth. Elsewhere, the renewal in core city population growth was accompanied by a slowdown in suburban housing construction. This homebuilding slowdown was not solely the result of changing housing location preferences. In many communities, it was augmented by increasingly restrictive land use and environmental regulations (Been et al. 2014).

These trends were both caused and affected by shifts in local incomes. In terms of causes, the arrival of well-paid creative-class workers in many older urban neighborhoods caused incomes and home values in those neighborhoods to soar. In terms of effects, this same dynamic often resulted in long-time and poorer residents being displaced. How did these trends affect income inequality in America's largest urban counties? To find out, I compared changes in 90/10 percentile ratios and MIMI values among the counties included in this analysis to measures of core city population growth, suburban vs. core city population growth, gentrification activity, and local land use regulation restrictiveness. These relationships are presented graphically in **Figure 5** and discussed below. In no case do I assert that increased core city population growth and gentrification activity, or more restrictive land use regulations are causing greater or lesser income inequality. As noted above, these relationships operate in both directions, often at the same time. Rather, the intent of Figure 5 is to establish whether there are consistent patterns that connect housing construction activity and regulation to nominal and spatial income inequality trends when measured at the county level.

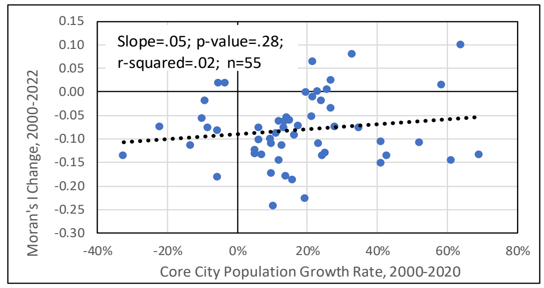
- **Core City Population Growth**: Panels 1A and 1B in Figure 5 compare core city population growth rates between 2000 and 2020 to same-period changes in nominal and spatial income inequality. The counties included in these two panels exclude those such as Montgomery County in Maryland or Contra Costa County in California which lack a core city. As evident from the flat trend line and low r-squared value, among the fifty-five counties that include both a large core city and surrounding suburbs, there is no clear association between 2000-to-2020 population growth rates and concomitant changes in nominal income inequality. There is some association between higher core city population growth rates and increasing spatial inequality, but it is not statistically significant. Among large core cities, recent population growth has neither added nor detracted from income inequality.
- **Suburban vs. Core City Population Growth:** To what extent is accelerated suburban population growth (i.e., "sprawl") associated with increased or decreased income inequality? To find out, I compared the ratio of suburban-to-urban population growth rates between 2000 and 2020 to same-period changes in nominal and spatial income inequality. As the two downward-sloping trend lines indicate, regardless of whether income inequality is measured nominally (Panel 2A) or spatially (Panel 2B), increased sprawl (i.e., additional suburban population growth relative to core city population growth) is associated with improved income equality. The fact that neither trend line is statistically significant is a function of the fact that these associations are principally determined by the counties at the extremes of

Figure 5: Comparing Core City Growth Rates, Sprawl, and Gentrification Activity with Changes in Nominal and Spatial Income Inequality, 2000-2020

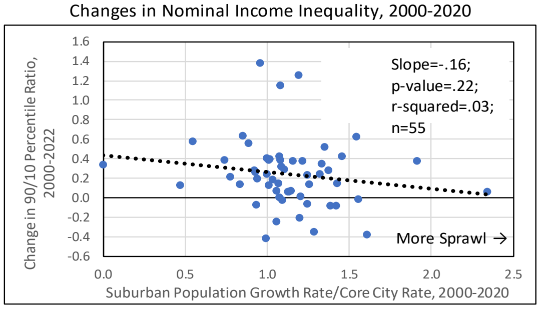
Panel 1A: Core City Population Growth Rates vs. Changes in Nominal Income Inequality, 2000-2020



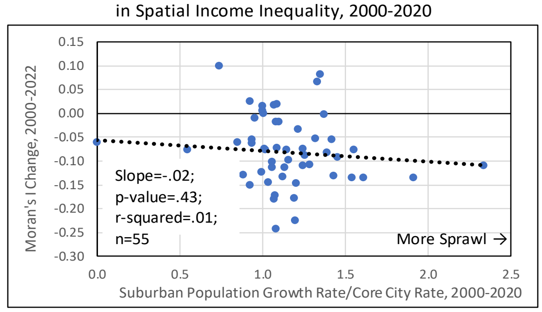
Panel 1A: Core City Population Growth Rates vs. Changes in Spatial Income Inequality, 2000-2020



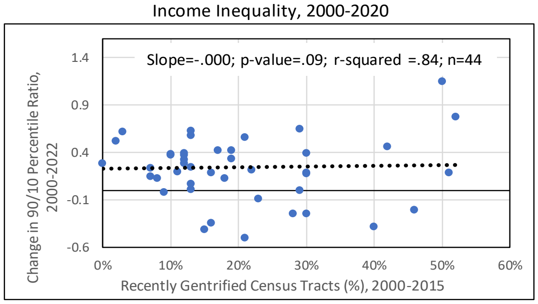
Panel 2A: Ratio of Suburban to Core City Population Growth vs. Changes in Nominal Income Inequality, 2000-2020



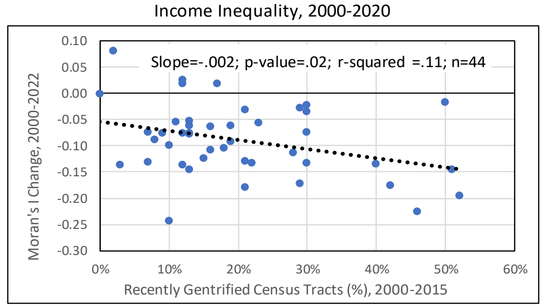
Panel 2A: Ratio of Suburban to Core City Population vs. Changes in Spatial Income Inequality, 2000-2020



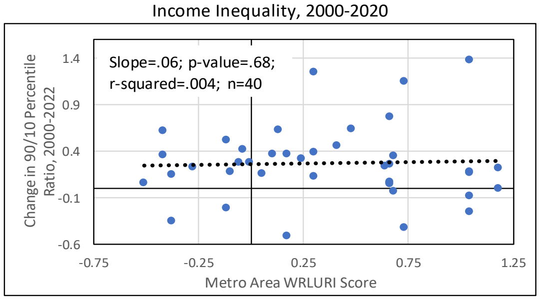
Panel 3A: City Gentrification Activity vs. Changes in Nominal Income Inequality, 2000-2020



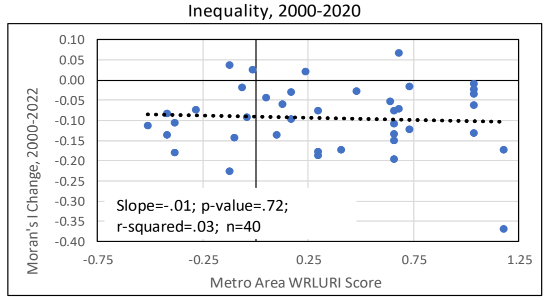
Panel 3A: City Gentrification Activity vs. Changes in Spatial Income Inequality, 2000-2020



Panel 4A: Land Use Restrictiveness vs. Changes in Nominal Income Inequality, 2000-2020



Panel 4B: Land Use Restrictiveness vs. Changes in Spatial Income Inequality, 2000-2020



both distributions such as El Paso County (Texas) on the low side of the sprawl distribution and Harris County on the high side.

- **Gentrification Activity:** Studies that compare gentrification activity among multiple cities or metropolitan areas are rare. Among the few is a 2015 *Governing Magazine*[10] report that identified the share of eligible census tracts in each of the country's 50 largest cities in which the threshold definition of gentrification was exceeded.[11] This share ranged from a low of 0% in El Paso (meaning that none of the census tracts in El Paso considered eligible to be gentrified were subsequently gentrified) to a high of 52% in Washington, DC. As the trend lines in Panels 3A and 3B indicate, increased gentrification activity in a core city was associated with a statistically significant improvement in county-level spatial income equality (Panel 3B) but no comparable change in nominal income equality (Panel 3B). Taking a deeper dive into the underlying data, the principal reason for the improvement in spatial equity among highly gentrified counties had more to do with the arrival of additional middle-income households than with the displacement of incumbent low-income households.

- **Regulatory Restrictiveness**: A 2016 study by Lens and Monkkonen comparing the relationship between the well-known Wharton Residential Land Use Regulation Index (WRLURI) for ninety-five large American cities and various measures of income segregation found more restrictive land use regulations to be associated with the higher levels of income inequality and income segregation among wealthy and middle-income neighborhoods but not among poor neighborhoods. Taking Lens & Monkkonen's analysis as a starting point and using an updated version of the WRLURI index (Gyourko et al. 2008, Gyourko et al. 2018), Panels 4A and 4B explore whether there is any association between stringent land regulations and changes in county-level income equality between 2000 and 2020. Among the forty counties included in these comparisons, WRLURI values range from a high of 1.18 in Alameda and Contra Costa Counties in California (indicating that the overall level of regulatory restrictiveness is 118% higher than the average for all the metro areas studied) to a low of -0.52 in St. Louis County. Although there is a slight positive association between regulatory restrictiveness and changes in nominal income inequality and a slight negative association with changes in spatial income inequality, neither association is remotely close to being statistically significant. Stringent land use regulations may make it more difficult to build housing and contribute to higher housing prices (Landis and Reina 2021), but they do not appear to be worsening income inequality as measured at the county level.

Except for increased gentrification activity, which is associated with increased spatial income equality, recent changes in county-level income inequality are largely unrelated to where population growth occurs and to whether it is limited by local land use restrictions. This is not to say that the openness of particular cities and counties to additional growth does not affect who

[10] https://www.governing.com/archive/gentrification-in-cities-governing-report.html (retrieved November 2023)

[11] A census tract was determined to be "gentrification eligible" if its median household income and median home value were both in the bottom 40th percentile of all tracts within a metro area at the beginning of the decade. To assess gentrification, growth rates were computed for eligible tracts' inflation-adjusted median home values and the percentage of adults with Bachelors' degrees. Gentrified tracts recorded increases in the top third percentile for both measures when compared to all others in a metro area.

can buy or rent a home in which neighborhoods, but rather that these variations in growth rates and regulations are not enough to affect whether county-level income inequality rises or falls.

V. POLICY TAKEAWAYS

However helpful concepts and indicators of income inequality may be for comparative purposes, this research reveals their utility as policy-making measures to be more limited. This is so for four reasons. The first is that when compared locally, nominal and spatial measures of income inequality do not necessarily track together. When measured at the county level, nominal inequality indicators like Gini coefficients and 90/10 percentile ratios have been rising, while spatial inequality measures like Moran's I have been falling. Whether urban income equality in America is improving or getting worse depends on whether one cares more about equality regardless of where people live, in which case, inequality is getting worse; or whether low-income and high-income families have opportunities to live in the same neighborhoods and communities, in which case it is improving. Even in circumstances where they agree, summary inequality measures like 90/10 ratios and Moran's I may obscure important intra-metropolitan or intra-county distributional differences. Second, in situations where there are tradeoffs between nominal and spatial inequality, such as with gentrification, the nature of those tradeoffs may be unclear or vary from place to place. Third, nominal and spatial inequality measures appear to have different drivers. Whether nominal income inequality is rising or falling depends on whether aggregate business and worker productivity (as measured by GDP per employee) is rising or falling. By contrast, changes in income segregation have less to do with what is occurring in the local economy and more to do with where poor households can find affordable housing. Fourth, when compared at the county scale, it appears that recent nominal and spatial income inequality trends are only tangentially associated with widening or narrowing residential segregation disparities, or with racialized income, poverty, and homeownership gaps.

What this means for policymakers is that they are better off focusing on non-distributional measures like poverty rates and average wages when considering alternative economic development, anti-poverty, and income support policies. Programs that raise the local minimum wage or provide for targeted job training may have a salutary effect on local poverty rates, but, depending on how frequently and where households move, may have only a minimal effect on nominal or spatial income inequality. Alternately, programs that build low-income housing across many different neighborhoods may be beneficial in terms of reducing spatial inequality while doing little to address the deeper challenge of lifting low-income residents out of poverty. In this regard, rather than thinking in terms of equalizing income outcomes, policymakers should focus on equalizing opportunities.

At the same time, and especially in places where income inequality is already extreme (e.g., cities or counties with 90/10 percentile ratios greater than 4.0 or MIMI values larger than 0.5) policymakers should think twice about policies and programs that further exacerbate the effects of income inequality like across-the-board property tax reductions or cutbacks in public transit service.

Finally, it is important to note that the Census Bureau has updated its online data reporting formats in recent years that make it much easier to identify income and housing disparities at the neighborhood and municipal levels. These include reporting average as well as median incomes, rents, and housing values by census tract (making it easier to understand the effects of extreme values) and distinguishing between white and non-white Hispanics. When coupled with powerful statistical tools like Moran's I and data visualization tools like PolicyMap (https://www.policymap.com/) or the mapping tools included with the Census Bureau's data retrieval website (https://data.census.gov/map), these make it easier than ever for city governments and non-profit and civic organizations to identify the severity and extent of demographic, economic and spatial disparities.

Appendices can be viewed by clicking here.

REFERENCES

Been, V., Madar, J., & McDonnell, S. (2014). Urban Land-Use Regulation: Are Homevoters Overtaking the Growth Machine? *Journal of Empirical Legal Studies*, 11(2), 227-265.

Berube, A., & Holmes, N. (2016). City and metropolitan inequality on the rise, driven by declining incomes. Brookings Institution, January 14.

Bischoff, K., & Reardon, S. F. (2014). Residential segregation by income, 1970–2009. *Diversity and Disparities: America Enters a New Century*, 43.

Chetty, R., Hendren, N., Kline, P., Saez, E., & Turner, N. (2014). Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *American Economic Review*, 104(5), 141-147.

Choi, J. H., McCargo, A., Neal, M., Goodman, L., & Young, C. (2019). Explaining the Black-White homeownership gap. Washington, DC: Urban Institute.

Farley, R., & Frey, W. H. (1994). Changes in the segregation of whites from blacks during the 1980s: Small steps toward a more integrated society. *American Sociological Review*, 23-45.

Federal Reserve Board of Governors. (2021). Wealth inequality and the racial wealth gap. The. (https://www.federalreserve.gov/econres/notes/feds-notes/wealth-inequality-and-the-racial-wealth-gap-20211022.html)

Florida, R. (2017). *The New Urban Crisis: Gentrification, Housing Bubbles, Growing Inequality, and What We Can Do About It.* Simon and Schuster.

Horowitz, J., Igienik, R., and Arditi R. (2020). "Most Americans Say There Is Too Much Economic Inequality in the U.S., but Fewer Than Half Call It a Top Priority" The Pew Research Center. https://www.pewresearch.org/social-trends/2020/01/09/trends-in-income-and-wealth-inequality/

Gyourko, J., Saiz, A., & Summers, A. (2008). A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index*. Urban Studies*, 45(3), 693-729.

Gyourko, J., Hartley, J. S., & Krimmel, J. (2021). The local residential land use regulatory environment across US housing markets: Evidence from a new Wharton index. *Journal of Urban Economics*, 124, 103337.

Iceland, J., & Scopilliti, M. (2008). Immigrant residential segregation in US metropolitan areas, 1990–2000. *Demography*, 45(1), 79-94.

Jargowsky, P. 1996. Take the money and run: Economic segregation in U.S. metropolitan areas. *American Sociological Review* 61: 984-98.

Kitov, I., & Kitov, O. (2013). The dynamics of personal income distribution and inequality in the United States. Available at SSRN 2306463. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2306463)

Landis, J., & Reina, V. J. (2021). Do Restrictive Land Use Regulations Make Housing More Expensive Everywhere? *Economic Development Quarterly*, 35(4), 305-324.

Lens, M. C., & Monkkonen, P. (2016). Do strict land use regulations make metropolitan areas more segregated by income? *Journal of the American Planning Association*, 82(1), 6-21.

Massey, Douglas S., and Mary J. Fischer. 2003. "The Geography of Inequality in the United States, 1950-2000." In *Brookings-Wharton Papers on Urban Affairs*, edited by William G. Gale and Janet Rothenberg Pack, pp. 1-40. Brookings.

Mayer, S. (2001). How Growth in Income Inequality Increased Economic Segregation. Working Paper 230. Chicago: Joint Center for Poverty Research.

Portes, A., & Zhou, M. (1992). Gaining the upper hand: Economic mobility among immigrant and domestic minorities. *Ethnic and Racial Studies*, 15(4), 491-522.

Reardon, S. F., & Bischoff, K. (2011). Income inequality and income segregation. *American Journal of Sociology*, 116(4), 1092-1153.

Reardon, S. F., Bischoff, K., Owens, A., & Townsend, J. B. (2018). Has income segregation really increased? Bias and bias correction in sample-based segregation estimates. *Demography*, 55(6), 2129-2160.

Sommeiller, E., Price, M., & Wazeter, E. (2016). Income inequality in the US by state, metropolitan area, and county. Economic Policy Institute (https://www.epi.org/publication/income-inequality-in-the-us/)

Watson, T. (2006a) "Measuring Income Segregation." Unpublished manuscript

Watson, T., Carlino, G., & Ellen, I. G. (2006). Metropolitan growth, inequality, and neighborhood segregation by income [with comments]. *Brookings-Wharton Papers on Urban Affairs*, 1-52.

Williams, D. R., & Rucker, T. D. (2000). Understanding and addressing racial disparities in health care. *Health Care Financing Review*, *21*(4), 75.

Weathers, E. S., & Sosina, V. E. (2022). Separate remains unequal: Contemporary segregation and racial disparities in school district revenue. *American Educational Research Journal*, *59*(5), 905-938.

Wong, D. W., & Das Gupta, D. (2023). Age-race-ethnicity segregation in the United States: Where do minority older adults stand? *Population, Space and Place*, 29(4), e42.