Trends in U.S. Spatial Inequality: Concentrating Affluence and a Democratization of Poverty

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Abstract

We study trends in income inequality across U.S. states and counties 1960-2019 using a mix of administrative and survey data sources. Both states and counties have diverged in terms of per-capita pre-tax incomes since the late 1990s, with transfers serving to dampen this divergence. County incomes have been diverging since the late 1970s. These trends in mean income mask opposing patterns among top and bottom income quantiles. Top incomes have diverged markedly across states since the late 1970s. In contrast, bottom income quantiles and poverty rates have converged across areas in recent decades.

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1 Introduction

The gap between rich and poor places in America is often cited as a failure of modern capitalism to provide widely shared economic growth. Have U.S. spatial income disparities grown more or less pronounced in recent decades? While much has been made of the Great Divergence between highly skilled metropolitan areas and the rest of the United States (Moretti, 2012), a central tenet of the regional growth literature remains the "iron law of convergence" that per-capita incomes tend to grow more rapidly in poorer areas (Barro and Sala-i-Martin, 1991; Berry and Glaeser, 2005; Barro, 2015; Ganong and Shoag, 2017). In this paper, we study trends in income inequality across U.S. states and counties over the period 1960-2019, with particular attention to how these trends depend on the notion of income considered and the feature of the income distribution used to rank communities.

We begin by establishing that both states and counties have been diverging in terms of per-capita pre-tax incomes since the late 1990s, with counties exhibiting a steady rise in income inequality since the 1970s. The pace of this increase in regional income dispersion exceeds that of the well-documented growth in aggregate inequality across people (Autor, 2014; Piketty, Saez and Zucman, 2018). While in the 1970s the variance across counties of log per-capita incomes explained as little as 5% of the variance of log incomes across individuals, today county income dispersion accounts for 10% of the variance across individuals. Including taxes and transfers in the income measure reduces the level of inequality, as does accounting for local price variation. However, these adjustments yield only a modest dampening of the rise in county level inequality in recent decades.

Next, we show that these trends in average per-capita incomes mask substantial heterogeneity across the income distribution. Two broad patterns emerge. First, there has been a "democratization of poverty" across U.S. counties, with both adult and youth poverty rates converging across counties in recent decades. This pattern is also reflected in a substantial deconcentration of means-tested transfers across counties. Likewise, in survey data, the bottom quantiles of post-transfer household income have been converging across states since the early 1990s. While this trend has not, to our knowledge, been directly remarked upon in the past, it is broadly consistent with Autor (2019)'s observation that the urban wage premium appears to have declined for less skilled workers and with work in progress by Rinz and Voorheis (2021). Second, in line with Moretti (2012) and Manduca (2019), we find that spatial trends in per capita income inequality reflect an increasing "concentration of affluence." While median household incomes have exhibited a gradual rise in dispersion across counties since 1990, top income quantiles, measured either in survey or administrative data, have diverged markedly across states since the late 1970s.

Our findings indicate that trends in spatial income disparities are more complex than is commonly appreciated. While mean incomes have been diverging across counties for decades, spatial disparities in bottom incomes and poverty rates have been receding. Understanding the causes and consequences of these opposing trends is an important challenge for future research.

2 Measuring spatial income inequality

Let i index geographic areas such as states or counties and F_i the distribution of income in that area, which we assume is continuous. The quantity $v_i = \int_0^1 \omega\left(F_i^{-1}(\tau)\right) F_i^{-1}(\tau)\, d\tau$ measures the welfare of area i, where $F_i^{-1}(\cdot)$ is the quantile function of income in area i and $\omega(\cdot)$ is a weighting function that depends on income *levels*. When $\omega(\cdot) = 1$, v_i simply measures the per-capita income in community i.[1] We begin our analysis by proxying v_i with per-capita income and then examine other measures that reflect different weightings of income quantiles.

Bourguignon (1979) proposed the following welfare-theoretic measure of between group inequality

$$B = \ln(\bar{v}) - \sum_i s_i \ln v_i,$$

where $\bar{v} = \sum_i s_i v_i$ and s_i is the population share of area i. The B index is scale invariant and reflects logarithmic inequality aversion: a utilitarian planner who seeks to maximize $\overline{\ln v} = \sum_i s_i \ln v_i$ would be willing to trade a 1% loss in $\bar{v}$ for a reduction in B of 0.01.

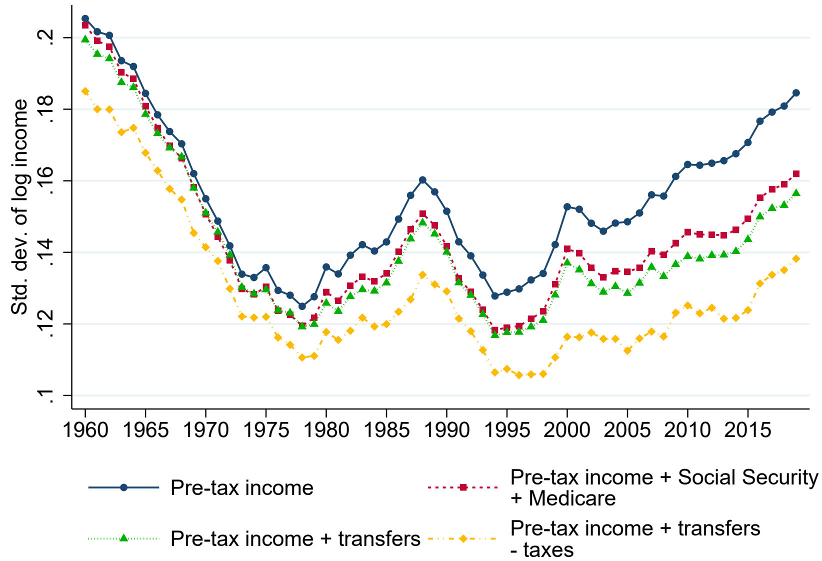
In the Appendix we show that $B \approx \frac{1}{2} \sum_i s_i \left(\ln v_i - \overline{\ln v}\right)^2$. Hence, the Bourguignon index is a close cousin of the familiar variance of logarithm measure of dispersion. In what follows, we rely on population weighted versions of this more transparent measure of dispersion to summarize spatial income disparities. Equally weighted estimates are provided in the Appendix.

3 Diverging mean incomes

Figure 1 plots the standard deviation across states of the logarithm of four measures of per capita personal income drawn from the Bureau of Economic Analysis (BEA), definitions of which are provided in the figure note. All four measures exhibit a W-shaped pattern, with

[1] Ranking communities by per-capita income is easily accommodated within a utilitarian framework. For example, with Cobb-Douglas preferences, indirect utility is proportional to after-tax income.

Figure 1. Income dispersion across U.S. states

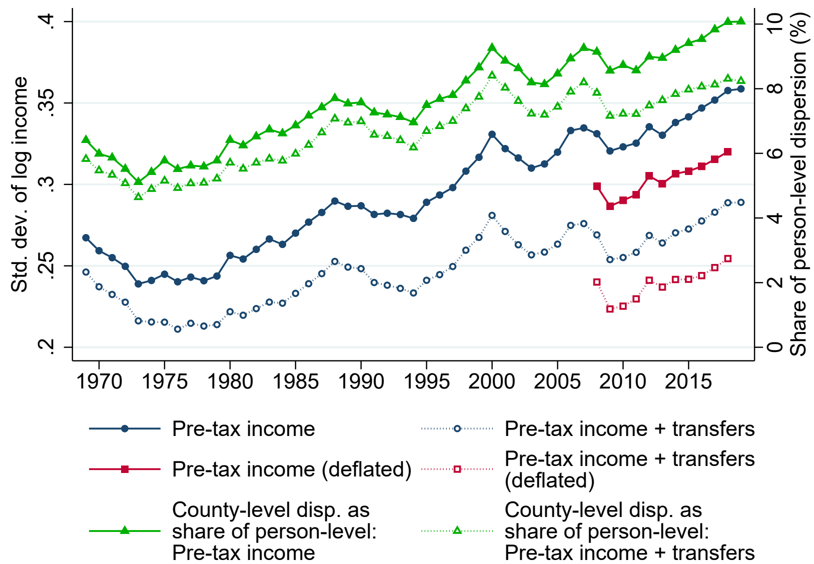


Note: This figure plots the population-weighted standard deviation across states of the logarithm of four measures of per capita income. Pre-tax income equals wages, employer-provided benefits, proprietors' income, dividends, interest, and rent and excludes capital gains and thereby corporate retained earnings. Social Security includes Social Security Disability Insurance. Transfers include all major government transfers including Social Security and Medicaid. Taxes include all major federal, state, and local taxes except sales taxes. Source: Bureau of Economic Analysis.

sharp declines during the 1960s and 1970s, a short-lived increase in dispersion during the 1980s, a decline in the early 1990s, and a sustained growth in dispersion from the mid 1990s to the present. Accounting for transfers slightly lowers the level of geographical dispersion in early years but has a more substantial effect in later years. Most of this impact is driven by Social Security and Medicare. Accounting for taxes further dampens the recent rise of inequality: cross-state dispersion in per-capita post-tax incomes in 2019 roughly equals its 1970 level. If society exhibited logarithmic inequality aversion over per capita incomes after taxes and transfers, a planner would be willing to reduce the average income of U.S. states by $\frac{1}{2}(.14)^2 \times 100 = 1.0\%$ in order to eliminate the state dispersion in incomes found in 2019.

Much of the seminal empirical work on regional income convergence (e.g., Barro and Sala-i-Martin, 1991) relied on data from decades when cross-state dispersion was falling. Using more recent data, Ganong and Shoag (2017) find that poorer states continue to exhibit slightly faster income growth rates, oft referred to as "β-convergence." As Young, Higgins and Levy (2008) note, however, β-convergence need not yield "σ-convergence" – a reduction in cross-sectional dispersion across areas. In fact, all four of our measures exhibit strong σ-*divergence* over the past 20 years. The increase in the standard deviation of log per-capita pre-tax incomes across states between 1995 and 2019 is roughly four times as large as the

Figure 2. Income dispersion across U.S. counties



Note: The first four series plot the population-weighted standard deviation across counties of the logarithm of two measures of BEA per capita income. Deflated measures divide nominal income by BEA regional price parities. The last two series plot the population-weighted variance of BEA county-level log per capita income divided by the variance of DINA person-level log income. Source: Bureau of Economic Analysis and DINA.

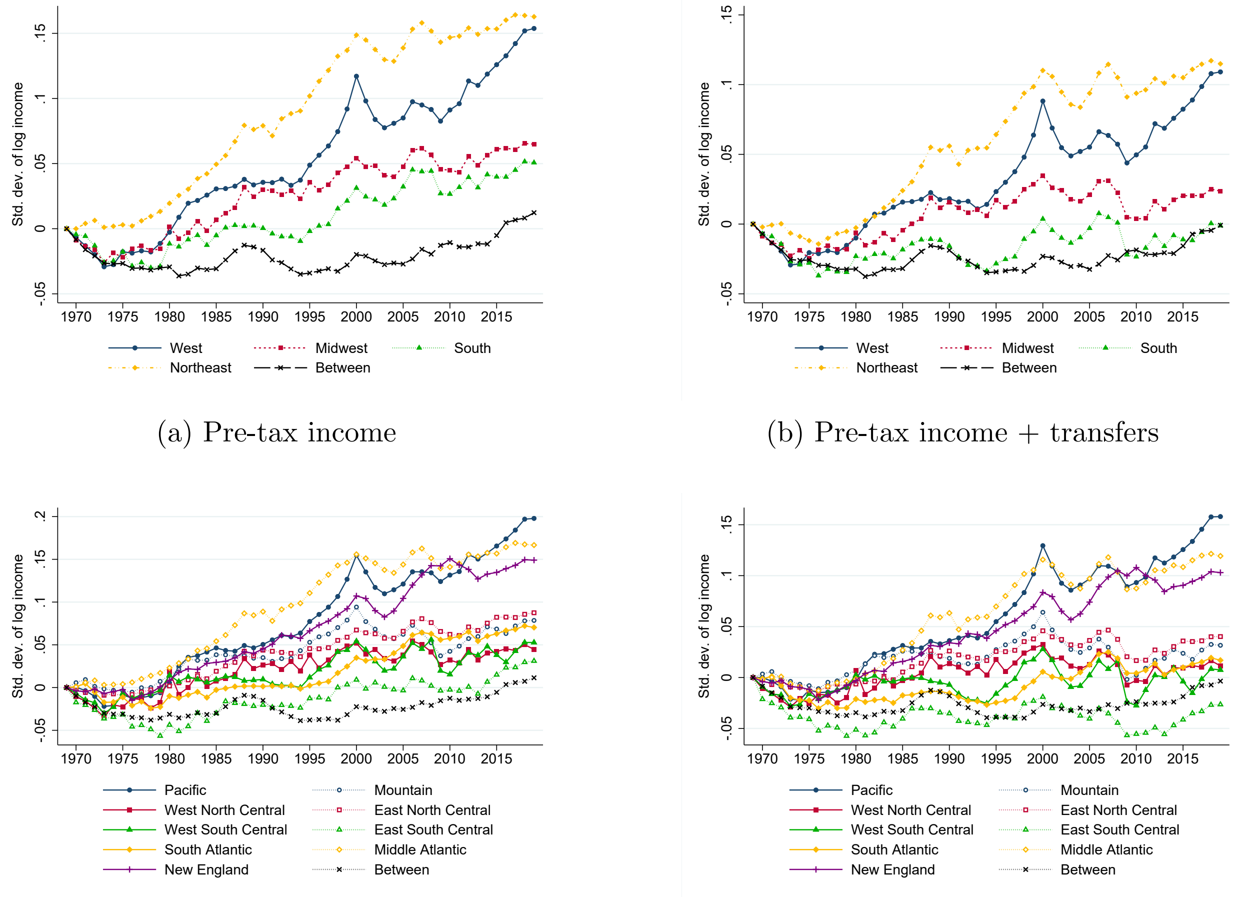
1970-1998 increase studied by Young, Higgins and Levy (2008).

Figure 2 plots the standard deviation across counties of two measures of log per capita income. The baseline level of dispersion across counties is nearly twice as high as that across states. In 1975, for example, a standard deviation increase in county log per-capita income entailed a roughly 25% increase, while a standard deviation increase in state log per-capita income entailed only a 14% increase. In contrast to the W shaped pattern found for states in Figure 1, cross-county dispersion increased steadily from 1975 to 2019.

A large literature, summarized in Autor (2014), documents that inequality also increased across individuals over this period. However, the variance across counties has also risen as a share of the total variance of log pre-tax income across U.S. individuals, as measured in the Distributional National Accounts (DINA) of Piketty, Saez and Zucman (2018).[2] While in 1975 log-income dispersion across counties accounted for only 5% of dispersion across individuals, by 2019, county dispersion contributed roughly 10% of the total income variance across individuals. Accounting for transfers (county-level taxes are not available) again dampens the rise in geographic dispersion, particularly in the wake of the Great Recession, but still yields a rise in the share of individual inequality explained by counties from 5%

[2]To deal with small and negative incomes in the DINA, we winsorize incomes from below at $5,000 (deflated to 2018 dollars) before taking the log. Varying this cutpoint changes the share of total inequality explained by counties but has little effect on trends.

Figure 3. Income dispersion across U.S. counties by region



(a) Pre-tax income

(b) Pre-tax income + transfers

(c) Pre-tax income

(d) Pre-tax income + transfers

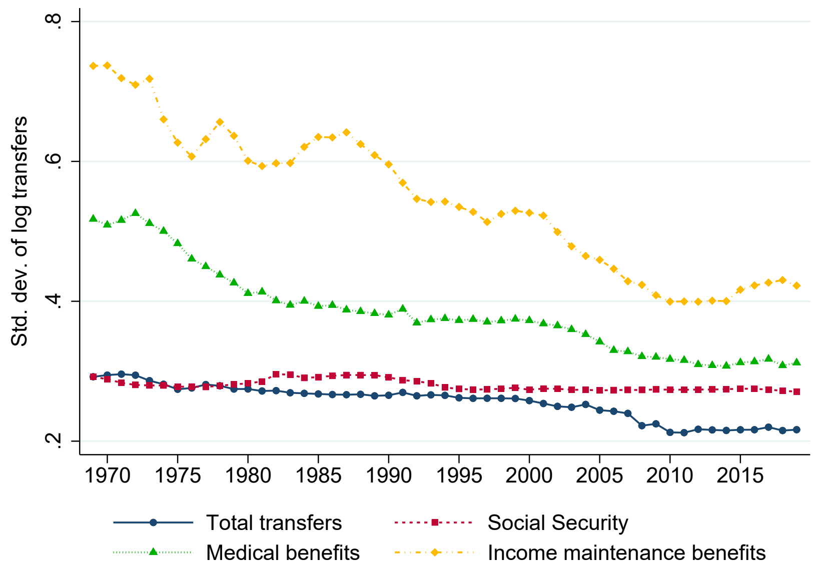
Note: These figures plot the population-weighted standard deviation across counties of the logarithm of two measures of BEA per capita income within Census regions and divisions. They also plot the population-weighted standard deviation of log mean income across regions and divisions ("between" dispersion). Series are normalized by subtracting their value in 1969. Source: Bureau of Economic Analysis.

to 8%.[3] This pattern is in keeping with the work of Manduca (2019), who concludes that only about half of the σ-divergence in mean family incomes across commuting zones between 1980 and 2013 is attributable to increasing national inequality across individuals.

An important difficulty with spatial income comparisons is that prices differ across locations (Moretti, 2013). Deflating our income measures using state by metropolitan area level price indices from BEA, in the years for which they are available, lowers the standard

[3]DINA pre-tax income includes Social Security and unemployment benefits, private pension distributions, and imputed corporate retained earnings and excludes Social Security and unemployment taxes and private pension contributions. DINA transfers and taxes are imputed when not directly observed in federal tax data. While DINA pre-tax income aggregates to national income, our DINA post-tax income measure does not, as we do not allocate collective consumption expenditures such as national defense to individuals.

Figure 4. Transfer dispersion across U.S. counties



Note: This figure plots the population-weighted standard deviation across counties of the logarithm of transfer per capita income. Medical benefits primarily comprise Medicare and Medicaid. Income maintenance benefits primarily comprise Supplemental Security Income, the Earned Income Tax Credit, food stamps, and cash welfare. Total transfers comprise the three categories plus unemployment benefits and education assistance among other transfers. Source: Bureau of Economic Analysis.

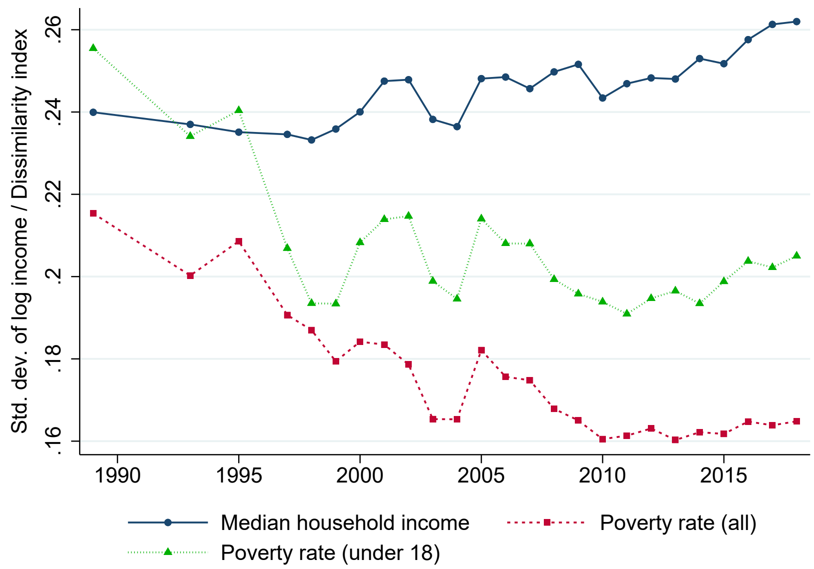
deviations as expected. However, deflating does little to the measured rise in cross-county dispersion.

The upper panels of Figure 3 display estimates of dispersion within Census regions along with the between region component of variance. Between region income inequality has remained remarkably stable over the past 40 years. In contrast, dispersion across counties in the West and Northeast has risen dramatically. The lower panels of Figure 3 reveal that much of this increase took place in the Middle Atlantic, Pacific, and New England Census divisions. Cross-division inequality has remained remarkably stable, indicating that inequality patterns are not driven by coastal states drifting apart from inland communities. Rather, dispersion in the fortunes of counties within these states is driving the steady increase in county level inequality.

4 Democratization of poverty

A recurrent finding in Figures 1 and 2 has been the increasing divergence between pre- and post-transfer measures of income dispersion. Figure 4 plots the standard deviation across counties of log per-capita transfers. The sustained decrease in geographic transfer dispersion

Figure 5. Dispersion in poverty rates and median household income across U.S. counties



Note: This figure plots the population-weighted standard deviation across counties of the logarithm of median household income and the dissimilarity index of county poverty rates. Household incomes include social security, SSI, welfare, unemployment insurance, and pension payments. A person is poor when their pre-tax family income plus certain cash transfers falls below a national threshold that varies by year, family size, and number of children. Source: Census Small Area Income and Poverty Estimates.

over our sample period indicates that government payments are becoming more evenly spread across U.S. communities. The geographic concentration of income maintenance programs such as the EITC, food stamps, and SSI has fallen especially sharply.

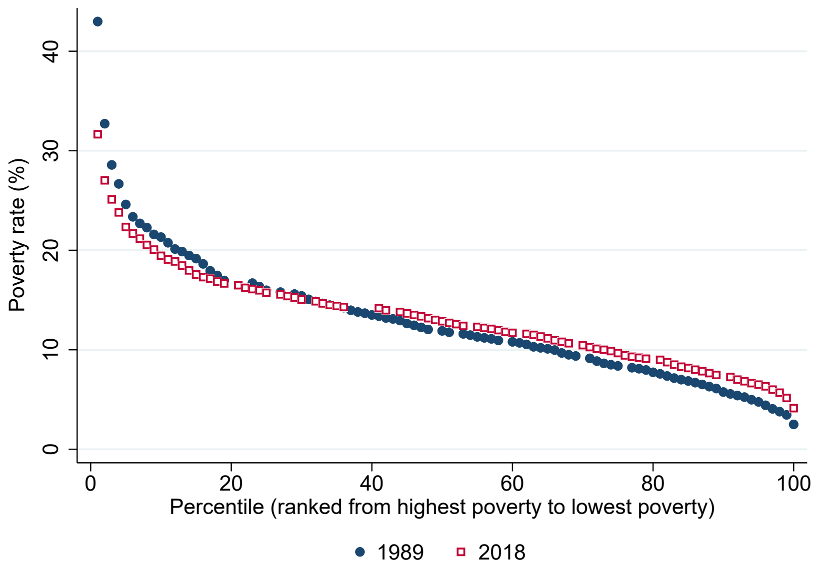
Figure 5 plots Census estimates of county poverty rates and median household incomes. County dispersion in median incomes has grown more slowly than the corresponding dispersion in per-capita post-transfer incomes depicted in Figure 2. Between 1990 and 2018, for example, dispersion in per-capita post-transfer incomes grew by 4 log points, while dispersion of median household incomes grew by only 2 log points. This divergence hints that trends in per-capita dispersion may be driven by households with very high incomes.

To measure the dispersion of poverty, we report the dissimilarity index of poverty rates, which gives the share of people that would need to move for all counties to have the same poverty rate.[4] Poverty rates have converged rather dramatically across counties since the 1990s, with the dissimilarity index plummeting by roughly a quarter by 2018. Youth poverty rates exhibit a similar pattern, indicating this phenomenon is not driven exclusively by trends among the elderly.[5]

[4] The dissimilarity index can be written $\frac{1}{2}\sum_i |P_i - NP_i|$, where P_i denotes the share of all poor people located in county i and NP_i the share of all non-poor people in county i.

[5] The methodology underlying Census Small Area Income and Poverty Estimates changed in 2005. In

Figure 6. County poverty rate by percentile



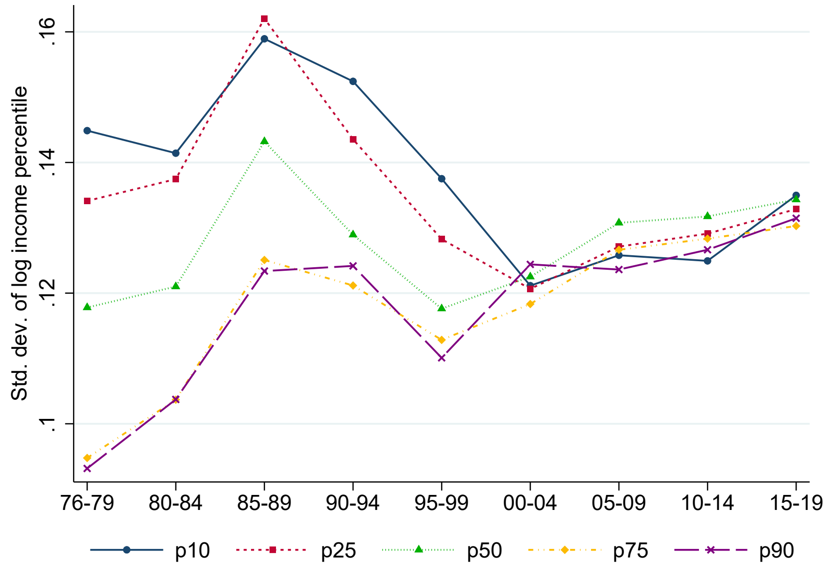
Note: This figure plots mean county poverty rates (considering all ages) by population-weighted percentiles, separately for 1989 and 2018. Source: Census Small Area Income and Poverty Estimates.

In the Appendix, we document three additional facts. First, poverty rates have equalized both within and between Census regions (Figure A.2). The between region component has played a dominant role in this equalization post-2000 as poverty rates rose in the Northeast and Midwest relative to the South and West (Figure A.3). Second, counties that were very poor in 1990 had large reductions in poverty by 2018, while those that were less poor had substantial poverty increases (Figure A.4). Finally, the poverty dissimilarity index also fell dramatically between the 1960 and 1980 Censuses (Figure A.5).

Figure 6 provides a deeper dive into recent changes in the spatial distribution of poverty rates. While national poverty rates changed little between 1989 and 2018, the tails of the county poverty rate distribution contracted. In the Appendix we show that a similar pattern emerges when grouping counties by decile or when examining youth poverty rates. Though the variability of poverty rates across counties has declined, it is worth noting that poverty remains highly concentrated. Gaubert, Kline and Yagan (2020) document even more pronounced concentration of poverty among Census tracts, which they show can provide a motive for place based subsidies to poor areas.

the Appendix we report historical estimates based upon Decennial Censuses and find similar results.

Figure 7. Dispersion in state income percentiles



Note: This figure plots the population-weighted standard deviation across states of percentiles of the logarithm of household income. The data have been pooled into 5 year intervals and PCE-deflated to 2012 dollars. Each quantile's bias corrected variance is computed by subtracting its average squared standard error from its sample variance across states. Standard errors are computed via bootstrap resampling with 300 draws. All computations use household weights. Source: IPUMS CPS ASEC files 1976-2019.

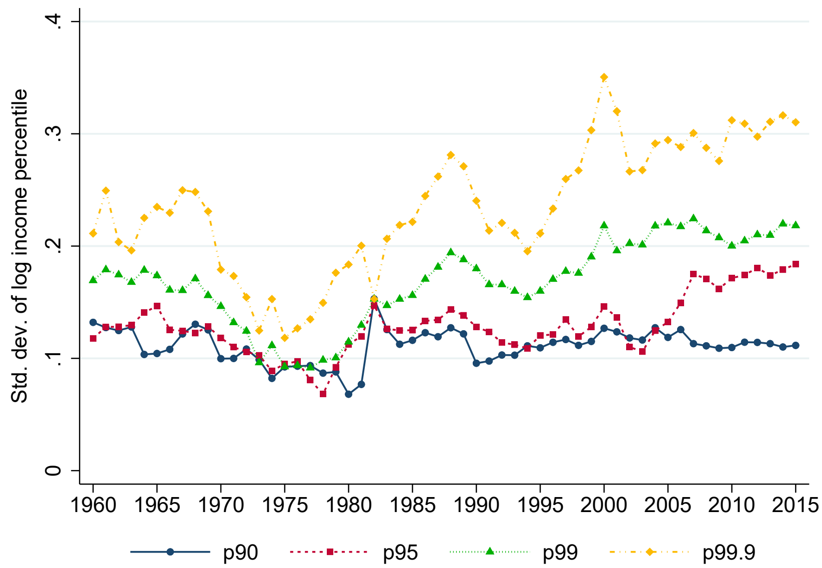
5 Concentration of affluence

The finding that poverty rates have become more equal across counties, while per-capita incomes have grown more dispersed, strongly suggests that high income households have increasingly segregated themselves to particular counties. Consistent with this hypothesis, Manduca (2019) finds that the growth between 1980 and 2013 in the coefficient of variation of mean family income across commuting zones is highly sensitive to the exclusion of top earners. To generate a more complete picture of this pattern, Figure 7 reports the dispersion across states of various percentiles of log household income measured in the March Supplement of the Current Population Survey (CPS).

Although CPS income definitions differ somewhat from those of the BEA, we have attempted to approximate the post-transfer income concepts reported in Figures 1 and 2.[6] To account for sampling error in the quantile estimates, we pool the data across 5-year intervals and bias correct the standard deviation of each quantile using the standard error

[6] To measure income we use the IPUMS-CPS variable INCTOT, which includes labor earnings, business income, welfare, social security, unemployment insurance, worker's compensation, and pensions.

Figure 8. Dispersion in state top income percentiles



Note: This figure plots the taxpayers-weighted standard deviation across states of top percentiles of the logarithm of gross income. Gross income equals adjusted gross income minus unemployment compensation and taxable Social Security benefits. Series includes capital gains. Source: Sommeiller and Price (2018).

estimates in each state.[7]

Consistent with the previously documented decline in poverty concentration, Figure 7 reveals that the dispersion of the bottom quantiles of state income has declined since 1990. Prior to 2000, geographic dispersion in the lower quantiles exceeds that found in the upper quantiles. By the 2015-2019 interval, cross-state dispersion was roughly equal across quantiles at roughly 13 log points. This convergence is driven both by an increase in the dispersion of top incomes across counties and a reduction in the dispersion of bottom incomes across counties.

A limitation of the CPS is that incomes are top coded. Figure 8 provides a closer look at the dispersion of top income quantiles by state using estimates derived from tax data by Sommeiller and Price (2018). The dispersion of the 99.9th percentile exhibits a W-shaped pattern similar to that of per-capita incomes displayed in Figure 1. Evidently, an important force driving the post-1995 rise in cross-sectional dispersion (σ-divergence) in per-capita state incomes is the growing dispersion across states in the amounts of income their highest income residents receive.

[7]Standard deviations for each quantile τ are computed as $\sqrt{S_\tau - \bar{V}_\tau}$ where S_τ is the sample variance of the quantile estimates and $\bar{V}_\tau$ is the average across states of their squared bootstrap standard errors.

6 Taking stock

Our findings paint a more nuanced story than the common refrain that American communities are growing apart. Mean incomes are diverging across areas but those means give outsize influence to individuals with especially high incomes. In contrast, median incomes, which arguably provide a better measure of the well-being of a typical household, exhibit more muted divergence over the past thirty years.

The equalization of poverty rates across space we document aligns closely with independent evidence that bottom income percentiles and means-tested transfers are converging across locations. Given that the migration flows of less educated workers are only weakly related to area income (Ganong and Shoag, 2017), we suspect this democratization of poverty is not driven primarily by a reshuffling of households. An interesting question for future research is the extent to which changes in labor market institutions such as the minimum wage or transfer programs such as disability insurance are driving these trends.

The increasing geographic concentration of high income households we document is broadly consistent with the well known rise in top incomes across individuals. Perhaps influenced by these trends, coastal states including New York and California have recently enacted or increased "millionaire taxes" on households with high incomes. Assessing whether place based millionaire taxes will be subverted by income shifting or real migration responses is a priority for future research.

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Appendix

Approximating the Bourguignon Index

The first term of B can be written:

$$\ln\left(\sum_i s_i v_i\right) = \ln\left(\sum_i s_i \exp\left(\ln v_i\right)\right).$$

A second order Taylor approximation of $\exp(\cdot)$ around the point $\overline{\ln v}$ yields

$$\exp\left(\ln v_i\right) \approx \exp\left(\overline{\ln v}\right)\left\{1 + \left[\ln v_i - \overline{\ln v}\right] + \frac{1}{2}\left[\ln v_i - \overline{\ln v}\right]^2\right\}.$$

Employing this approximation yields

$$\ln\left(\sum_i s_i v_i\right) \approx \overline{\ln v} + \ln\left(1 + \frac{1}{2}\sum_i s_i\left[\ln v_i - \overline{\ln v}\right]^2\right).$$

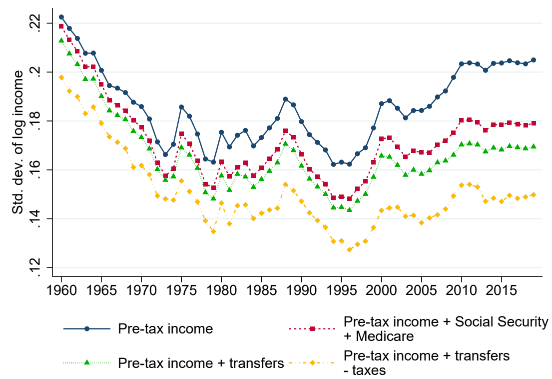
Hence, we can write

$$\begin{aligned} B &\approx \ln\left(1 + \frac{1}{2}\sum_i s_i\left[\ln v_i - \overline{\ln v}\right]^2\right) \\ &\approx \frac{1}{2}\sum_i s_i\left[\ln v_i - \overline{\ln v}\right]^2, \end{aligned}$$

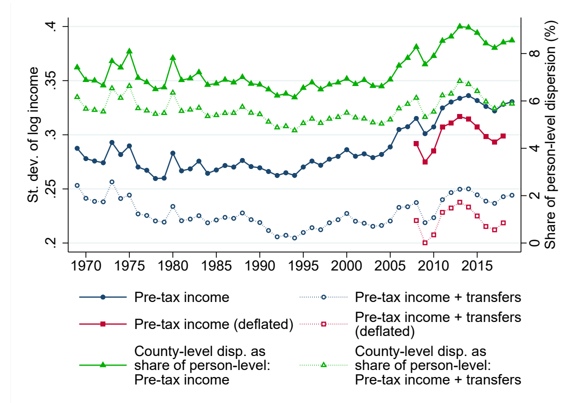
where the second line uses the approximation $\ln(1+x) \approx x$. This second approximation is extremely accurate in our setting because the variances we study lie far below one.

Additional Results

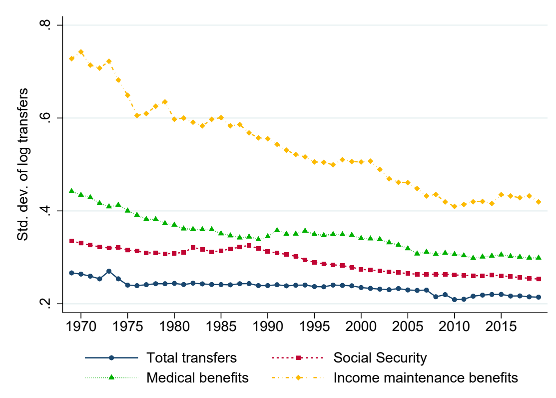
Figure A.1. Unweighted results



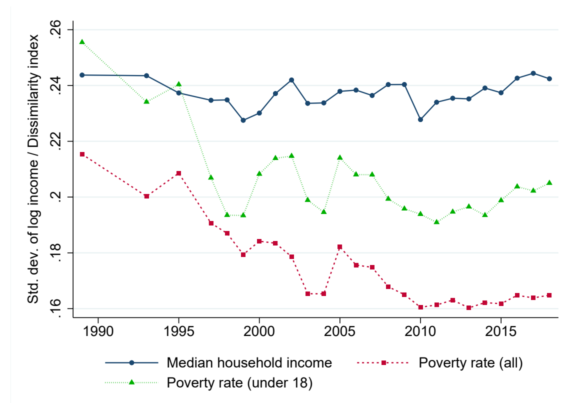
(a) Figure 1



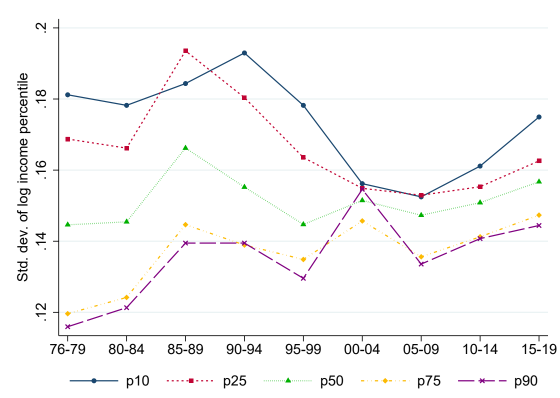
(b) Figure 2



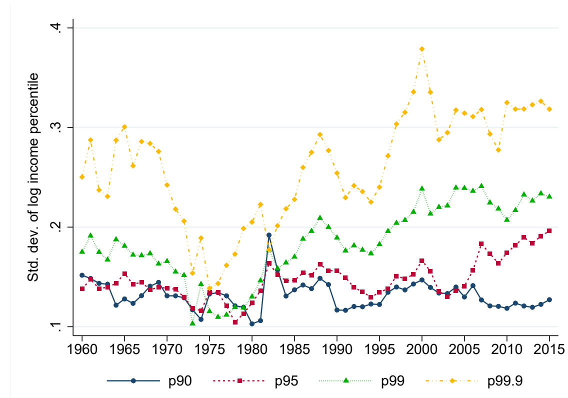
(c) Figure 4



(d) Figure 5



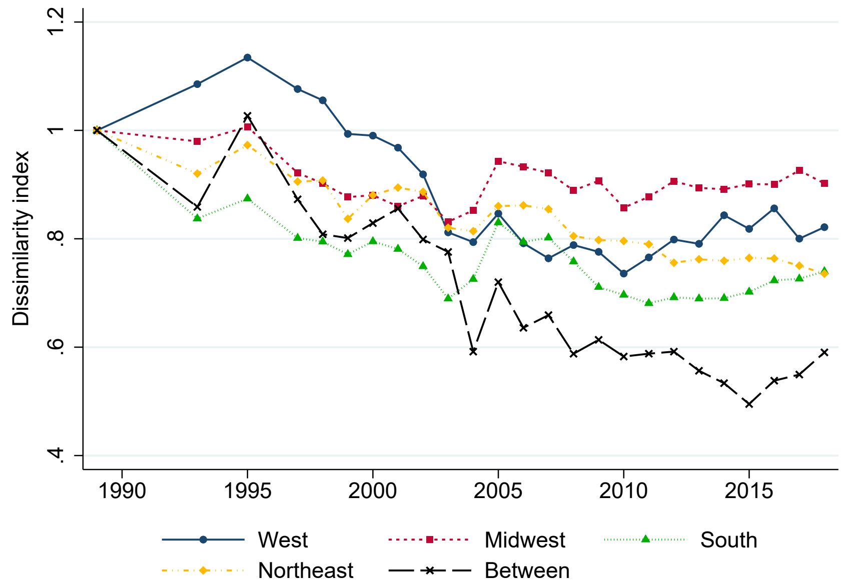
(e) Figure 7



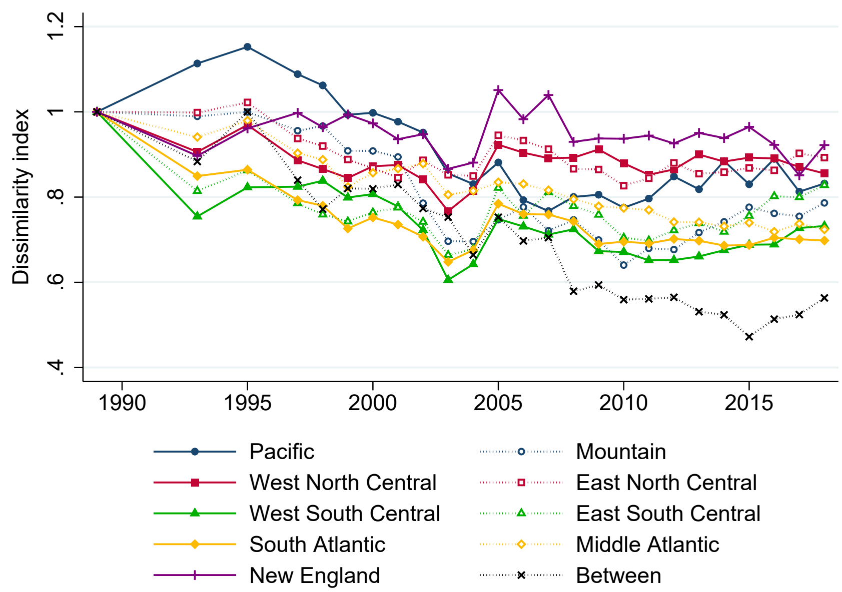
(f) Figure 8

Note: The above panels reproduce the figures in the text assigning equal weight to each geographic unit.

Figure A.2. Regional poverty results



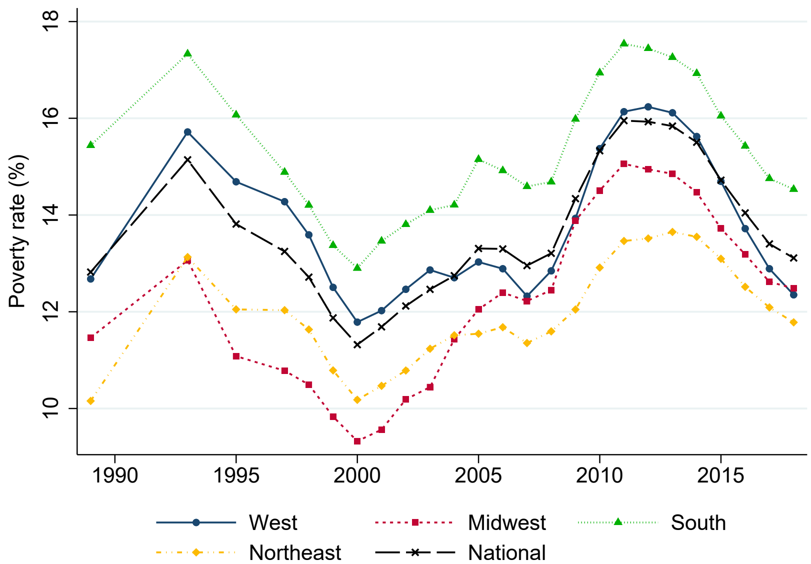
(a) By Census region



(b) By Census division

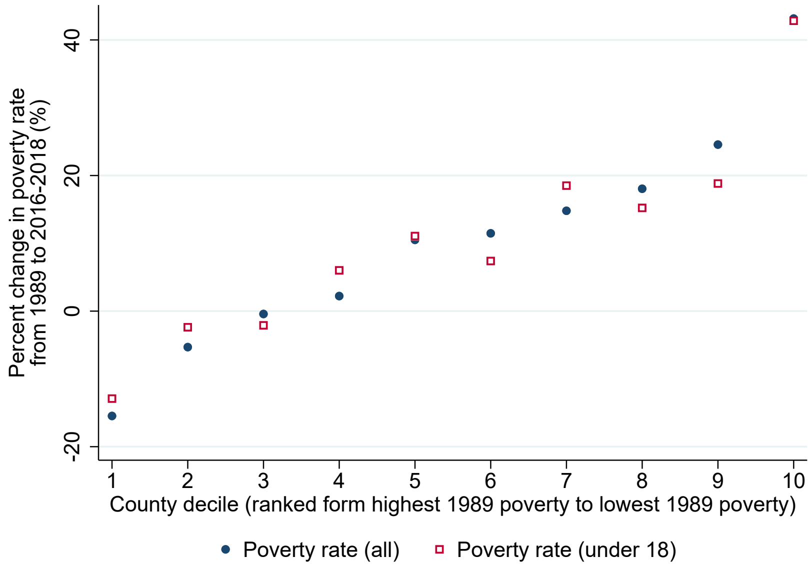
Note: These figures plot the dissimilarity index of county poverty rates within Census regions and divisions. They also plot the dissimilarity index of mean poverty rates across regions and divisions ("between" dispersion). Series are normalized dividing by their value in 1989. Source: Census Small Area Income and Poverty Estimates (SAIPE).

Figure A.3. Mean poverty rate by Census region



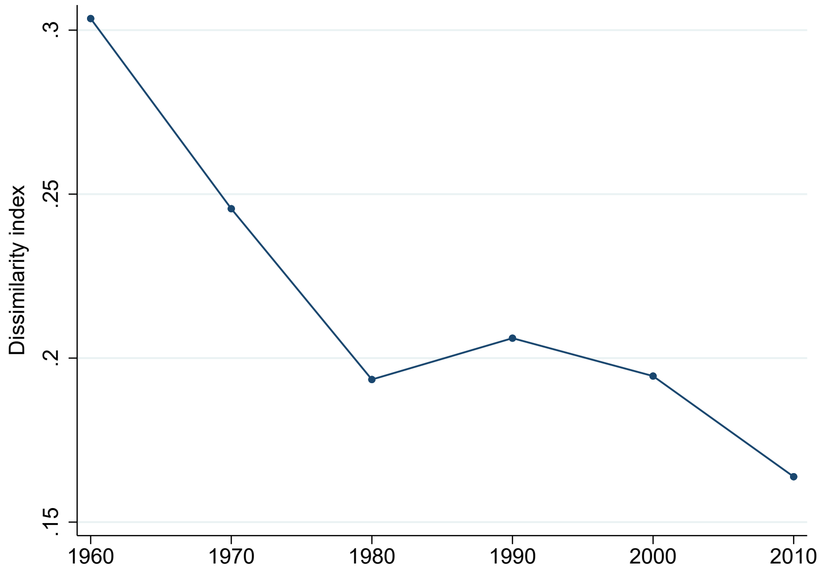
Note: This figure plots the mean poverty rate by Census region using county-level data. Source: Small Area Income and Poverty Estimates (SAIPE)

Figure A.4. Change in mean poverty rate by decile



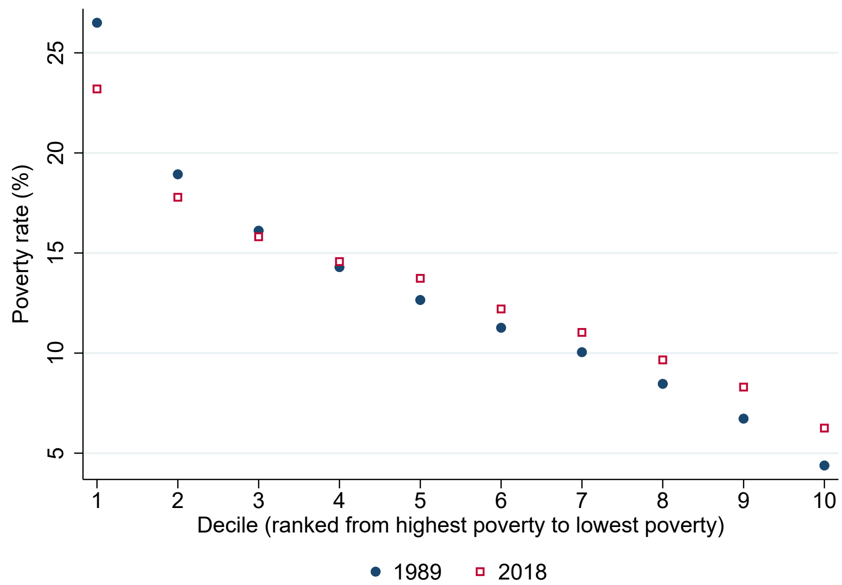
Note: This figure plots the log difference in mean county poverty rates between 1989 and the average 2016-2018 by 1989 county poverty rate rank. Data for 1989 is taken from 1990 Decennial Census and data for 2016-2018 is taken from SAIPE. Source: 1990 Decennial Censuses and Census Small Area Income and Poverty Estimates (SAIPE)

Figure A.5. Poverty rate dissimilarity index

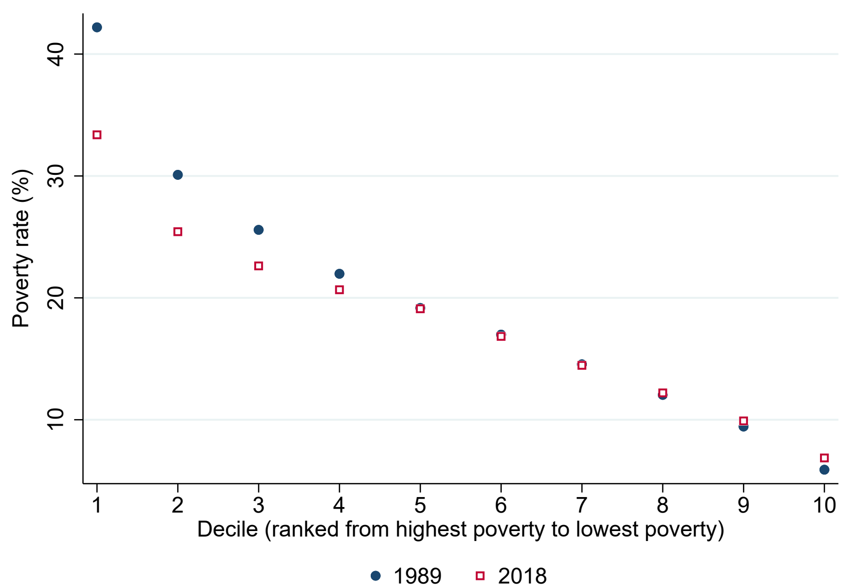


Note: This figure plots the dissimilarity index of the poverty rate using county-level Decennial Census data.
Source: 1980, 1990, 2000 Decennial Censuses and 5 year (2008-2012) ACS averages

Figure A.6. Mean poverty rate by decile



(a) All ages



(b) Under 18

Note: These figures plot mean poverty rates by population-weighted deciles built from county-level data, separately for 1989 and 2018. Panel (a) considers poverty rates for all ages. Panel (b) considers poverty rates for ages under 18. *Source*: Census Small Area Income and Poverty Estimates.