Growing Apart? Recent Trends in Spatial Income Inequality

By Cecile Gaubert, Patrick Kline, Damián Vergara, and Danny Yagan*

The gap between rich and poor places in America is often cited as a failure of modern capitalism to provide widely shared economic growth. In Gaubert, Kline and Yagan (2020) we show that when places differ in their distribution of real incomes, indexing taxes and transfers to location can meaningfully reduce the efficiency costs of redistribution.

Have the income disparities motivating place-based redistribution 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.

Our first key finding is 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.

Second, means-tested transfers have become significantly less spatially concentrated over the past 30 years. This reduction is driven in part by a rapid convergence of poverty rates across counties during the 1990s. More generally, cross state dispersion in the bottom quantiles of income has fallen since the 1980s, a finding consistent with Autor (2019)'s observation that the urban wage premium has declined for less skilled workers.

Third, trends in the dispersion of per-capita area incomes are largely driven by top earners. The dispersion across states and counties of median household incomes has grown very modestly over the past 30 years, while the dispersion of 99.9th percentiles of state incomes has risen sharply. On net, these findings suggest the potential equity gains associated with place-based taxation of top incomes have grown stronger in recent decades.

I. 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. We begin our analysis by proxying v_i with per-capita income and then examine other mea-

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sures that reflect different weightings of income quantiles.

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

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

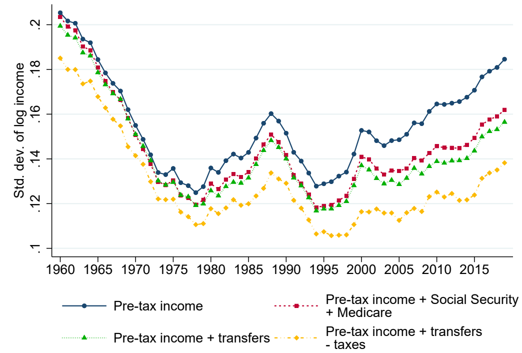
where $\bar{v} = \sum_i s_i v_i$ and s_i is the population share of area i. The B index is scale invariant and reflects logarithmic inequality aversion: a utilitarian planner who seeks to maximize $\overline{\ln v} = \sum_i s_i \ln v_i$ would be willing to trade a 1% loss in $\bar{v}$ for a reduction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

In the Online 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 Online Appendix.

II. Income dispersion across states and counties

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 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

Figure 1. Income dispersion across U.S. states



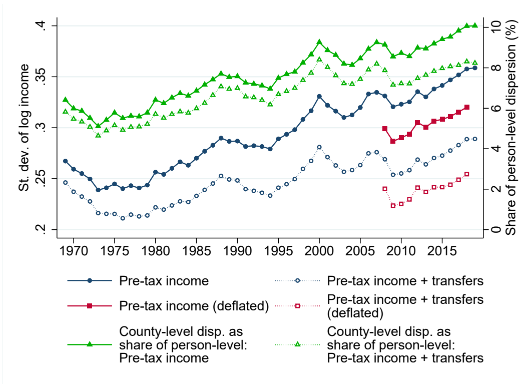
Note: This figure plots the population-weighted standard deviation across states of the logarithm of four measures of per capita income. Pre-tax income equals wages, employer-provided benefits, proprietors' income, dividends, interest, and rent and excludes capital gains and thereby corporate retained 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.

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 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 exam-

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.

ple, 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. In the Online Appendix, we show that this growth is largely driven by coastal Census divisions in the Northeast and West.

A large literature, summarized in Autor (2014), documents that inequality also increased across individuals over this period. Interestingly, 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).[1] 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% to 8%.[2]

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

III. The 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 3 plots the standard deviation across counties of log per-capita transfers. The sustained decrease in geographic transfer dispersion over our sample period indicates that government payments are becoming more evenly spread across U.S. communities. Payments from income maintenance programs such as the EITC, food stamps, and SSI have grown especially dispersed. Is this democratization of means-tested transfers a sign that poor households are deconcentrating throughout the United States, or are states adjusting the generosity of their implementations of these programs?

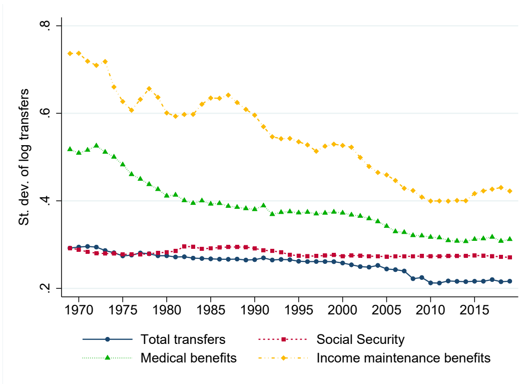
Figure 4 explores this question using Census estimates of county poverty rates and median household incomes. To measure the dispersion of poverty, we report the dissimilarity index of poverty rates, which gives the share of people that would need to move for all counties to have the same poverty rate.[3] Poverty rates have con-

[1]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.

[2]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.

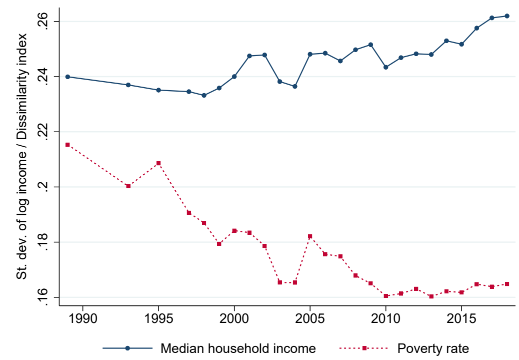
[3]The dissimilarity index can be written

FIGURE 3. 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.

FIGURE 4. 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 (SAIPE).

verged rather dramatically across counties since the 1990s, with the dissimilarity index plummeting by roughly a quarter. In the Online Appendix, we show that poverty rates have equalized both within and between Census regions, with the between region component playing a dominant role since 2000. These findings suggest that much of the drop in transfer dispersion has to do with changes in the spatial composition of households.

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.

IV. The dispersion of top incomes

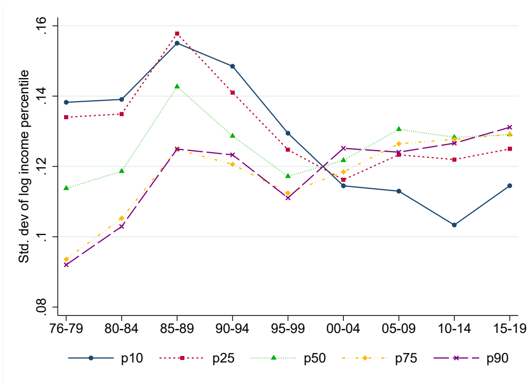
The finding that poverty rates have become more equal across counties, while per-capita incomes have grown more dispersed, strongly suggests that high income households have increasingly segregated themselves to particular counties. To generate a more complete picture of this pattern, Figure 5 reports 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 replicate the post-transfer income concepts reported in Figures 1 and 2.[4] To aid precision, we work with 5-year averages and deflate income to the midpoint of each interval. We refrain from computing per-capita incomes which, unlike the quantiles we study, are likely sensitive to CPS top-coding. To account for sampling error in the quantiles, we bias correct the stan-

$\frac{1}{2}\sum_i |P_i - NP_i|$, 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. Online Appendix Figure A.III provides additional measures of poverty concentration trends.

[4] 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 5. Dispersion in state income percentiles



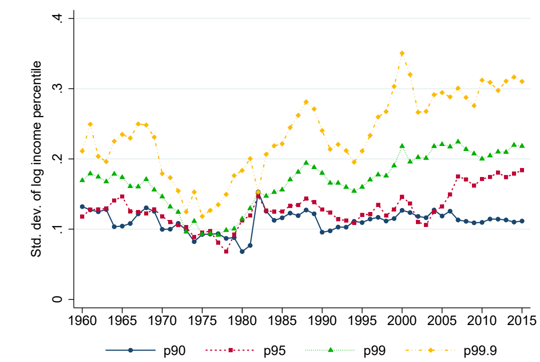
Note: This figure plots the population-weighted standard deviation across states of percentiles of the logarithm of household income. The data have been pooled into 5 year intervals and PCE-deflated to midpoint equivalent dollars. State identifiers are unavailable 1967-1975. Each quantile's bias corrected 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 1962-2019.

dard deviation of each quantile using the standard error estimates in each state.

Consistent with the aforementioned decline in poverty concentration, Figure 5 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. For instance, in the 1980-1984 interval, the standard deviation of the 10th percentile of state income was 14 log points, the standard deviation of the 25th percentile was 13.5 log points, while that of the 90th percentile was only 10 log points. By the 2015-2019 interval, cross-state dispersion was roughly equal across quantiles at 12-13 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. Put differently, what it means to be poor in America has become more geographically standardized, while what it means to be rich has become more variable across states.

Figure 6 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 dis-

Figure 6. 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).

persion 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.

V. Whither place-based redistribution?

Our findings paint a more nuanced story than the usual observation that American communities are drifting apart. Mean incomes are drifting apart but those means give outsize influence to households with extremely high incomes. In contrast, median incomes, which arguably provide a better measure of the well-being of a typical household, exhibit more stable dispersion over the past thirty years.

There are several possible policy takeaways from these facts. First, the increasing geographic concentration of high income households provides a motive for spatially indexing top tax rates. Indeed, many states including New York and California have recently considered levying "millionaire taxes" on households with very high incomes. Arizona recently passed a tax increase on incomes over $250,000, while Illinois floated a similar proposal that failed. Assessing whether such taxes will be subverted by income shifting or real migration responses is a priority for future research.

Second, though poverty rates have equalized somewhat across counties, dispersion in median incomes remains substantial and has been inching upwards over the past decade. Returning to Figure 4, if society exhibited logarithmic inequality aversion over median household incomes, a planner would be willing to reduce the average median income of U.S. counties by approximately $\frac{1}{2}(.26)^2 \times 100 = 3.3\%$ in order to eliminate the county dispersion in median incomes found in 2019. Poverty dispersion also remains high, suggesting that optimal place-based transfers to high-poverty communities are likely non-trivial (Gaubert, Kline and Yagan, 2020).

Finally, it is notable that the dispersion of median incomes remains elevated following the Great Recession. This finding, which is consistent with the hysteresis effects documented by Yagan (2019), aligns with the notion that spatial disparities reflect not only patterns of uneven economic growth but also the persistent effects of temporary shocks. An interesting topic for future research is the extent to which place-based subsidies should be used to insure households against spatially uneven shocks.

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Online 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

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

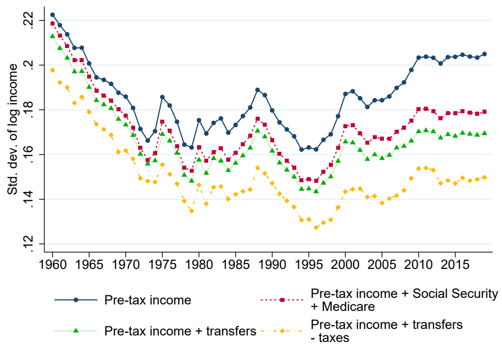
Hence, we can write

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

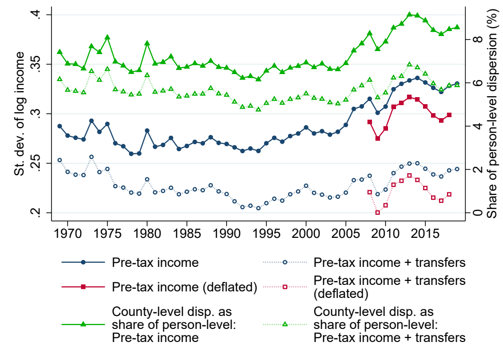
where the second line uses the approximation $\ln(1+x) \approx x$. This second approximation is extremely accurate in our setting because the variances we study lie far below one.

Additional results

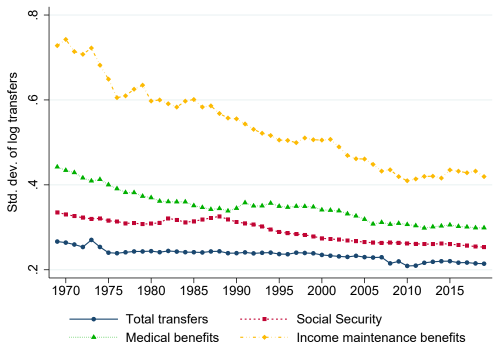
FIGURE A.I. UNWEIGHTED RESULTS



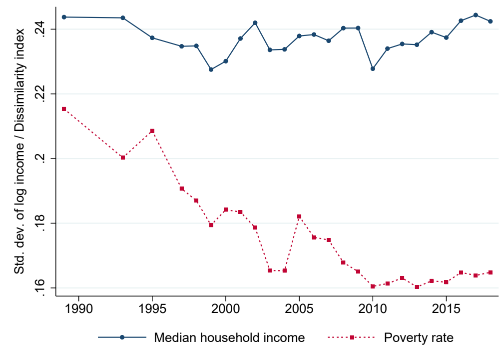
(a) Figure 1



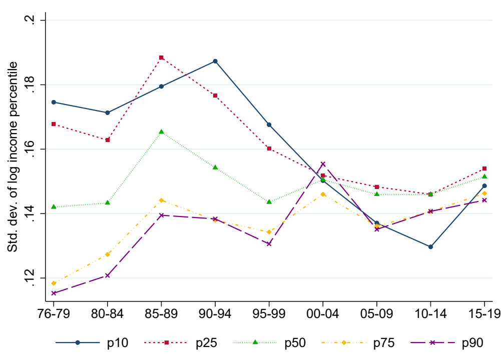
(b) Figure 2



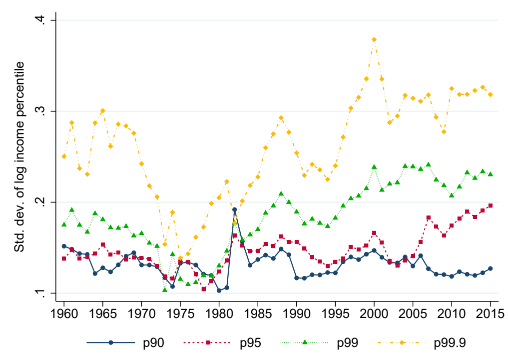
(c) Figure 3



(d) Figure 4



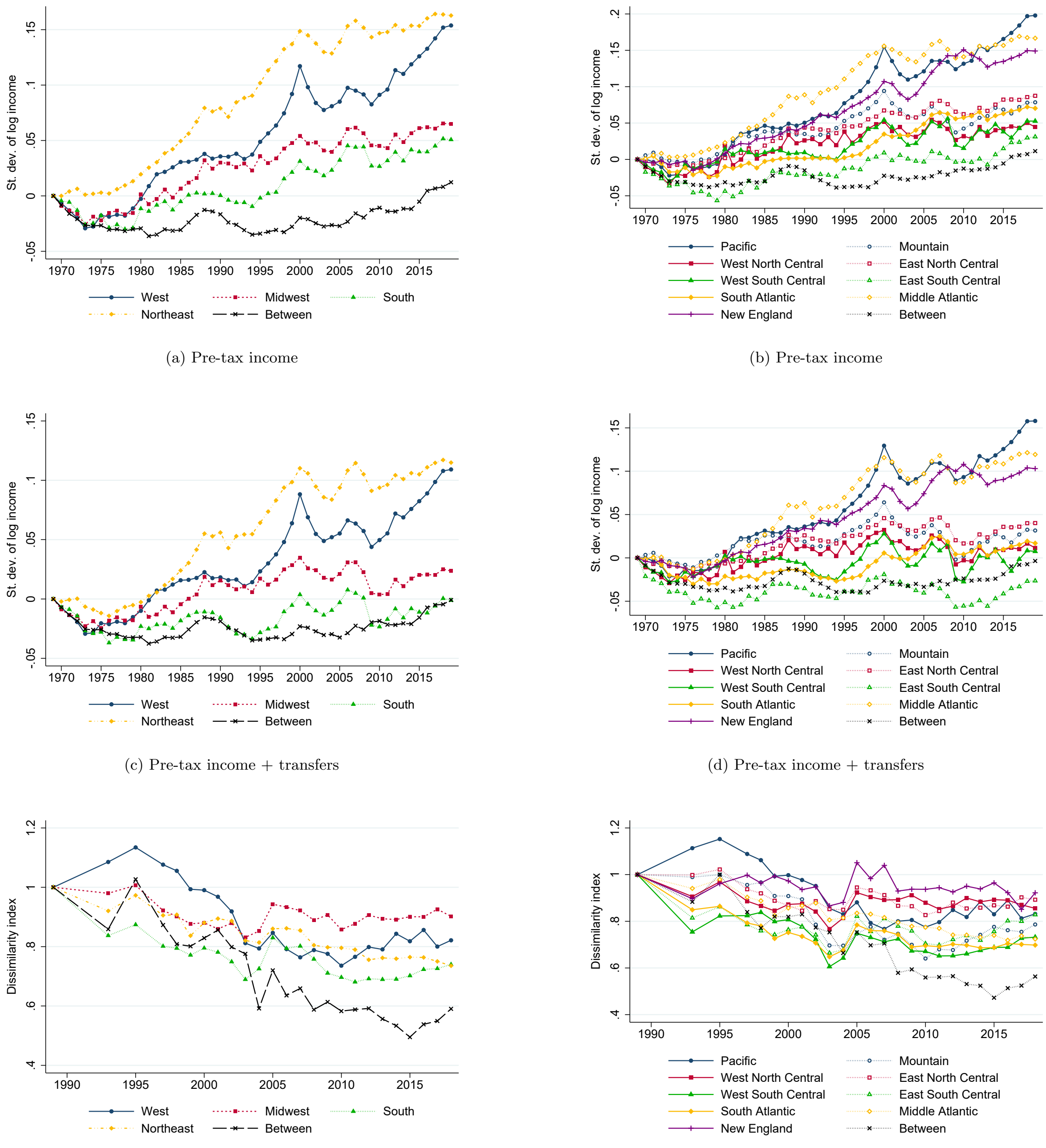
(e) Figure 5



(f) Figure 6

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

Figure A.II. Regional results



(a) Pre-tax income

(b) Pre-tax income

(c) Pre-tax income + transfers

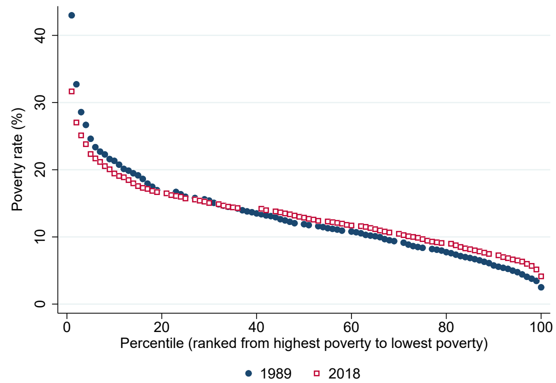
(d) Pre-tax income + transfers

(e) Poverty rate

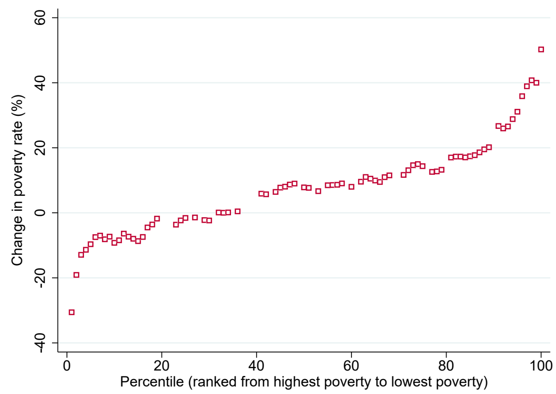
(f) Poverty rate

Note: These figures plot the population-weighted standard deviation across counties of the logarithm of two measures of BEA per capita income and the dissimilarity index of county poverty rates within Census regions and divisions. They also plot the population-weighted standard deviation of log mean income across regions and divisions and the dissimilarity index of mean poverty rates across regions and divisions ("between" dispersion). Income series are normalized by subtracting their value in 1969. Poverty rate series are normalized dividing by their value in 1989. *Source*: Bureau of Economic Analysis and Census Small Area Income and Poverty Estimates (SAIPE).

Figure A.III. Additional poverty results



(a) Mean poverty rate by percentile



(b) Change in mean poverty rate by percentile

Note: These figures plot mean poverty rates by population-weighted percentiles built from county-level data. Panel (a) separately plots the distribution of mean poverty rates in 1989 and 2018. Panel (b) plots the percent change in mean poverty rates by percentile between 1989 and 2018. Source: Census Small Area Income and Poverty Estimates (SAIPE).