

## SPATIAL POLICIES<sup>‡</sup>

# Trends in US Spatial Inequality: Concentrating Affluence and a Democratization of Poverty<sup>†</sup>

By CECILE GAUBERT, PATRICK KLINE, DAMIÁN VERGARA, AND DANNY YAGAN\*

Have US 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; Barro 2015; Ganong and Shoag 2017). In this paper, we study trends in income inequality across US 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 pretax 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 (Piketty, Saez, and Zucman 2018). While in the 1970s the variance across counties of log per capita incomes explained as little as 5 percent of the variance of

log incomes across individuals, today county income dispersion accounts for 10 percent 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.

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 US 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 posttransfer 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’s (2019) 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 have diverged markedly across states since the late 1970s.

### 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  $v_i = \int_0^1 \omega(F_i^{-1}(\tau)) F_i^{-1}(\tau) d\tau$  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

<sup>‡</sup>*Discussants:* David Autor, Massachusetts Institute of Technology; David Rezza Baqaee, University of California-Los Angeles; Adrien Bilal, Harvard University.

\*Gaubert: UC Berkeley (email: [cecile.gaubert@berkeley.edu](mailto:cecile.gaubert@berkeley.edu)), Kline: UC Berkeley (email: [pkline@berkeley.edu](mailto:pkline@berkeley.edu)); Vergara: UC Berkeley (email: [damianvergara@berkeley.edu](mailto:damianvergara@berkeley.edu)); Yagan: UC Berkeley (email: [yagan@berkeley.edu](mailto:yagan@berkeley.edu)). We thank David Autor, Enrico Moretti, Emmanuel Saez, and Owen Zidar for helpful discussions. Cecile Gaubert acknowledges support from NSF CAREER grant #1941917.

<sup>†</sup>Go to <https://doi.org/10.1257/pandp.20211075> to visit the article page for additional materials and author disclosure statement(s).

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 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  $\ln \bar{v}$  would be willing to trade a 1 percent loss in  $\bar{v}$  for a reduction in  $B$  of 0.01.

In the online Appendix, we show that  $B \approx (1/2) \sum_i s_i (\ln v_i - \ln \bar{v})^2$ . 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. 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). 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 posttax 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 US states by  $(1/2)(0.14)^2 \times 100 = 1.0$  percent in order to eliminate the state dispersion in incomes found in 2019.

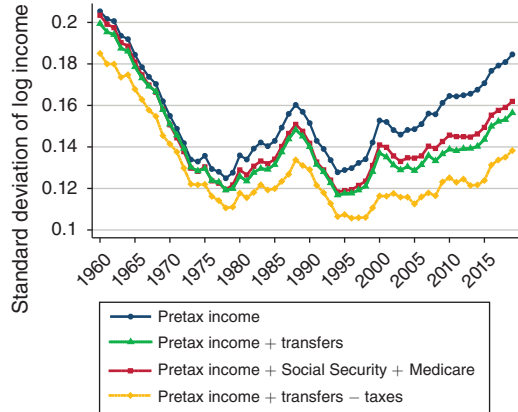


FIGURE 1. INCOME DISPERSION ACROSS US STATES

Notes: This figure plots the population-weighted standard deviation across states of the logarithm of four measures of per capita income. Pretax income equals wages, employer-provided benefits, proprietors’ income, dividends, interest, and rent but 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: BEA

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 “ $\beta$  convergence.” However,  $\beta$  convergence need not yield “ $\sigma$  convergence”—a reduction in cross-sectional dispersion across areas. In fact, all four of our measures exhibit strong  $\sigma$  divergence over the past 20 years. The increase in the standard deviation of log per capita pretax 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 example, a standard deviation increase in county log per capita income entailed a roughly 25 percent increase, while a standard deviation increase in state log per capita income entailed only a 14 percent 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.

The series in Figure 2 depicted with triangle markers show that the variance across counties has also risen as a share of the total variance of log pretax income across US individuals, as measured in the Distributional National Accounts (DINA) of Piketty, Saez, and Zucman (2018).<sup>1</sup> While in 1975 log income dispersion across counties accounted for only 5 percent of dispersion across individuals, by 2019, county dispersion contributed roughly 10 percent 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 percent to 8 percent.<sup>2</sup>

An important difficulty with spatial income comparisons is that prices differ across locations. 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. 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

<sup>1</sup>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 cut point changes the share of total inequality explained by counties but has little effect on trends.

<sup>2</sup>DINA pretax income includes Social Security and unemployment benefits, private pension distributions, and imputed corporate retained earnings but 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 pretax income aggregates to national income, our DINA posttax income measure does not, as we do not allocate collective consumption expenditures such as national defense to individuals.

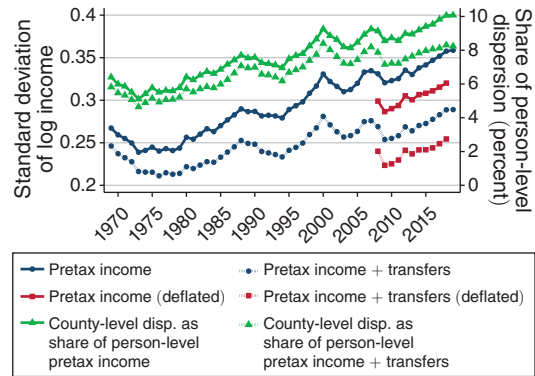


FIGURE 2. INCOME DISPERSION ACROSS US COUNTIES

*Notes:* 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 at the state and metropolitan portion level. 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:* BEA and DINA

in geographic transfer dispersion over our sample period indicates that government payments are becoming more evenly spread across US communities. The geographic concentration of income maintenance programs such as the Earned Income Tax Credit (EITC), food stamps, and Supplemental Security Income (SSI) has fallen especially sharply.

Figure 4 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 posttransfer incomes depicted in Figure 2. Between 1990 and 2018, for example, dispersion in per capita posttransfer 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.<sup>3</sup>

<sup>3</sup>The dissimilarity index can be written  $(1/2)\sum_i |P_i - NP_i|$ , where  $P_i$  denotes the share of all poor people located in county  $i$  and  $NP_i$  the share of all nonpoor people in county  $i$ .

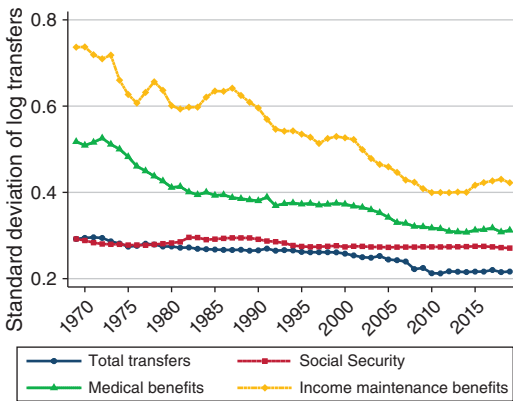


FIGURE 3. TRANSFER DISPERSION ACROSS US COUNTIES

*Notes:* 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 SSI, EITC, food stamps, and cash welfare. Total transfers comprise the three categories plus unemployment benefits and education assistance among other transfers.

*Source:* BEA

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.<sup>4</sup>

In the online Appendix, we document three additional facts. First, poverty rates have equalized both within and between census regions. The between-region component has played a dominant role post-2000, as poverty rates rose in the Northeast and Midwest relative to the South and West. 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. Finally, the poverty dissimilarity index also fell dramatically between the 1960 and 1980 censuses.

Figure 5 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

<sup>4</sup>The methodology underlying Census Small Area Income and Poverty Estimates changed in 2005. In the online Appendix we report historical estimates based upon decennial censuses and find similar results.

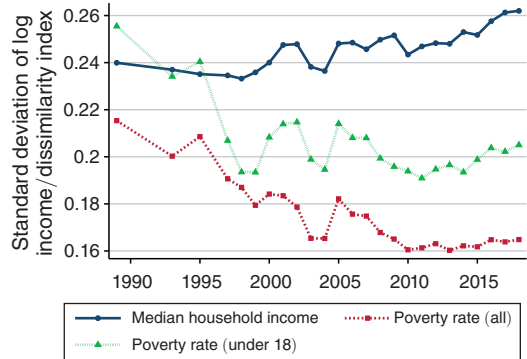


FIGURE 4. DISPERSION IN POVERTY RATES AND MEDIAN HOUSEHOLD INCOME ACROSS US COUNTIES

*Notes:* 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 pretax 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

county poverty rate distribution contracted. In the online Appendix, we show that a similar pattern emerges when grouping counties by decile or 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 demonstrate can provide a motive for place-based subsidies to poor areas.

#### IV. 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. Manduca (2019) finds that spatial divergence in mean family incomes 1980–2013 is sensitive to the exclusion of top earners. To generate a more complete picture of this pattern, Figure 6 reports the dispersion across states of various percentiles of log household

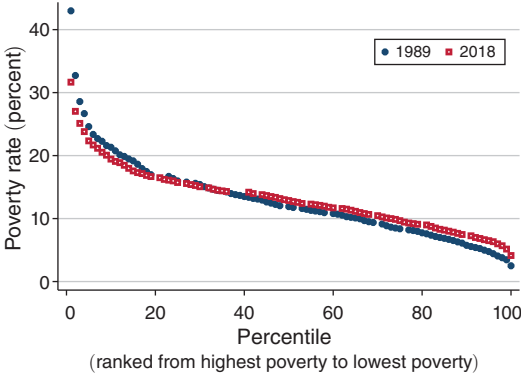


FIGURE 5. COUNTY POVERTY RATE BY PERCENTILE

Note: This figure plots mean poverty rates (considering all ages) by population-weighted percentiles built from county-level data, separately for 1989 and 2018.

Source: Census Small Area Income and Poverty Estimates

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 posttransfer income concepts reported in Figures 1 and 2.<sup>5</sup> To account for sampling error in the state-specific quantile estimates, we pool the data across five-year intervals and bias correct the standard deviation of each quantile using the standard error estimates in each state.

Consistent with the aforementioned decline in poverty concentration, Figure 6 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 by both 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. In the online Appendix, we report the dispersion of top income quantiles across

<sup>5</sup>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.

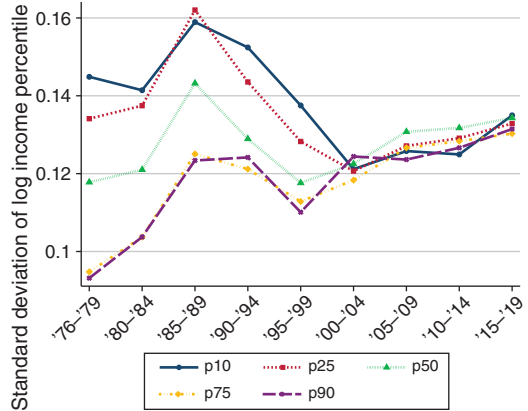


FIGURE 6. DISPERSION IN STATE INCOME PERCENTILES

Notes: This figure plots the population-weighted standard deviation across states of percentiles of the logarithm of household income. The data have been pooled into five-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

states using estimates derived from tax data by Sommeiller and Price (2018). The spatial dispersion of the 99.9th income 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 ( $\sigma$  divergence) in per capita state incomes is the growing dispersion across states in the amounts of income their highest-income residents receive.

### V. Taking Stock

Our findings paint a more nuanced story than the common refrain that US communities are growing apart. Mean incomes are diverging across areas, but those means give outsized 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 30 years.

The equalization of poverty rates across counties since 1990 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.

#### REFERENCES

- Autor, David H.** 2019. “Work of the Past, Work of the Future.” *AEA Papers and Proceedings* 109: 1–32.
- Barro, Robert J.** 2015. “Convergence and Modernisation.” *Economic Journal* 125 (585): 911–42.
- Barro, Robert J., and Xavier Sala-i-Martin.** 1991. “Convergence across States and Regions.” *Brookings Papers on Economic Activity* 21 (1): 107–82.
- Bourguignon, Francois.** 1979. “Decomposable Income Inequality Measures.” *Econometrica* 47 (4): 901–20.
- Ganong, Peter, and Daniel Shoag.** 2017. “Why Has Regional Income Convergence in the US Declined?” *Journal of Urban Economics* 102: 76–90.
- Gaubert, Cecile, Patrick Kline, and Danny Yagan.** 2020. “Place Based Redistribution.” Unpublished.
- Manduca, Robert A.** 2019. “The Contribution of National Income Inequality to Regional Economic Divergence.” *Social Forces* 98 (2): 622–48.
- Moretti, Enrico.** 2012. *The New Geography of Jobs*. Boston and New York: Houghton Mifflin Harcourt.
- Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman.** 2018. “Distributional National Accounts: Methods and Estimates for the United States.” *Quarterly Journal of Economics* 133 (2): 553–609.
- Rinz, Kevin, and John Voorheis.** 2021. “Re-examining Regional Income Convergence: A Distributional Approach.” Slides presented at 2021 ASSA Meeting.
- Sommeiller, Estelle, and Mark Price.** 2018. *The New Gilded Age: Income Inequality in the U.S. by State, Metropolitan Area, and County*. Washington, DC: Economic Policy Institute.
- Young, Andrew T., Matthew J. Higgins, and Daniel Levy.** 2008. “Sigma Convergence versus Beta Convergence: Evidence from US County-Level Data.” *Journal of Money, Credit and Banking* 40 (5): 1083–93.