Geographic Inequality in Social Provision and Redistribution in the U.S. States

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All errors are our own.

Abstract

In recent years, "inequality" has received an extraordinary amount of attention in political, policy, and academic circles. In the U.S. the conversation has been overwhelmingly national in scope. This national focus misses another enormously consequential axis of American inequality, one that has received inadequate attention in contemporary academic and policy circles – that is inequality by geography, specifically inequality across the 50 U.S. states. In this paper we contribute conceptually and empirically to our understanding of the role of subnational government (states) in social provision and redistribution, directing attention to the consequences of safety net decentralization—especially inequalities in social provision, and inequalities in poverty reduction. Using an unique dataset of comparable social provision indicators, we examine the magnitude of cross-state variation in the generosity of benefits and the inclusiveness of safety net provisions across the U.S. states, and compare it to the magnitude of cross-national policy variation among a set of high-income countries. We find that there is substantial cross-state inequality in social provision, and that this level of variation rivals the variability that is observed cross-nationally. To examine redistribution, we focus on poverty reduction among working-age households with children using the CPS ASEC data to explore the role of four redistributive mechanisms: federal transfers, state transfers, federal taxes, and state taxes. We find that state transfers and federal taxes reduce market income poverty rates substantially, and that the magnitude of these redistributive impacts varies across states. We conclude that these state-level variations in social provision and redistribution are meaningful forms of inequality – inequality in the treatment of similar needs and claims by people who happen to live in different states, and argue that this form of inequality deserves more sustained attention, particularly in regard to policy design.

1. Introduction

In recent years, "inequality" has received an extraordinary amount of attention in political, policy, and academic circles. This has, for the most part, focused on the distributional inequality of economic resources (earnings, income, wealth) across or within populations. This renewed attention to inequality, in turn, has a geographic dimension—focusing on distributional inequalities within a particular setting or jurisdiction (country, state, or local area), or comparing across jurisdictions. And the study of inequality has a policy dimension; it is attentive to both the causal and prescriptive importance of policy and policy variation—over time and across jurisdictions.

In this study, we draw on these themes to assess variation in social policy provision and redistribution across the fifty U.S. states. While we know that various forms of economic hardship (including poverty and income disparities) vary across states, we know much less about how state policies shape those outcomes. To address this, we examine two forms of cross-state inequality: inequality in social safety net provision and inequality in redistribution.

At the heart of our work is our conceptualization of cross-state policy variation as a crucial form of inequality. Inequality in both social provision and redistribution, we argue, should be viewed as important cases of unequal responses to citizens' needs, with those unequal responses determined simply by where people happen to reside. Concerns about geographic inequalities – such as those seen across the U.S. states – can be expressed in equity-related arguments, which maintain that all citizens in need should have equal access to public supports. They can also be expressed in social (or economic) rights arguments, which claim that access to basic resources should have the same standing as civil and political rights, and thus must be universally granted (Blank 1997; T.H. Marshall 1964).

Concerns about unequal responses to citizen needs were heightened by the substantial changes made to safety net policies in the welfare reform era of the 1990s. The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) reworked the safety net for economically-vulnerable families with children, most notably by replacing a federally-mandated entitlement with a discretionary, conditional right to cash assistance managed by state authorities. During this same period, federal lawmakers made other changes in the balance of federal and local control over assistance for low-income households, including imposing stricter requirements on states to collect child support obligations and creating incentives for states to expand child care and health insurance programs. Concerns about unequal responses were further magnified by the Great Recession. Jason DeParle, writing in the *New York Times*, captured this sentiment vividly in an article written during the height of the economic downturn. DeParle observed that the most vulnerable victims of the crisis, when seeking needed help, confronted "a jumble of disconnected programs that reach some and reject others, often for reasons of geography or chance rather than difference in need" (NYT, 5/9/2009).

Our presentation is organized as follows: In **Section 2**, we place our work within relevant research literatures, and lay out our central research questions. In **Section 3**, we present our data sources and, in **Section 4**, our analytic approach and methods. In **Section 5**, we provide a descriptive analysis of the magnitude of cross-state variation in social provision, using a unique dataset that captures two key dimensions of safety net policies – generosity of benefits and inclusiveness of receipt – across 10 critical programs that comprise key safety net policies for economically-marginalized families in the U.S. We close this section by extending our analysis to compare cross-state variation with cross-national variation. We demonstrate that variation across the U.S. states is at levels equal to, or greater than, variation across a set of high-income countries that represent diverse welfare state regimes.

In **Section 6**, we turn to variation in household income poverty, across the 50 U.S. states. Because the social provisions that we study are targeted on low-income families, we assess cross-state variation in absolute poverty rates among working-age households. Thus, our central economic outcome is not an indicator of (state-level) income inequality *per se*, but instead of (state-level) income poverty; the two outcomes, both measures of income distribution, are related but distinct. Within states, we estimate a decomposition technique that allows us to identify and weigh the policy elements that mitigate poverty produced in the market, and to assess how those "effects" vary across states. We also carry out this analytic exercise for the U.S. as a whole. Finally, working at the state-level, we associate our policy instruments – using a four-category policy framework – with state-specific measures of household poverty. Our poverty analyses disaggregate household income packages into sources (or factors) that allows us to assess multiple measures of poverty as well as the components of poverty mitigation. We present conclusions in **Section 7.**

2. Examining Social Safety Net Policies and Poverty among U.S. States

Unequal by Design

Multiple factors shape patterns of both social policy provision and income redistribution. A central claim in our work is that it is crucial to recognize the ways in which U.S. social policy is structured, and to consider the systematic consequence of those structures. In the U.S., as in many high-income countries, the welfare state encompasses tiers of assistance, with each serving different categories of persons. These tiers vary with respect to coverage, eligibility, benefit levels, financing, and the like. The programs in the top tier include centralized, contributory, federal benefits such as "social security"[1]; these are standardized, or uniform, "from coast to coast". The programs in the middle tier are those that are provided by employers, mainly occupational pensions and health insurance. The publicly-provided programs in the bottom tier are narrowly targeted, and means-tested (i.e., conditioned on low income and/or assets), and mainly funded by general revenues.

This tiered structure of provision is not unique to the U.S.; all welfare states use these mechanisms to some degree. What is somewhat unique to the U.S. is the degree to which the bottom-tier programs – the means-tested programs – have been, across their histories, decentralized. While the programs in the top tier are financed, administered, and authorized at the federal level, the majority of programs in the bottom tier involve some degree of devolved authority, or discretion, granted to lower levels of government. That means that subnational governments, primarily states', play key roles in administration, financing, and/or policymaking

[1] The official name for what is referred to, in the U.S., as "social security" is Old-Age, Survivors, and Disability Insurance (OASDI).

regarding rules, eligibility, and benefit levels. An important implication of this decentralized policy structure is that these bottom-tier programs, alone and in combination, vary dramatically across the states. In this paper, we examine the consequences of this decentralized structure for disparities across states in social provision and in redistribution.

U.S. Safety Net Policies and their Impact on Poverty

Many of the programs that comprise the social safety net were developed during the New Deal Era of the 1930s and War on Poverty and Great Society of the 1960s with policy designs that reflected the negotiated settlements of federalism and deference to local control (Lieberman 1998; Mettler 1998). In recent decades, federal policymakers have shifted policy authority downward, increasing the scope of state (and local) discretion across a number of programs. The extent and implications of the decentralized structure is one of the most under-appreciated features of safety net policies (Howard 1999; Pierson 1995).

Even in good economic times, the fragmented and largely decentralized public programs of support for working-age adults and their children has not had a strong record of achievement, either as a bulwark against poverty or as a mechanism for addressing social inequalities. This uneven record (and capacity) has been exaggerated in the last generation by the growing mismatch between changing labor markets and increased exposure to economic risk on one hand, and "policy drift" or retrenchment in basic social provision on the other (Meyers, Plotnick, and Romich 2011; Hacker 2006; Esping Andersen 1999) and changes in the responsiveness and cyclicity in specific programs (Bitler and Hoynes 2010; Bitler, Hoynes, and Kuka 2017; Bradley, Smeeding, and Ziliak 2018).

The social safety net for working-age adults and their dependents is structured as a patchwork of state-managed categorical programs with different goals, eligibility criteria, and target populations. As a result, poor families typically have access to only a small, idiosyncratic subset of available programs. Since the 1990s, we have also seen a pointed shift away from direct cash assistance for the poor, to a patchwork of in-kind benefits and services designed to facilitate participation in the paid labor market and federal tax credits for the working poor (Heinrich and Scholz 2009; Danziger 2010; Danziger, Danziger, Seefeldt, and Shaefer 2016; Tach and Edin 2017), all of which have both reflected and served to reinforce cultural ideas about deservingness among target populations in need (Shaefer, Edin, Fusaro, and Wu 2020; Moffitt 2015; Schneider and Ingram 1993).

In addition to looking at social provision, there is a rich body of work that examines the redistributive impacts of these policies, and specifically, their effectiveness at reducing poverty. Again, at the national level, this question has received a great deal of attention—particularly in the efforts to determine if we "won" the War on Poverty (Haveman, Blank, Moffitt, Smeeding, and Wallace 2015; Fox, Wimer, Garfinkel, Kaushal, Nam, and Waldfogel 2015), the consequences of a reconfigured safety net (Halpern-Meekin, Edin, Tach, and Sykes 2015; Collins and Mayer 2010; Ziliak 2009; Blank 2002), and in the growing literature on the efficacy of policy responses to the Great Recession (Bitler and Hoynes 2016; Larrimore, Burkhauser, and Armour 2015).

While most research on social provision and redistribution has focused on the national level, there are important exceptions. Ranging from work that documents the large cross-state variation in poverty rates for different demographic groups and/or using different measures of poverty (Semega, Kollar, Creamer, and Mohanty 2019; Fox 2019) to work that describes the substantial inequalities in provisions across states (Meyers, Gornick, and Peck 2001; Allard 2008; Lobao and Kraybill 2009; Soss, Fording, and Schram 2011; Bruch, Meyers, and Gornick 2018) to work that leverages these cross-state differences to explore the questions of how these differences arise and their consequences (Schaefer, et al. 2020; Baker 2019; Laird et al. 2018; Bitler et al. 2017).

This Study: Main Contribution and Central Research Questions

While there is increasing research at the state-level, our understanding of social provision has been slowed by the absence of high-quality, detailed, and comparable (harmonized) state policy data. At the same time, U.S. research on poverty reduction, via redistribution, has used a fairly narrow set of analytic approaches: 1) estimating total poverty reduction, by comparing poverty "before" and "after" taxes and transfers, where "before" is a simulated counterfactual; 2) distinguishing between taxes and transfers as different policy mechanisms; and 3) assessing program-specific estimates of poverty reduction (SPM).

In this paper, we address both of these gaps in our understanding of social policy and its impact. We contribute conceptually and empirically to our understanding of the role of subnational government (states) in social provision and redistribution, directing attention to the consequences of safety net decentralization—especially inequalities in social provision, and inequalities in poverty reduction.

In the realm of social provision, we make two important distinctions. First, we identify social safety net programs that have some degree of state discretion in financing, rulemaking, or administration. Second, we create comparable empirical measures of two key dimensions of social provision: generosity, a measure of spending per recipient; and inclusion, the share served among the "potentially needy" (that is, persons who are financially needy and broadly in the targeted category).[2]

In the realm of redistribution, we carry forward the distinction between federal and state roles to separate redistributive instruments that are centralized (i.e., operating at the federal level) from those that are partially or wholly decentralized (i.e., operating at the state level). As is common in cross-national redistributive analyses, we also distinguish between transfers and taxes as separate redistribution instruments or mechanisms. Combining these two axes of distinction results in four redistributional policy mechanisms: centralized / federal transfers; decentralized / state transfers; federal taxes; and state taxes.

With those distinctions in place, our analyses and results are structured around two sets of research questions:

Our first set of empirical analyses (see Section 5) concerns policy variation in social provision. Historically, there has been a lack of comparable, detailed, state-level data on safety net

[2] In this paper, we use the terms "inclusion" and "inclusiveness" interchangeably.

programs. That has made assessing policy variation – or policy inequality – across states surprisingly difficult. We use a unique dataset with comparable state-level policy measures, to tackle two questions related to social provision:

- What is the magnitude of cross-state variation in the generosity of benefits and the inclusiveness of safety net provisions across the U.S. states?

- How does the magnitude of cross-state policy variation within the U.S. compare to cross-national policy variation among a set of high-income countries?

Our second set of empirical analyses (see Section 6) concerns redistribution, specifically redistribution vis-à-vis the reduction of household poverty. We use household survey data (ASEC) supplemented with alternative estimation strategies (TAXSIM and TRIM) to examine the following two questions related to the contribution of the redistributive mechanisms:

- Considering the U.S. as a whole, how much poverty reduction is attributable to each of the redistributive mechanisms?

- How does the poverty reduction attributable to the redistributive mechanisms vary across the U.S. states?

3. Data

Data on Social Provision in the United States

The social provision data used in this paper are from the State Safety Net Policy (SSNP) dataset, which includes yearly state-level estimates of the generosity and inclusiveness of ten safety net programs from 1994 through 2018. The safety net programs included in these data are programs in which states have discretion in financing, administration, and/or rulemaking, and that influence the economic resources of economically-marginalized working-age adults and their dependents either directly (by providing cash) or indirectly (by providing other goods or services). The ten programs are: cash assistance (AFDC/TANF), food assistance (Food Stamps/SNAP), child health insurance (Medicaid and CHIP), child support enforcement, child care subsidies (CCBG/CCDF and TANF), early childhood education (Head Start and state pre-K programs), Unemployment Insurance (UI), targeted work assistance through AFDC/TANF, child disability assistance (SSI), and state income taxes.

The SSNP dataset has been assembled from publicly-accessible state and federal administrative records, and original population estimates calculated using the Annual Social and Economic Supplement (ASEC) of the Current Population Survey.[3] To compare aspects of safety net provision across states, we constructed, for each of the ten programs, measures of two key dimensions of social provision – the generosity of benefits and the inclusiveness of receipt.

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[3] The SSNP dataset was created by Marcia Meyers, Sarah Bruch, and Janet Gornick and is currently maintained by Sarah Bruch. ASEC data were obtained from the IPUMS-CPS database (Flood, King, Rogers, Ruggles, and Warren 2018).

Generosity is calculated by dividing total benefit spending by a state's caseload or number of recipients. The generosity measures are adjusted to constant (2018) dollars using the Bureau of Labor Statistics' Consumer Price Index Research Series (CPI-U-RS). To account for cost-of-living variation across states, the generosity measures are adjusted using the Bureau of Economic Analysis' Regional Price Parities by State and Metro Area (RPPs).[4]

Inclusion is calculated by dividing the number of actual program recipients in a state by the number of potentially needy individuals or families in the state. For means-tested programs, the estimate of the potentially needy is the number of individuals or families who (a) fall into categorically-eligible groups and (b) have market (pre-tax-pre-transfer) incomes below the federal poverty threshold, or below some percentage of the threshold depending on the income eligibility criteria of the program. (These measures are estimated using three-year moving averages from the ASEC).[5]

Table 1 provides a description of the construction of each policy indicator including data sources.[6]

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[4] The BEA RPP's are available for states and metro areas on a yearly basis. They are a weighted average of the price level of goods and services for the average consumer in one geographic region compared to all other regions in the U.S. This adjustment is a full basket adjustment at the state level, incorporating sources of income beyond simply geographically-adjusted rents. See the Appendix for more information about the BEA RPP cost-of-living adjustment.

[5] The potentially needy population denominators differ from estimates of the potentially eligible population which incorporate additional program- and state-specific eligibility criteria (see Urban Institute's TRIM3 for example). We have chosen to calculate the potentially needy population defined by broad categorical criteria of programs in order to capture the depth of program receipt in the economically needy population. This approach allows for comparability over time within programs such that even as the program eligibility rules change, the measure of the potentially needy stays the same.

To ensure that our population estimates are accurate, we compared these estimates to the closest possible counts from the Census and American Community Survey (ACS). We tabulated state-level counts of three- and four-year old children (used as the denominator for the early childhood education inclusion indicator) and single parent families (used as the denominator for the child support enforcement inclusion indicator) using Census data compiled for the years 1990 and 2000 and the ACS 2006-2010 five years sample, both from IPUMS-USA (Ruggles et al 2010). These state-level population counts were then compared to the estimates obtained from the CPS ASEC. In comparing the CPS ASEC to the Census and ACS counts of these two populations, we found that the percentage difference was generally 15% or below across states, ranging from five to nine states across years that exceed this threshold. The reason for this disparity is that the CPS person-level and household-level weights do not take marital status or this specific age group into account.

Additionally, we compare two poverty estimates from the ASEC against comparable Census and ACS figures, those of children under 18 in poverty and estimates of poor families. We compute similar percentage differences between these estimates and counts from the Census and ACS and find that the differences more often exceed the 15% threshold, and in certain states across years the percentage difference can exceed 80%. The considerable disparity between Census and ASEC counts for these poverty estimates is likely due both to the issue raised above in relation to the demographic counts, and to the differences in income definitions used for assessing poverty.

[6] In cases where there is a missing value for an observation (a state) or year, values are imputed using neighbor averages (i.e. average of year before and after the missing value). As with most administratively reported data, there is quite a bit of variability in the data obtained from many of the sources used in the construction of these policy

< Table 1>

These measures of generosity and inclusion are calculated yearly starting in 1994 and going through 2018, for each of the 10 types of assistance for all fifty states.[7] The SSNP data are unique in providing comparable measures across programs over an extended period of time.

Data on Cross-National Social Policy and Social Expenditures

Two data sources are used for our analysis of social policy variation across countries: the Comparative Welfare Entitlements Dataset (CWED), and the Organization for Economic Cooperation and Development's Social Expenditure Database (SOCX).

The CWED data – housed at the University of Connecticut and publicly-accessible – contain information on the institutional features of social insurance programs in 33 countries (Scruggs, Jahn, and Kuitto 2017).[8] The CWED data capture characteristics of unemployment insurance, sickness insurance, and standard and minimum pensions. Specifically, they include generosity indexes, replacement rates, eligibility criteria, and coverage.[9] For our analyses, we use the CWED data to capture generosity, replacement rates, and coverage, for each of the three programs.

The SOCX data – collected by the OECD and publicly-accessible – contain reliable and internationally comparable statistics on public and (mandatory and voluntary) private social expenditure at the program level as well as net (after tax) social spending indicators (Adema and Fron 2019).[10] For our analyses, we use the SOCX aggregated spending measures (as a percent of GDP) on old-age and survivors cash benefits, disability and sickness cash benefits, family cash benefits, and family in kind benefits.

These cross-national social policy indicators, which are standard in comparative research, are not a perfect match for our SSNP policy indicators; however, they provide a reasonable conceptual and empirical match. Our comparative analyses, using the CWED and SOCX data, include eighteen high-income countries: Denmark, Finland, Netherlands, Norway, Sweden, Austria, Belgium, France, Germany, Italy, Australia, Canada, Japan, Switzerland, Ireland, New Zealand,

indicators. To help reduce this type of measurement variability, the indicator values are top and bottom coded at two standard deviations from the mean for that year, and are "double-smoothed" by first using three year moving averages in the construction of the numerators and denominators as well as "smoothing" the final indicator using three year moving averages.

[7] The first year of data for child care is 1998, and the last year is 2017. Child health insurance generosity is calculated from 1994 through 2013.

[8] CWED data can be found at http://cwed2.org/.

[9] For details on how the generosity indexes are created, see Lyle Scruggs (2014) "Social Welfare Generosity Scores in CWED 2: A Methodological Genealogy", CWED Working Paper 01.

[10] SOCX data available at: http://www.oecd.org/social/expenditure.htm.

United States, and United Kingdom. These countries cut across the three major welfare state regime types, as reported in the widely-cited work of Gøsta Esping-Andersen (1990).

Data for Analysis of Redistribution through Transfers and Taxes

We use the ASEC data, for the years 2015-2017 to create a three-year average for 2016, to examine redistribution – specifically, redistribution that mitigates poverty using the U.S. Census Bureau poverty thresholds. The ASEC data include standardized and comparable measures, over time, for more than 40 income sources.[11] The ASEC data are widely used, by government agencies and academic researchers, to study income distribution in the United States.

Household Income Measures

Household income measures are created using the income component measures available in the ASEC data. We create five household income measures, the first of which is market (pre-tax-pre-transfer) income, which includes market-based sources of income such as wages and salary, self-employment earnings, and private retirement income (see Table 2 for all full list of income components). We also create four additional income measures; these capture increases and decreases in market income associated with the four redistributive policy mechanisms: federal transfers, state transfers, federal taxes, and state taxes.[12]

< Table 2>

Federal and state taxes are estimated using the National Bureau of Economic Research (NBER) TAXSIM program (version 32), a microsimulation tool that estimates the total tax liabilities or refunds using survey data (Feenberg and Coutts 1993).[13] TAXSIM provides federal and state income tax estimates that include federal payroll taxes, federal and state income tax schedules, and specific federal and state tax deductions, exemptions and credits. Household composition and income data generated from the ASEC microdata are inputted into the TAXSIM program to obtain estimates of state and federal tax liabilities and refunds for all households.[14]

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[11] ASEC data used in these analyses were obtained from the IPUMS-CPS database (Flood, King, Rogers, Ruggles, and Warren 2018).

[12] State transfers refer to transfer programs that have some degree of state discretion in financing, administration, or rulemaking. Federal transfers refer to transfer programs that are wholly centralized in financing, administration, or rulemaking. More details on the types and levels of state discretion can be found in Bruch et al. 2018.

[13] More information on the TAXSIM program as well as direct links to the internet portal are available on the NBER website at: http://users.nber.org/~taxsim/. TAXSIM provides accurate estimations of individual state's tax liabilities and credits for households using formulas that are updated annually to encompass changes in state and federal tax codes by Daniel Feenberg and staff at the NBER. Imputed tax measures are also available in the CPS data using various administrative data sources (see O'Hara 2004). Comparisons of the two methods have noted that the TAXSIM procedure is more accurate in the estimation of tax credits such as the EITC (see Wheaton and Shantz 2016 for a more extensive comparison and discussion). The tax liability values provided by these two methods are highly correlated (0.94-0.98) for households in the years included in our analyses.

[14] In each year of our data, a proportion of households surveyed by the ASEC are assigned a tax filer status of nonfiler. While nonfilers can be dependents some nonfilers are households heads with dependents or spouses. The

Demographic Focus

We focus our analysis of redistribution within one household type: working-age households with children. These are defined as households that are headed by an adult, 18 to 64 years old, and that include resident children under age 18. We limit our analyses to these households because many of the safety net programs in the SSNP dataset are targeted at children – e.g., child health insurance, child support enforcement, child care subsidies, and early childhood education; likewise, many of the state transfer programs are similarly targeted at children or their families (e.g., public assistance, school lunch). In future analyses, we will compare these redistribution results to those in working-age households without children and to elderly-headed households.

Poverty Measurement

We use the Census Bureau's Poverty Thresholds to determine whether a household is living in absolute[15] poverty.[16] These thresholds vary by the size of the family, the number of dependent children, and the age of the head. We apply the thresholds to households using our multiple income definitions.[17]

Benefit Underreporting

Concerns about benefit underreporting have attracted much recent attention. Underreporting, especially in low-income households, is increasingly viewed as an important source of measurement error in household surveys such as the ASEC; this type of measurement error would bias estimates of poverty and poverty reduction. In general, there are three approaches for correcting or adjusting for benefit underreporting: linking administrative and survey data;

NBER TAXSIM32 program has no rubric for calculating tax liabilities and refunds for nonfilers because as nonfilers they have no tax information to analyze. In calculating our income factors, we exclude all household heads and spouses classified as nonfilers from the TAXSIM calculations and therefore a proportion of households in each year have no income data for state or federal taxes. This is a total of 34,451 households in the 2015-2017 years which represents 16% of the ASEC CPS sample in each year. These households are included in the poverty reduction analyses and given values of "0" for federal and state taxes.

[15] We use the term "absolute poverty" here to indicate that we classify households as poor if their income falls below thresholds intended to capture minimum acceptable living standards; this approach is used, nearly universally, in U.S. poverty research and policy analysis. In contrast, in many other high-income countries, especially within Europe, poverty thresholds are set as a percentage of national median incomes; that approach corresponds to the concept of "relative poverty". Throughout this paper, when we refer to "poverty", we always refer to absolute poverty thresholds and rates.

[16] United States Census Bureau Poverty Thresholds by Size of Family and Number of Children are obtained from https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html.

[17] There are two important differences between the Census Bureau's Official Poverty Measure and the measurement strategy used in this paper. First, the Census Bureau's poverty thresholds are applied to families using the Census Bureau's definition of a family. In this paper, the thresholds are applied to households using the Census Bureau's definition of a household. Second, the Census Bureau uses money income as their income definition which differs from the income definition used in this paper (see Table 2 for a listing of the income components in each income definition).

matching to aggregate totals in administrative data; and using simulated data of benefit receipt, based in part on administrative data (Parolin 2019; Meyer and Wu 2018; Fox et al. 2017; Meyer and Mittag 2015; Wheaton 2008). In this paper, we use the third approach, implementing a process created by Parolin, which uses the Urban Institute's Transfer Income Model (TRIM3) and applies it to three types of means-tested benefits whose receipt is reported in in the ASEC: SNAP, TANF, and SSI.[18]

We present two sets of estimates, one based on the unadjusted ASEC data, and one using the ASEC with the TRIM3 correction. The difference between these two provides insight into the potential degree to which underreporting affects our estimations of poverty reduction due to these three crucial means-tested programs. This is substantively important, as it affects how we interpret the efficacy of these programs in reducing poverty in working-age households with children.

4. Analytic Approach and Methods

Social Provision

To assess the magnitude of variation in safety net provision, we first look at cross-state variation or inequality in levels of generosity and inclusiveness, using the absolute values observed at different points in the distribution of states. For each of the 10 programs, we identify and compare levels (of policy generosity and inclusiveness) at the median, near the top (the 90th percentile state), and near the bottom (the 10th percentile state). For comparative purposes, we also estimate the level of cross-state variation/inequality using a summary inequality statistic – the Gini coefficient.[19] We use the Gini coefficient to compare the magnitude of variation observed across the 50 U.S. states, based on our SSNP data, with the magnitude of variation seen across a group of high-income countries (identified above), using social policy data from the CWED and SOCX datasets.

Redistribution

To examine the extent of redistribution – specifically, poverty reduction – attributable to each of the four redistributive policy mechanisms (federal transfers, state transfers, federal taxes, state taxes), we estimate the change in the poverty rate for working-age households with children

[18] The TRIM3 data are used to correct for the underreporting of three means-tested benefits estimates (SNAP, TANF, and SSI). In constructing the TRIM3 data, the Urban Institute employ an imputation model to identify and correct the reporting of these means-tested incomes for households that it predicts are underreporting. The TRIM3 are designed to append the CPS ASEC data and provides values that can be used to replace or "correct" the ASEC values for these means-tested benefits. For more information on the TRIM3 estimation of benefit receipt, see Zedlewski and Giannarelli 2015. Zachary Parolin has utilized the TRIM3 data to estimate more accurate measures of poverty using the CPS ASEC data using a method to replace CPS ASEC values with those provided in the TRIM3 data. For more information on the correction procedure, see Parolin 2019. The effect of Parolin's correction procedure, which we utilize, is more extensively discussed in the Appendix alongside a discussion of how the Urban Institute's assumptions on benefit underreporting differ from those we use in this analysis.

[19] Gini coefficients are calculated in Stata using the "inequal7" which allows for zero and negative values (which occurs in the state income tax generosity indicator).

using income definitions that include income from these four redistributive mechanisms (federal transfers, state transfers, federal taxes, and state taxes).[20]

While some researchers prefer to begin, analytically, with disposable household income (post-tax-post-transfer income) and decompose "backwards" to market income, we chose to do the reverse. Though we understand the downside – it may not be ideal to begin with a simulated counterfactual rather than with the actual income available to the household – we decided to begin with market income, as it seemed more analytically intuitive (to start with market income and to "add" transfers and taxes) and because this sequence is most common in the cross-national research that inspired much of our work.

Researchers estimating types and degrees of redistribution often aim to assess and compare the effects of multiple redistributive mechanisms, asking how much each contributes to reducing, say, income inequality across households or poverty rates. These studies often face a common challenge; that is, how to deal with the fact that many decomposition techniques produce results that are sensitive to the order in which the redistributive instruments are introduced. In our analyses, we use an approach designed to achieve order-independence: we calculate the redistributive effects of each of our four main redistributive mechanisms, estimating these effects across the possible permutations.[21] We then present the average poverty reduction attributable to each redistributive mechanism (e.g. the average of the 16 permutations/orderings with unique values), the minimum and maximum estimates, and four estimates of specific orderings adding state transfers and taxes first and last. These last sets of estimates are then further illustrated by calculating the percentage of the total poverty reduction attributed to each of the four redistributive mechanisms.[22] We use this estimation procedure first at the national level, before turning to the state level, to examine how poverty reduction attributable to each of the four redistributive mechanisms varies across states.[23]

5. Results – Social Provision

Cross-State Inequality in Social Provision

[20] This approach to estimate poverty reduction does not, of course, account for behavioral changes that would be expected due to the receipt of transfers or taxes, such as a reduction in paid work effort (Bitler and Karoly 2015). It does, however, provide a useful descriptive portrait of how various income sources contribute to reducing poverty rates. This approach, common in cross-national studies, is often referred to as an accounting exercise.

[21] Note that four policy instruments can be arranged into 24 permutations. Because these 24 permutations include only 16 unique values, we present, and average, results across only 16 permutations (see Appendix for more information).

[22] The average values cannot be decomposed into proportions of the total poverty reduction because the four average values are not obtained from the same decomposition.

[23] Estimating poverty reduction due to different redistributive mechanisms does not take into account demographic or labor market variation across states.

Table 3 displays the 50 state median, 10th and 90th percentiles, standard deviation, and Gini coefficient for the generosity and inclusion indicators for each program in 2018.

< Table 3>

We find that there is substantial cross-state inequality in safety net provision across all ten programs. The greatest cross-state inequality in benefit generosity is found in cash assistance (*Gini coefficient* = 0.234) followed by Unemployment Insurance (*Gini coefficient* = 0.152).The lowest levels of cross-state inequality in benefit generosity are in food assistance (*Gini coefficient* = 0.076) and Supplemental Security Income (*Gini coefficient* = 0.049).[24]

The greatest cross-state inequality in the inclusiveness of receipt is found in cash assistance (*Gini coefficient* = 0.394), preschool/early education (*Gini coefficient* = 0.319), and child care (*Gini coefficient* = 0.287). The two programs with the least cross-state inequality in the inclusiveness of receipt are food assistance (*Gini coefficient* = 0.096) and child health insurance (*Gini coefficient* = 0.079).

To give this cross-state inequality substantive meaning, it is helpful to examine the generosity and inclusiveness of programs at various points in the state distribution. If the differences are small, then the case can be made that while there are inequalities in provision across states, it should not be a focus of our attention. However, if differences are substantively large, then it provides strong evidence that these are meaningful differences for families in terms of what they receive and the likelihood of receiving it. Figure 1 displays the range of cross-state variation in generosity for each of the safety net programs in terms of the dollar amount per recipient on benefits or to provide the service. Figure 2 displays the range of cross-state variation in inclusion for each of the safety net programs in terms of the proportion of potentially eligible that receive assistance.

In cash assistance/TANF (the program with the greatest cross-state inequality), the average benefit received by families at the 50 state median was just above $4,000 in 2018 compared to families receiving approximately $2,000 in states near the 10th percentile and almost $6,500 in states near the 90th percentile. The difference between the average amount spent on benefits for families in the most and least generous states is substantial (more than $4,000) representing more than a doubling of the benefit received by those at the lower end of the generosity distribution. Turning to inclusion, only five out of 100 poor families with children receive cash assistance in states near the 10th percentile while approximately 40% of poor families with children receive cash assistance in states near the 90th percentile. Notably, even in the top end of the inclusion distribution fewer than half of poor families with children receive cash assistance.

[24] We do not interpret the Gini coefficient for state income tax generosity. The state income tax generosity measure includes negative values (which indicate tax liabilities) and zero values (which indicate that a single family of three does not owe any taxes or receive any tax benefits at the poverty line). Inclusion of negative and zero values in calculating the Gini coefficient can yield values greater than one. To our knowledge there is not a standard normalization approach or agreement about whether it is appropriate to adjust the Gini coefficient to bound the values to be between zero and one in situations where these represent real values (see Raffinetti, Siletti, and Vernizzi 2016 and Battisti, Porro, and Vernizzi 2019 for a discussion of this issue). We also use caution in interpreting the generosity values for cash assistance-based work assistance due to both the extremely large amounts reported by some states, and the widely varying values reported by states (see Burnside and Schott 2020 for an excellent analysis of state spending of TANF block grants).

In Unemployment Insurance, an unemployed worker received an average of about $5,200 in states near the median of the distribution, only about $3,500 in states near the 10th percentile, and double that amount (about $7,000) in states near the 90th percentile. Again, this is a substantial difference in average benefits received on average by unemployed workers in states at different locations on the generosity distribution. In terms of inclusiveness, fewer than 15% of unemployed workers receive Unemployment Insurance in states near the bottom of the inclusion distribution whereas three times that share (45%) receive benefits states near the top of the inclusion distribution.

In preschool/early education, the average amount spent per child at the median is about $8,700. However, the amount spent per child at the 90th percentile is double that spent at the 10th percentile (almost $11,000 compared to about $5,300). Inequality in inclusion is even more dramatic between states at the 90th percentile compared to those near the 10th percentile: 43% of three-and-four year olds in preschool/early education compared to fewer than 10% - a difference of over 30 percentage points.

One of the programs with the least cross-state inequality is food assistance (SNAP). However, even in a program characterized as having relatively less cross-state inequality, the difference in average benefits received and the inclusiveness of receipt is not negligible. The average amount received varies from approximately $2,600 in states near the 10th percentile compared to just above $3,600 in states near the 90th percentile representing a difference of approximately $1,000 (about a third of the average benefit amounts). There is also a substantial difference in the inclusion of low-income families in the program across states: there is a 30 percentage point difference in the rate of inclusion between states near the 10th and 90th percentiles (0.785 compared to 1.189).[25]

These results demonstrate that, across a wide range of safety net programs cross-state inequality in benefit levels and inclusiveness are in most cases, substantively large enough to represent meaningful differences for families. Living in one state versus another is hugely consequential for the social safety net one will encounter.[26]

Cross-National Comparison

In part two of the social provision analyses, we explore the relative magnitude of cross-state inequality in social provision to cross-national social provision using the set of countries that Esping-Andersen relied on in developing a typology of welfare regimes.

[25] In states near the 90th percentile, the inclusion measure indicates that over 100% of families with pre-tax-pre-transfer incomes less than 130% of the poverty threshold are receiving food assistance. This results from several factors including the fact that the income measure we are using is not parallel to how income and assets are valued for program eligibility, and that states can get federal CHIP matching funds for child coverage up to 300 percent of the federal poverty level (FPL).

[26] In previous work, Sarah Bruch, Marcia Meyers, and Janet Gornick explored how the levels of cross-state inequality in provision are related to the levels of state discretion in financing, administration, and rule-making. They found that in programs designed with greater state discretion, there is greater cross-state inequality in provision (Bruch, Meyers, and Gornick 2018).

Table 4 displays the Gini coefficients for SSNP, CWED, and SOCX measures of social provision for 2010, which is the most recent year comparable across all three datasets.

< Table 4>

While there are no directly comparable measures for the SSNP generosity and inclusion indicators, the most similar are the CWED generosity and coverage measures. The SOCX aggregated spending measures are less parallel, but we include them to help contextualize the magnitude of cross-national variation.

The magnitude of cross-national variation across the 18 high-income country sample used from the CWED data is comparable to the magnitude of cross-state variation across the U.S. states. This is true for both generosity and inclusion. Looking first at generosity, the least amount of cross-national variation in CWED generosity measures is for pension generosity (*Gini coefficient* = 0.097), and the highest is observed in sickness generosity (*Gini coefficient* = 0.211). The most directly comparable generosity measure is for unemployment (*Gini coefficient* = 0.152). The comparable Unemployment Insurance generosity measure in the SSNP data has less cross-state variation in 2010 (*Gini coefficient* = 0.099) but, as seen in Table 3, this increased by 2018 (*Gini coefficient* = 0.152).[27]

Regarding the inclusiveness of receipt, the most similar cross-national measures are the CWED coverage measures. In this case, the magnitude of variation is much greater across the U.S. states inclusion measures (*Gini coefficient* = 0.088 for food assistance to *Gini coefficient* = 0.300 for cash assistance) compared to the corresponding range for the cross-national CWED coverage measures (*Gini coefficient* = 0.045 for pensions to *Gini coefficient* = 0.71). Again, the most direct program comparison can be made across programs for unemployed workers, and again, the magnitude of variation is larger in the cross-state inclusiveness of receipt (*Gini coefficient* = 0.121) than in the cross-national coverage rates (*Gini coefficient* = 0.071).

Using these related social policy indicator measures to compare the magnitude of variation or inequality in provision across the U.S. states and the subset of countries used to distinguish welfare regimes, we find that overall there are similar levels of variation. This provides compelling evidence that the magnitude of variation in social provision across the U.S. states is not only substantively meaningful for families in terms of what they encounter when seeking assistance in various states, but in fact rivals the variability that is observed cross-nationally.

6. Results – Redistribution

In the redistribution analyses, we examine the distributional impacts attributable to four redistributive mechanisms: federal transfers, state transfers, federal taxes, and state taxes focusing on poverty reduction among working-age households with children.

As discussed in the analytic methods section above, one of the most influential analytic decisions in determining the poverty reduction attributable to each of the redistributive mechanisms is the

[27] The degree of cross-state inequality in Unemployment Insurance generosity was at its lowest point in the past 25 years in the 2008-2010 period likely due in part to the temporary provisions supporting unemployed workers affected by the Great Recession. Yearly cross-state inequality measures are not included in this paper, but are available upon request.

order in which to include them in the income definition. Figures 3 to 6 display the proportion of working-age households of children lifted above the absolute poverty threshold with the addition of income from each of the redistributive mechanisms. The bars in each figure represent the 16 permutations or possible orderings with unique values. As expected, when a redistributive mechanism is added earlier in the sequence, there is a larger poverty reduction attributed to it. For example, the largest poverty reduction attributed to federal transfers (0.0168 which corresponds to a 1.7 percentage point reduction in poverty) is obtained when federal transfers are added to market income prior to the three other redistributive mechanisms. The same pattern is true for the largest poverty reduction attributed to federal taxes (0.0408), state transfers (without the TRIM3 correction 0.0368, with the TRIM3 correction 0.0498), and state taxes (0.0018) being derived from decompositions in which they are added to market income first. These results confirm the sequence- or ordering-dependent nature of attributing redistributive impacts to specific redistributive mechanisms.

National Analyses

Table 5 displays the poverty reduction attributable to each of the redistributive mechanisms. The table includes the minimum and maximum values (obtained from adding the income from that source earlier or later in the sequence), and the average value (obtained by averaging all 16 of the possible values). For example, the poverty reduction for working-age households with children attributable to federal taxes varies from a minimum of 0.0309 (or a 3.1 percentage point reduction in poverty) to a maximum of 0.0408 (4.1 percentage point reduction in poverty), and an average of 0.0357 (3.6 percentage point reduction).

Table 5 also displays the poverty reduction attributable to state transfers with and without the TRIM3 correction for underreporting of benefits. As expected, the estimates of poverty reduction among working-age households with children attributable to state transfers are larger when using estimates that include the TRIM3 correction for underreporting. The average poverty reduction attributed to state transfers using the TRIM3 correction is 0.0435 (or a 4.4 percentage point reduction in poverty) compared to an average of 0.0321 (or a 3.2 percentage point reduction) without the correction for underreporting of benefits.[28]

Among working-age households with children, state transfers play the largest role in poverty reduction (4.4 percentage point reduction), followed by federal taxes (3.6 percentage point reduction), federal transfers (1.4 percentage point reduction), and then state taxes (0.2 percentage point reduction). Part of the explanation for the large role attributable to state transfers is the large dollar amount received from this source by working-aged households with children with market incomes below the poverty line ($8,303) compared to much smaller amounts received by these households from federal taxes ($3369) and state taxes ($150).

Table 6 provides poverty decomposition information for four specific orderings or possible sequences along with estimates of the percentage of the total poverty reduction (from market to disposable) attributable to each of the four redistributive mechanisms. Given our focus on the role of states, the table provides estimates that result from adding state transfers or taxes either

[28] All results described and included in tables and figures use the estimates for state transfers that include the TRIM3 correction for underreporting of benefits.

first or last. In the case where state transfers are added to market income first, fully 48% of the poverty reduction is attributable to this mechanism, whereas when added last it comprises 43% of the total poverty reduction. The role of state taxes even when added as the first redistributive mechanism is minimal, accounting for only 1% of the total poverty reduction. The percentage of the total poverty reduction attributable to federal taxes and transfers varies most across these specific orderings, with federal taxes accounting for between 33-42% of the total reduction, and federal transfers accounting for between 13-17%.

While these results in this section highlight the importance of the order in which the redistributive mechanisms are added to market income, the range of poverty reduction estimates do not vary widely. Overall these results provide support for the importance of state transfers given the substantively large impact that this redistributive mechanism has in poverty reduction for working-age households with children.

State Analyses

The analyses above provide a national-level look at the poverty reduction attributable to the four redistributive mechanisms. The analyses in this section provide parallel state-level analyses that allow us to examine how rates of market and disposable poverty among working-age households with children and the contributions to poverty reduction of each redistributive mechanism vary across states.

Figure 7 displays market and disposable poverty for working-age households with children in 2016 by state. States vary tremendously in the proportion of working-age households with children who fall under the poverty threshold when only accounting for market sources of income (from a high of 27.8% in Mississippi to a low of 9.3% in Minnesota). These wide differences in market income poverty are reduced substantially in all states. However, the amount of poverty reduction varies across the states. Poverty is reduced by a greater degree with the addition of income from the four redistributive mechanisms in states that have higher proportions of working-age households with children falling under the poverty threshold when only market sources are considered. In other words, a greater proportion of working-age households with children are lifted out of poverty through transfers and taxes in states with higher market income poverty. For example, while Mississippi has the highest proportion of working-age households with children in poverty when only accounting for market sources of income, it also has the largest poverty reduction (14.5%). The smallest poverty reduction attributable to transfers and taxes is observed in North Dakota (5.3%) which has a relatively low proportion of working-age households with children who fall beneath the poverty threshold when only market sources of income are considered (11.9%). Due to this pattern of redistribution – greater poverty reduction in high market poverty states – disposable poverty levels are less variable across states (3.1% to 13.1%) than market poverty for working-age households with children (9.3% to 27.6%).

Figure 8 displays the average poverty reduction attributable to each of the four redistributive mechanisms in 2016 by state.[29] There are several important findings observed in this figure. First, the magnitude of the poverty reduction attributable to each redistributive mechanism varies widely across the states. The poverty reduction attributable to state transfers varies the most,

[29] The average is derived from the 16 possible orderings of each redistributive mechanism with unique values.

from a high of a 6.4 percentage point poverty reduction to a low of 2.2. The poverty reduction attributable to federal taxes also varies considerably, from a high of reducing poverty by 5.5 percentage points to a low of 1.3. Federal transfers have a relatively smaller role in reducing poverty among working-age households with children, with only a few states having poverty reduced more than 2.5 percentage points (Arkansas, Kentucky, and West Virginia). The poverty reduction attributable to state taxes is very small. The two states with the largest poverty reduction attributable to state taxes are still less than 1 percentage point (New York with a 0.91 percentage point reduction and Minnesota with a 0.58 percentage point reduction).

Second, the relative magnitude of the poverty reduction attributable to each of the redistributive mechanisms varies across the states. In the vast majority of states the greatest poverty reduction among working-age households with children is attributable to state transfers followed by federal taxes, federal transfers, and finally, state taxes. However, there are six states where federal taxes play the largest role in reducing poverty (Mississippi, Kentucky, Arizona, Louisiana, Alabama, and Georgia, ranging from 5.5 to 4.6 percentage point reductions). And, there is one state (Rhode Island) where federal transfers play a larger poverty reduction role (2.2 percentage point reduction compared to federal taxes (1.6 percentage point reduction).

Third, there are differences in the relationship between the level of market income poverty among working-age households with children and the amount of poverty reduction attributable to each of the four redistributive mechanisms. The strongest association is between market poverty and federal taxes (correlation = 0.799), followed by state transfers (correlation = 0.771), federal transfers (correlation = 0.596), and state taxes (correlation = -0.235). However, there are stronger associations between disposable income poverty among working-age households and the poverty reduction attributable to each of the redistributive mechanisms but follow a similar pattern. The strongest association is between disposable poverty and federal taxes (correlation = 0.706), followed by federal transfers (0.517), state transfers (correlation = 0.627), and state taxes (correlation = -0.325).

7. Discussion/Conclusion

The decentralized nature of the social safety net for economically vulnerable families with children is one of the most important and least carefully studied structural features of the U.S. welfare state. The extent of cross-state variation in the generosity and inclusiveness of safety net provision is substantively large and meaningful for economically needy families.

Some variation in social provision across states may be an expected outcome of the highly decentralized structure of the U.S. safety net. Given that most of the U.S. programs are subject to some degree of federal oversight, however, it is surprising to observe variation equal to or greater than that observed across the countries that comprise different welfare regimes.

The redistribution analyses presented here highlight the utility of opening the “black box” of pre-post or market-disposable total poverty reduction estimates. By examining in greater detail the relative contribution of four redistributive mechanisms, and identifying the unique contributions of state transfers and taxes, these analyses highlight the important role of decentralized policy designs and the role of subnational governments.

The poverty reduction analyses also point to the important insights that can be gained by conducting not only national, but also state-level analyses of redistribution. The analyses shed light on how states vary in their levels of market and disposable income poverty, their total poverty reduction, as well as the relative contribution of the redistributive mechanisms. This result is not surprising given the substantial cross-state variation documented in the first part of the paper. The analyses presented here also complement other recent work examining state-level differences in poverty using different conceptual frameworks and analytical techniques (see for example, Laird et al. 2018).

Cross-national variation has motivated a substantial comparative literature examining the causes and consequences of alternative welfare state regime types. Attention has been far less sustained in the area of cross-state variation in social provision and redistribution. Designing safety net policies to allow for state or local discretion in financing, policy and administrative discretion by U.S. states has produced not one but multiple social safety net approaches, or regime types, that vary substantially in treatment of similar individuals and their families.[30]

The cross-state variation in social provision and the variation across states in redistribution and specifically, poverty reduction, reported in this paper are meaningful forms of inequality – inequality in the treatment of similar needs and claims by people who happen to live in different states. We argue that this form of inequality deserves more sustained attention, particularly in regard to policy design. In designing policies, there is a clear trade-off between uniformity through national provision, reflective of equality in social rights and equity considerations, and variability through state or local provision reflective of inequality in social rights and a lack of concern about equity in provision (Obinger, Castles, and Leibfried 2005), or as Aaron Wildavsky (1985) famously noted, "federalism means inequality."

While more research on the consequences of a decentralized safety net is needed, there is compelling evidence that these consequences are troubling. Given these cross-state inequalities in provision and redistribution, we believe it is imperative to consider these forms of inequality as we evaluate potential policy changes and alternative policy options for social provision and redistribution.

[30] In a working paper, Sarah Bruch, Yu-Ling Chang, Marcia Meyers and Janet Gornick use the SSNP generosity and inclusion policy indicators to explore whether there are unique state approaches or regimes of social provision that are consistent over time.

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Table 1. Social Safety Net Policy (SSNP) Measure Descriptions and Data Sources

Program	Dimension	Measure Construction
Cash Assistance	Generosity	From 1994 to 1996, average yearly cash benefit in AFDC. From 1997 to 2014, calculated as state and federal dollars spent on cash benefits in TANF program[1] divided by the monthly average number of recipient families. [2]
	Inclusion	From 1994 to 1996, numerator is monthly average number of families receiving AFDC.[3] From 1997 to 2014, numerator is monthly average number of families receiving TANF. [2] Denominator is number of pre-tax and transfer poor families with children (at 100% Federal Poverty Level [FPL]).
Child Support	Generosity	Child support distributions per child support case in which a child support collection was made on an obligation.[4]
	Inclusion	Number of child support cases for which a collection was made on an obligation[4] divided by the number of single parent families with children.
Food Assistance	Generosity	Expenditures on benefits divided by the number of participating households.[5]
	Inclusion	Number of households with children participating[6] divided by the number of pre-tax and transfer poor families with children (130% FPL).
Unemployment Insurance	Generosity	Average weekly benefit received multiplied by the average number of weeks of receipt.[7]
	Inclusion	Number of recipients in all program divided by the total number of unemployed. [7]
Supplemental Security Income	Generosity	Average yearly child disability benefit received (includes federally administered state supplementation payments).[8]
	Inclusion	Number of children < 18 receiving SSI[8] divided by the number of pre-tax and transfer poor children < 18 (200% FPL)
State Income Tax	Generosity	State income tax that a single-parent family of three pays when their income is at the poverty line.[9]
	Inclusion	Proportion of poor single parent families of 3 (100% FPL) under state income tax threshold for single parent family of 3.[9]
Preschool and Early Education	Generosity	Federal and state expenditures on Head Start and state pre-K divided by the number of children enrolled in Head Start and state pre-K.[10]
	Inclusion	Children enrolled in state pre-K and Head Start divided by the number of children 3-4 years old.[10]
Targeted Work Assistance	Generosity	Federal and state expenditures on work related activities including transportation divided by the number of participating families.[11]
	Inclusion	From 1994 to 1996 is number of JOBS participants divided by average number of families receiving AFDC. From 1997 to 2013 is number of families meeting work requirements divided by average number of families receiving TANF.[12]

Child Health Insurance	Generosity	Federal and state expenditures on Medicaid child eligibles (94-98) beneficiaries (99-12) and SCHIP enrollees divided by the number of Medicaid child eligibles (94-98) beneficiaries (99-12) and SCHIP enrolled children.[13]
	Inclusion	Medicaid eligibles (94-98) beneficiaries (99-12) and SCHIP enrolled children[14] divided by the under 18 pre-tax and transfer poor population (300% FPL).
Child Care	Generosity	Total spending (CCDF and TANF) on child care per child served by TANF and CCDF.[15]
	Inclusion	Number of children served by TANF and CCDF[14] divided by the number of pre-tax and transfer poor children under 13 (100% FPL).

[1] Green Book 1994-96; ACF TANF Financial Data 1997-2014. Starting in 2000 includes State Separate Program expenditures.
[2] Green Book 1994-96; OFA Caseload Data 1997-2014. Starting in 2000 includes State Separate Program caseloads.
[3] Green Book 1994-96 AFDC average monthly family recipients.
[4] OCSE Annual Report to Congress 1994-2014.
[5] USDA Food and Nutrition Service Food Stamp Program Data 1994-2014.
[6] USDA, Food and Nutrition Service, Characteristics of Food Stamp Households Annual Reports 1994-2014.
[7] Department of Labor Employment and Training Administration Unemployment Insurance Data Summaries 1994-2014.
[8] Social Security Administration SSI Annual Statistical Reports 1994-2014.
[9] To calculate the state income tax liability or refund for a single-parent family of three at the poverty line and the state income tax threshold at which a single-parent family of three has a tax obligation, we follow a methodology first used by the CBPP and continued by the NCCP which uses the online NBER TAXSIM tax calculation tool. TAXSIM is a microsimulation tool that provides estimates of state and federal income tax liabilities from survey data. This tool is used to calculate the state income tax liability or refund for a single-parent family of three at the poverty line by inputting the U.S. Census Bureau annual poverty thresholds for families of different compositions. The results provided by TAXSIM are an estimate of the state and federal tax liability for a family of a given composition when their income is at the poverty threshold. To obtain the state income tax threshold at which a single-parent family of three has a tax obligation, we input records of single-parent families of varying incomes for all fifty states. Each state contains one single-parent family record with an income between $0 and $65,000, with each differing from the prior record by increments of $100. The results provided by TAXSIM we then use to compare against the records we use as input to identify the income value in any given state at which a single-parent family would obtain a tax obligation to obtain our threshold.
[10] Children's Defense Fund 1994 and 1999; National Institute for Early Education Research State of Preschool 2002-2014; ACF Head Start Fact Sheets 1994-2009.
[11] Green Book 1994-96; ACF TANF Financial Data 1997-2014.
[12] Green Book 1994-96; HHS ACF TANF Work Participation Rates Data 1997-2013. OFA Caseload Data 1997-2014. Starting in 2000 includes State Separate Program caseloads.
[13] DHHS Centers for Medicare and Medicaid Services, Medicaid Statistical Information Services National MSIS Tables 1994-2012; Kaiser Family Foundation State Health Facts 1998-2009; Centers for Medicare and Medicaid Services CMS-21 CHIP Expenditure Reports 2010-14.
[14] Congressional Research Service Report (Gish Report) 1992-2000; Green Book 1992-2001; ACF CCDF State Expenditure Data 2003-2014; ACF TANF Financial Data 1997-2014.
[15] ACF CCDF Data Tables 1998-2014. ACF TANF Financial Data 1997-2014.
[16] U.S. Dept. of HUD, VMS Data 1996-2014.

Table 2. CPS ASEC Income Components

Market Income	
wage and salary	rent, royalties, estate, and trust income
self-employment earnings	interest
farm income	dividends
retirement[a]	friend/family financial assistance
survivor pensions[a]	alimony
disability pensions[a]	interest from retirement accounts
annuities[a]	other income not otherwise classified[b]

Federal Transfers	**State Transfers**
Social Security	public assistance
veterans' benefits	Unemployment Insurance
	Workers' Compensation
	Supplemental Security Income
	child support
	food assistance[c]
	school lunch[c]
	housing subsidy[d]
	energy subsidy[d]

Federal Taxes[e]	**State Taxes[e]**
Liabilities	*Liabilities*
Income tax liability	Income tax payments
FICA	
Credits	*Credits*
Earned income tax credit	State earned income tax credit
Child credit	Property credit
Child care tax credit	State child care and other tax credits

[a] All sources of retirement, survivor, and disability pensions are included see below for detailed list.
[b] See below for detailed information about what is included in "other" income
[c] Reported at the family level.
[d] Reported at the household level.
[e] Derived from NBER's TAXSIM program.

Table 3. U.S. Social Safety Net Policy Indicators: Distribution Statistics, 2018

	Median	*Standard Deviation*	*Gini Coefficient*	*10th Percentile*	*90th Percentile*
Generosity					
Cash Assistance	$4,155	1945	0.234	$2,006	$6,409
Child Support	$3,169	486	0.082	$2,642	$3,918
Food Assistance	$3,235	433	0.076	$2,595	$3,671
Unemployment Insurance	$5,200	1414	0.152	$3,542	$7,055
Supplemental Security Income	$8,149	711	0.049	$7,052	$8,989
State Income Taxes [a]	$64	581	0.886[c]	-$149	$1,197
Preschool/Early Education	$8,756	2076	0.139	$5,319	$10,853
Targeted Work Assistance	$17,199	36,835	0.548	$4,931	$54,632
Child Health Insurance [b]	$2,082	575	0.139	$1,690	$3,260
Child Care [b]	$6,206	1507	0.123	$5,171	$8,743
Inclusion					
Cash Assistance	0.174	0.145	0.394	0.054	0.408
Child Support	0.817	0.240	0.160	0.586	1.182
Food Assistance	1.013	0.176	0.096	0.785	1.189
Unemployment Insurance	0.255	0.116	0.237	0.127	0.455
Supplemental Security Income	0.037	0.012	0.174	0.020	0.055
State Income Taxes [a]	0.347	0.116	0.184	0.233	0.542
Preschool/Early Education	0.237	0.144	0.319	0.081	0.427
Targeted Work Assistance	0.151	0.117	0.359	0.045	0.363
Child Health Insurance	1.117	0.158	0.079	0.911	1.295
Child Care [b]	0.160	0.111	0.287	0.096	0.345

Note: Values are reported in 2018 constant dollars. Generosity measures are cost-of-living adjusted using the BEA RPPs, see Appendix for more information.

[a] State income tax values are calculated only for the 41 states that have state income taxes.

[b] Last year of data is 2013 for child health insurance generosity, and is 2017 for child care generosity and inclusion.

[c] The state income tax generosity measure includes negative values (which indicate tax liabilities) and zero values (which indicate that a single family of three does not owe any taxes or receive any tax benefits at the poverty line). Inclusion of negative and zero values in calculating the Gini coefficient can yield values greater than one (see footnote 24 for a greater discussion of this issue).

Table 4. Cross-National Comparison between SSNP and CWED and SOCX Policy Measures: Distribution Statistics, 2010

	Gini Coefficient[c]
U.S. States, N=50 (SSNP Generosity)	
Cash Assistance	0.224
Child Support	0.073
Food Assistance	0.068
Unemployment Insurance	0.099
Supplemental Security Income	0.047
State Income Taxes [a]	1.026[c]
Preschool/Early Education	0.142
Targeted Work Assistance	0.432
Child Health Insurance	0.136
Child Care	0.145
U.S. States, N=50 (SSNP Inclusion)	
Cash Assistance	0.300
Child Support	0.155
Food Assistance	0.088
Unemployment Insurance	0.121
Supplemental Security Income	0.194
State Income Taxes [a]	0.142
Preschool/Early Education	0.299
Targeted Work Assistance	0.183
Child Health Insurance	0.091
Child Care	0.234
Three Worlds of Welfare Capitalism Countries, N=18 (CWED) [b]	
Unemployment Generosity	0.152
Unemployment Family Replacement Rate	0.096
Unemployment Coverage	0.071
Sickness Generosity	0.211
Sickness Family Replace. Rate	0.212
Sickness Coverage	0.061
Pensions Generosity	0.097
Pensions Family Replace. Rate	0.098
Pensions Coverage	0.045
Three Worlds of Welfare Capitalism Countries, N=18 (SOCX) [b]	
Disability & Sickness Cash Benefits (as % GDP)	0.224
Family Cash Benefits (as % GDP)	0.259
Family In Kind Benefits (as % GDP)	0.296
Old-Age & Survivors Cash Benefits (as % GDP)	0.234

[a] State income tax values are calculated only for the 41 states that have state income taxes.
[b] For details on CWED measures, see Scruggs, Jahn, and Kuitto 2017. The pension coverage rates are only available for between 10-13 countries. For details on the SOCX aggregated spending measures, see Adema and Fron 2019.
c The state income tax generosity measure includes negative values (which indicate tax liabilities) and zero values (which indicate that a single family of three does not owe any taxes or receive any tax benefits at the poverty line). Inclusion of negative and zero values in calculating the Gini coefficient can yield values greater than one.

Table 5. Poverty Reduction by Redistributive Mechanism, Working-age Households with Children, 2016

Redistributive Mechanism	Estimate Ordering	Dollar Amount	Poverty Reduction
Federal Transfers			
	Average	$3,015	0.0141
	Minimum		0.0122
	Maximum		0.0168
State Transfers (w/o TRIM3)			
	Average	$6,259	0.0321
	Minimum		0.0289
	Maximum		0.0368
State Transfers (w/ TRIM3)			
	Average	$8,303	0.0435
	Minimum		0.0396
	Maximum		0.0498
Federal Taxes			
	Average	$3,369	0.0357
	Minimum		0.0309
	Maximum		0.0408
State Taxes			
	Average	$150	0.0012
	Minimum		0.0007
	Maximum		0.0018

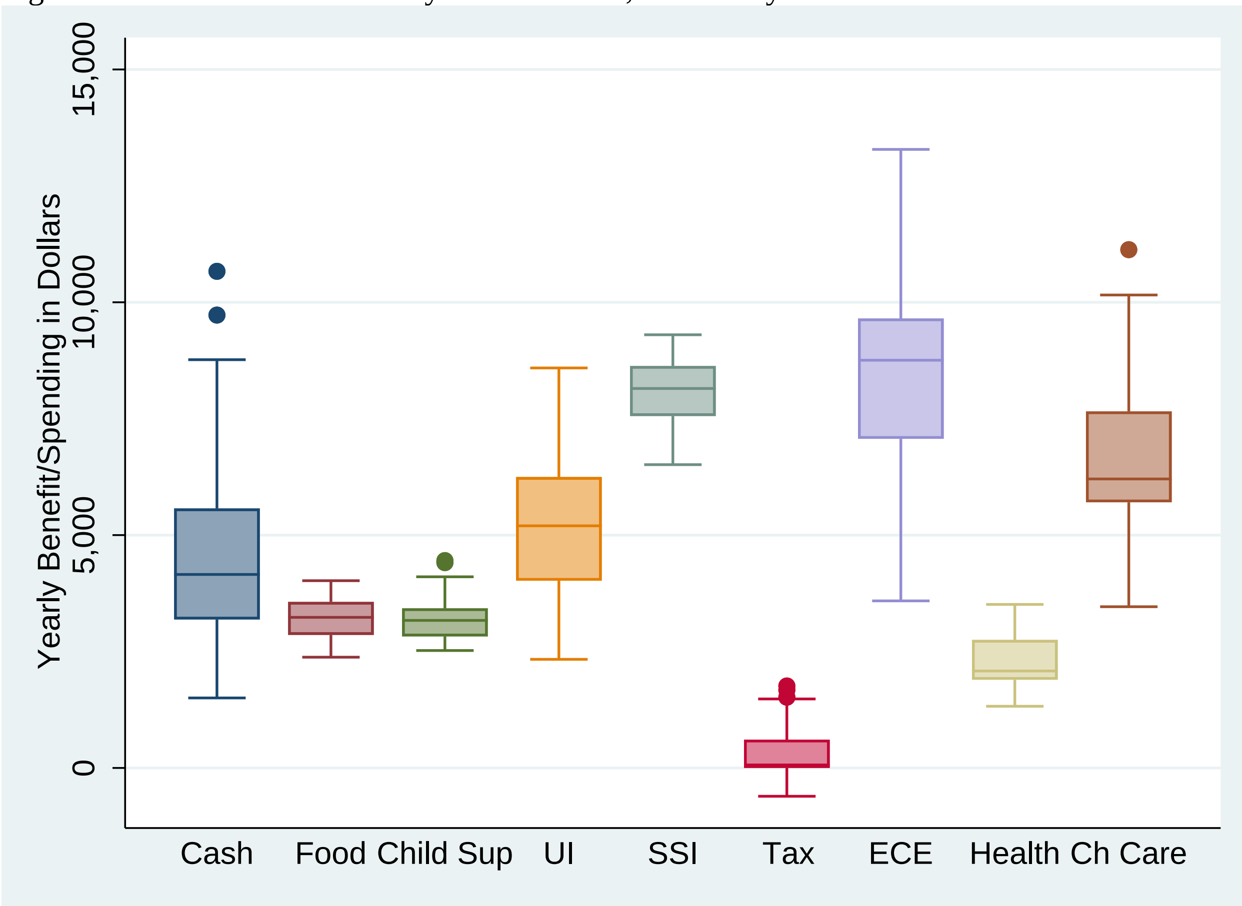
Note: The average value represents the average poverty reduction estimate of all permutations/orderings with unique values of the redistributive mechanism. Minimum and maximum reductions are the smallest and largest poverty estimates associated with adding that redistributive mechanism. See Figures 3-6 for all values for each redistributive mechanism. Absolute poverty reductions are taken from decomposition using state transfers adjusted with the TRIM3 correction for underreporting with the exception of the "State Transfers w/o TRIM3" estimates. Dollar amounts are the average dollar amount received from each redistributive mechanism by working-age households with children with income below the poverty line when only considering market sources of income.

Table 6. Poverty Reduction by Redistributive Mechanism with Specific Orderings, Working-age Households with Children, 2016

Estimate Ordering	Market Income Poverty	Poverty Reduction Attributable to				Disposable Income Poverty
		Federal Transfers	Federal Taxes	State Transfers	State Taxes	
State Transfers First	0.1692	0.104	0.0732	0.1229	0.1208	0.0732
Absolute Reduction		0.0167	0.0309	0.0463	0.0020	
Percentage of Total Reduction		17%	33%	48%	2%	
State Transfers Last	0.1692	0.1161	0.1283	0.0732	0.1148	0.0732
Absolute Reduction		0.0122	0.0408	0.0416	0.0012	
Percentage of Total Reduction		13%	42%	43%	2%	
State Taxes First	0.1692	0.0732	0.0873	0.1208	0.1677	0.0732
Absolute Reduction		0.0141	0.0355	0.0469	0.0014	
Percentage of Total Reduction		15%	36%	48%	1%	
State Taxes Last	0.1692	0.1553	0.1161	0.0739	0.732	0.0732
Absolute Reduction		0.0138	0.0392	0.0412	0.0007	
Percentage of Total Reduction		14%	41%	43%	1%	

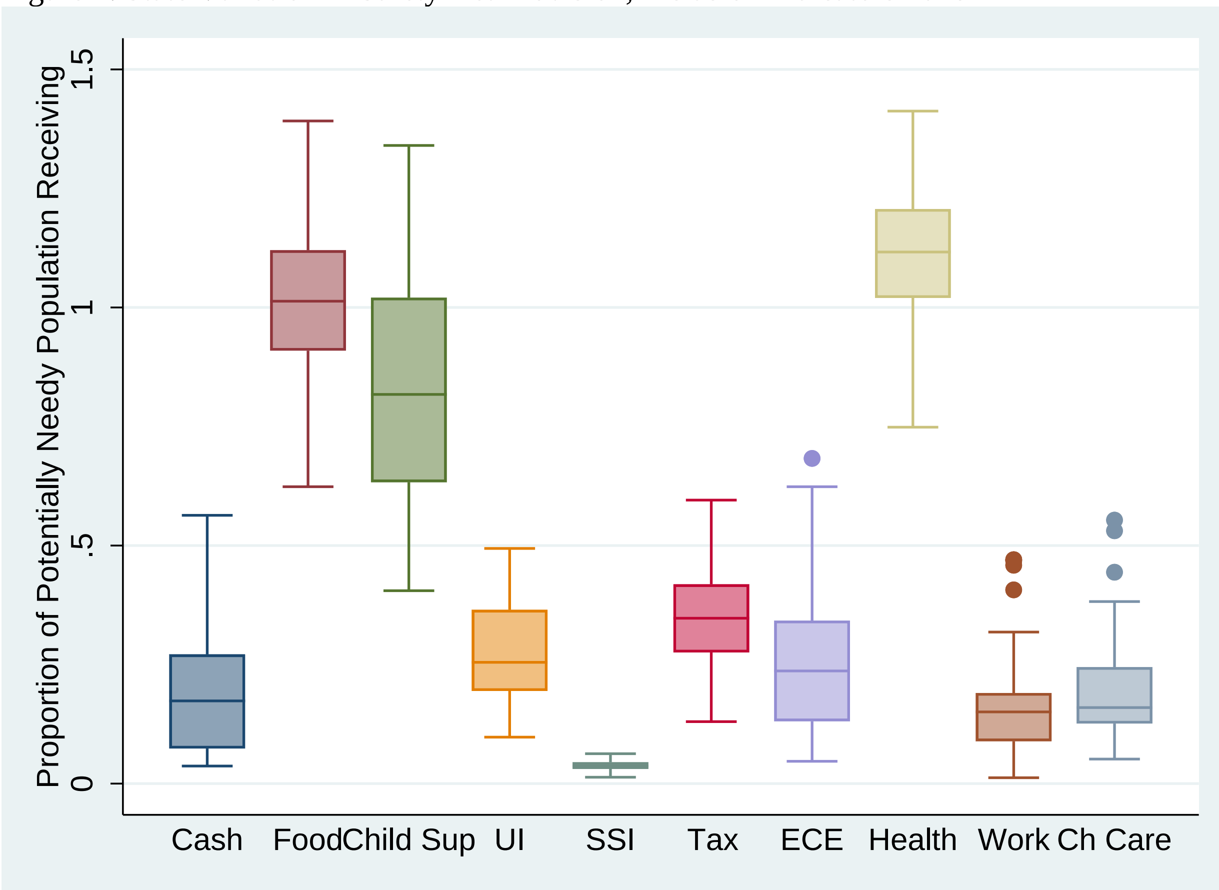
Note: The values in the State Transfers First panel are taken from the following permutation: state transfers, state taxes, federal transfers, and federal taxes. The values in the State Transfers Last panel are taken from the following permutation: federal taxes, federal transfers, state taxes, and state transfers. The values in the State Taxes First panel are taken from the following permutation: state taxes, state transfers, federal taxes, federal transfers. The values in the State Taxes Last are taken from the following permutation: federal transfers, federal taxes, state transfers, state taxes. The calculations included in this table are using state transfers adjusted with the TRIM3 correction for underreporting.

Figure 1. State Variation in Safety Net Provision, Generosity Indicators 2018



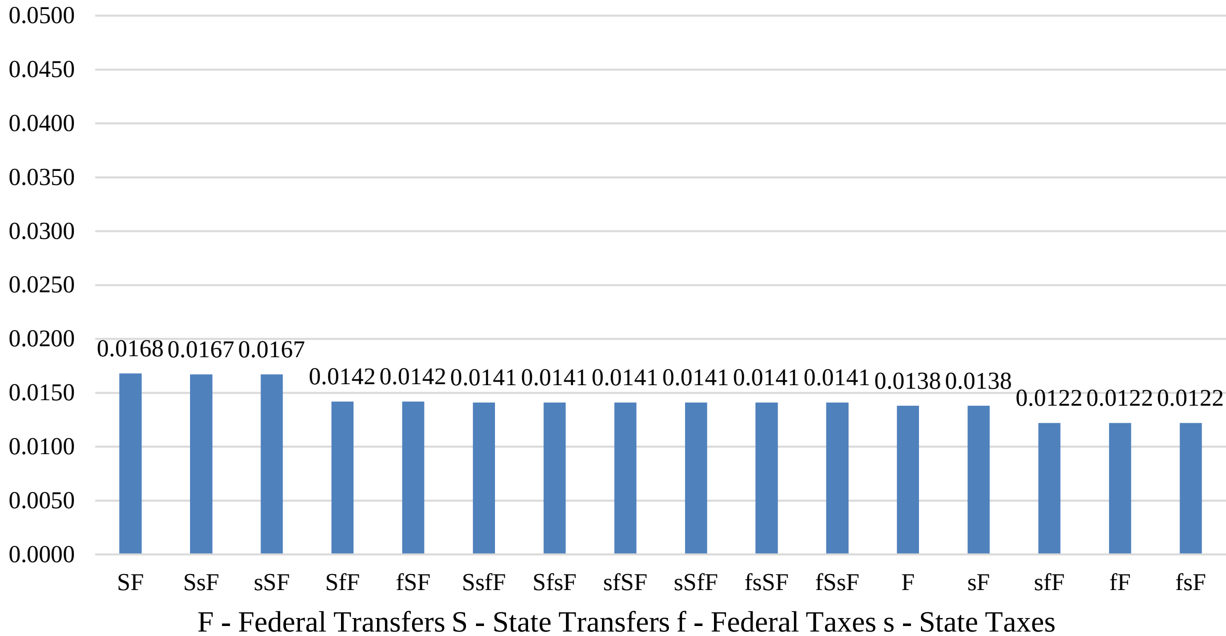
Note: Cash=cash assistance; Food=food assistance; Child Sup=child support; UI=Unemployment Insurance; SSI=Supplemental Security Income; Tax=state income taxes; ECE=preschool/early care and education; Health=child health insurance; Ch Care=child care. Colored box indicates the inter-quartile range (25th & 75th percentiles), with the median highlighted; the length of the whiskers are at 1.5 times the IQR; values outside of that range are represented by dots. Cash-assistance based work training is not represented on the graph due to the extreme scale difference.

Figure 2. State Variation in Safety Net Provision, Inclusion Indicators 2018



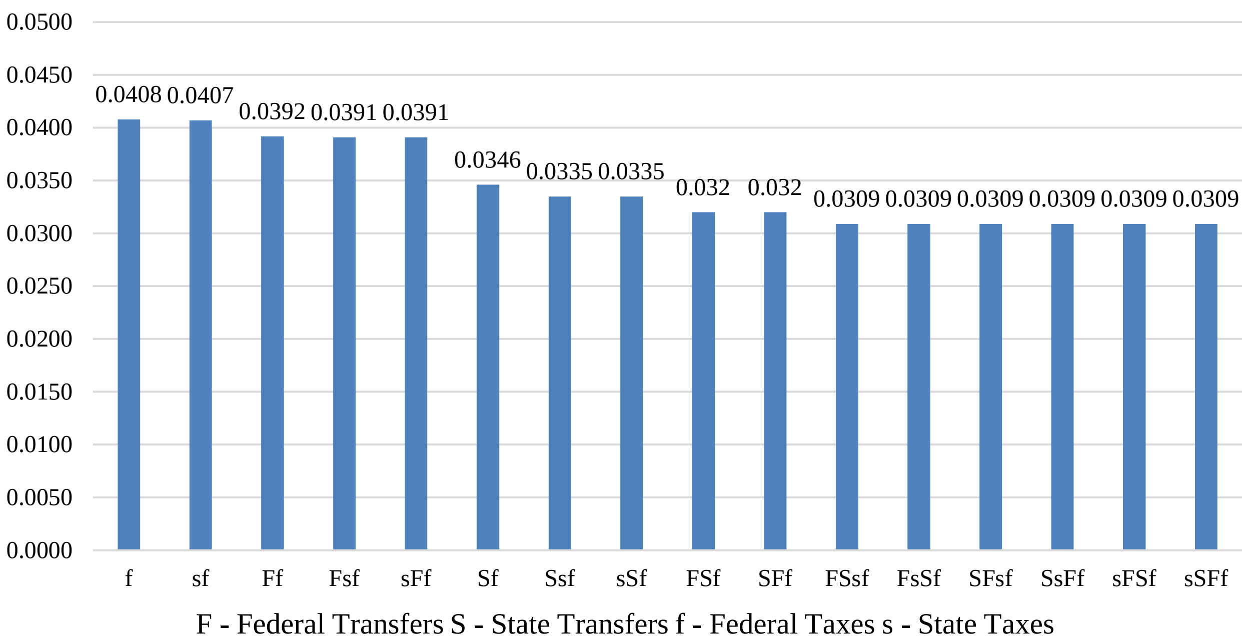
Note: Cash=cash assistance; Food=food assistance; Child Sup=child support; UI=Unemployment Insurance; SSI=Supplemental Security Income; Tax=state income taxes; ECE=preschool/early care and education; Health=child health insurance; Ch Care=child care. Colored box indicates the inter-quartile range (25th & 75th percentiles), with the median highlighted; the length of the whiskers are at 1.5 times the IQR; values outside of that range are represented by dots.

Figure 3. Reductions in Poverty Attributable to Federal Transfers, Working-age Households with Children, 2016



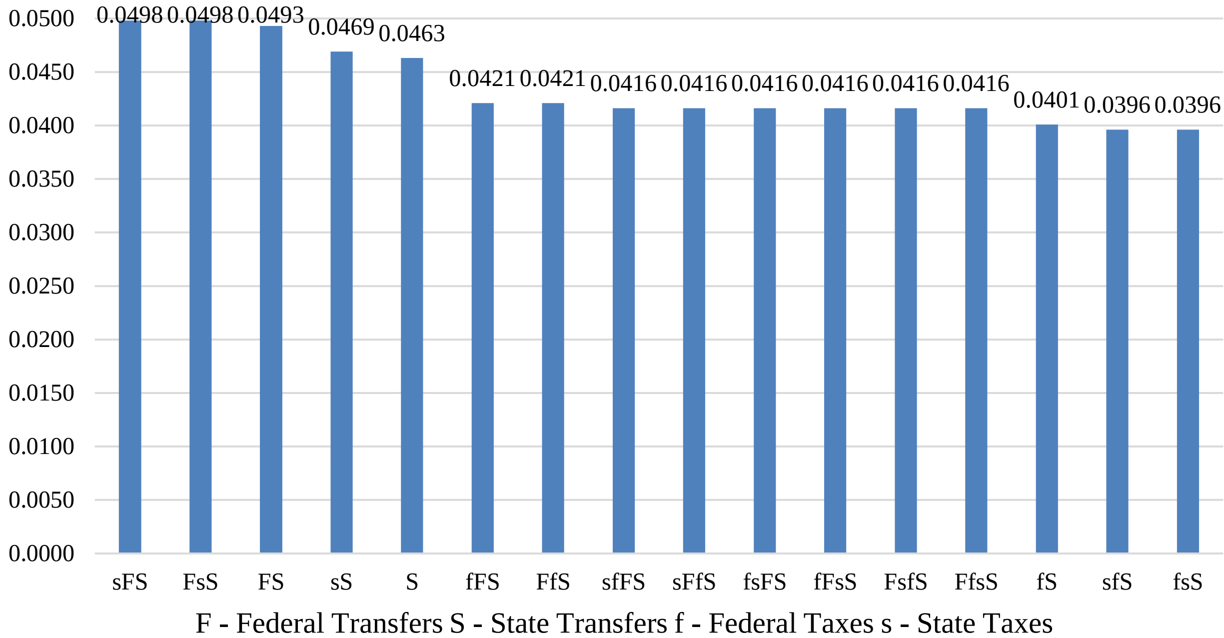
Note: Bars represent the percentage point reduction in absolute poverty among working-age households with children when federal transfers are added to the household's market income. The 16 bars display all the permutations (different orderings) of the redistributive mechanisms with unique values.

Figure 4. Reductions in Absolute Poverty Attributable to Federal Taxes, Working-age Households with Children, 2016



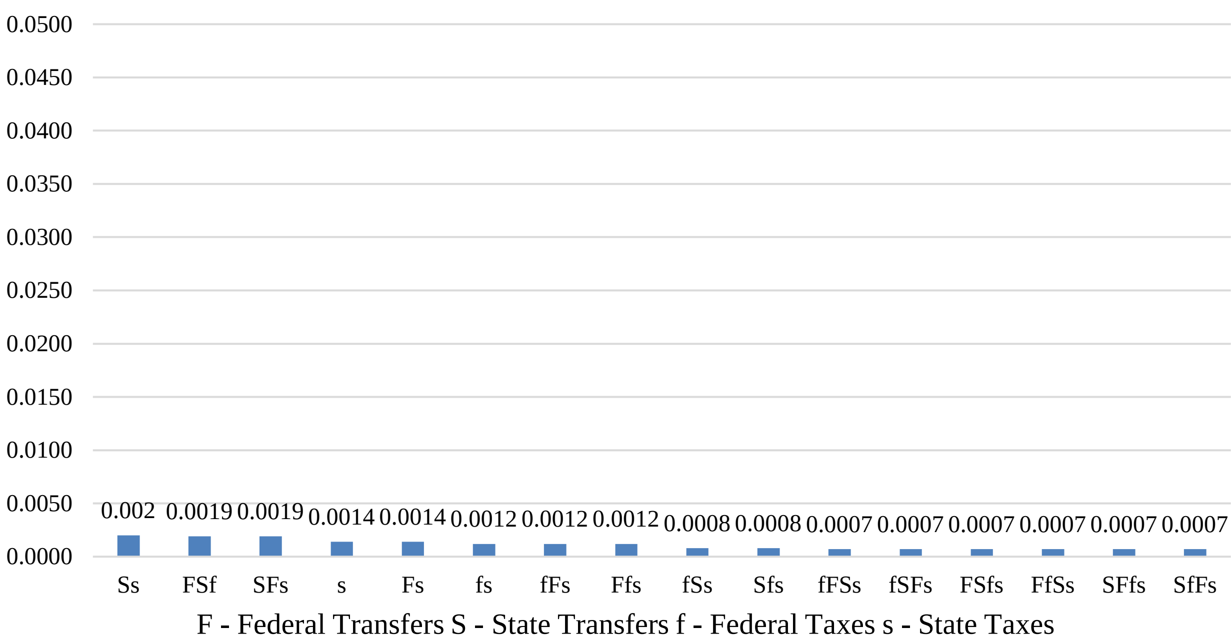
Note: Bars represent the percentage point reduction in absolute poverty among working-age households with children when federal taxes are added to the household's market income. The 16 bars display all the permutations (different orderings) of the redistributive mechanisms with unique values.

Figure 5. Reductions in Absolute Poverty Attributable to State Transfers, Working-age Households with Children, 2016



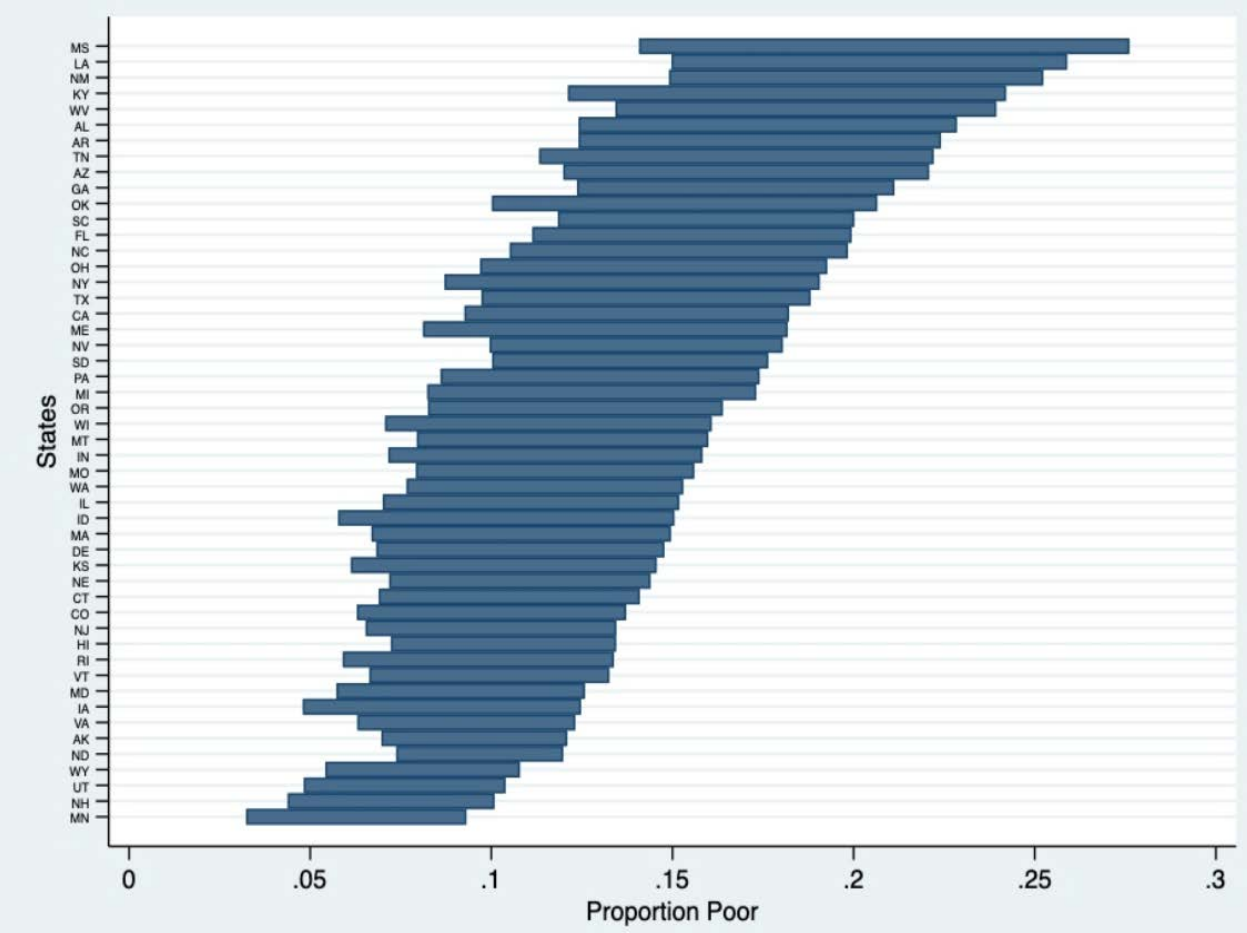
Note: Bars represent the percentage point reduction in absolute poverty among working-age households with children when state transfers are added to the household's market income. The 16 bars display all the permutations (different orderings) of the redistributive mechanisms with unique values.

Figure 6. Reductions in Absolute Poverty Attributable to State Taxes, Working-age Households with Children, 2016



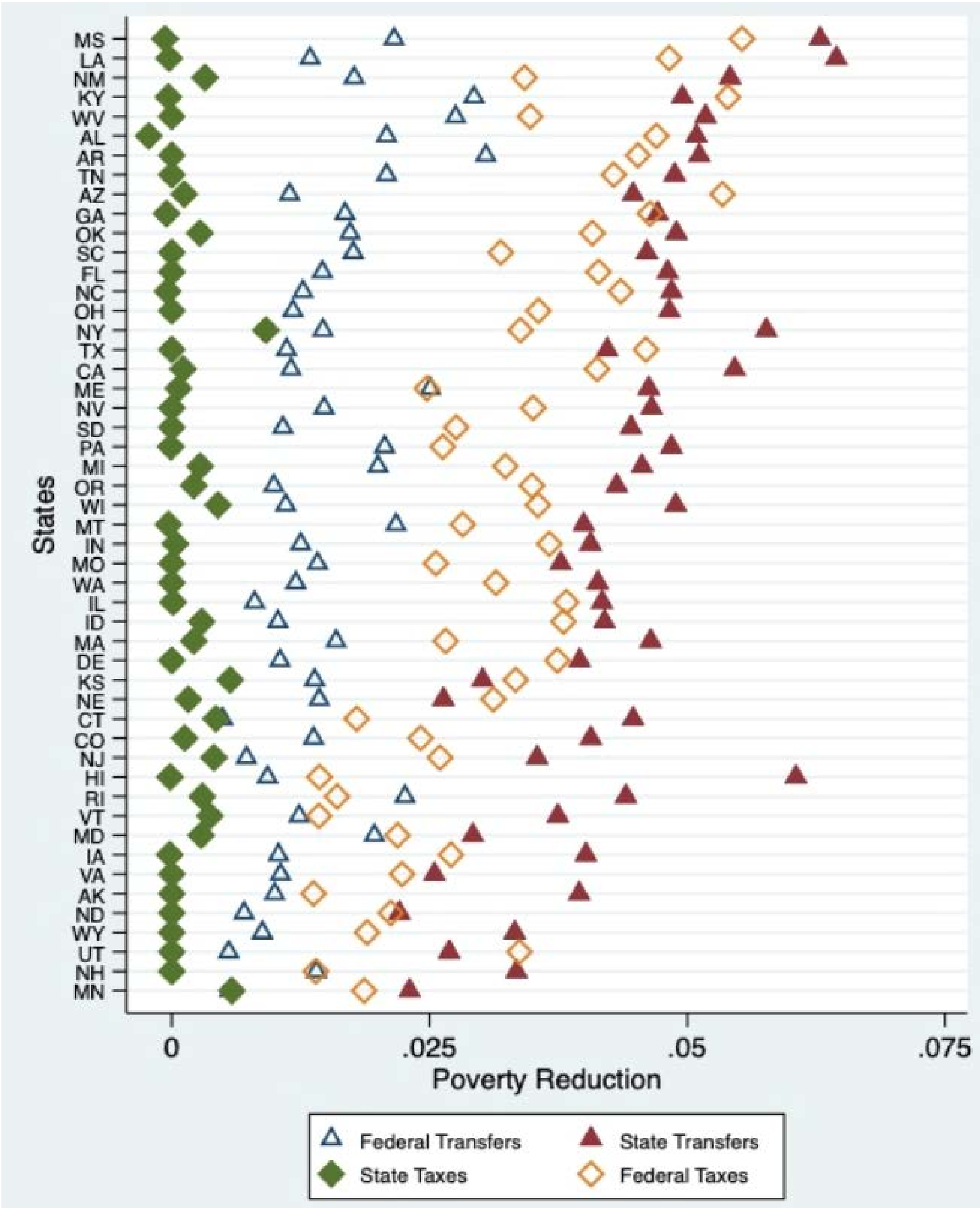
Note: Bars represent the percentage point reduction in absolute poverty among working-age households with children when state taxes are added to the household's market income. The 16 bars display all the permutations (different orderings) of the redistributive mechanisms with unique values.

Figure 7. Market and Disposable Poverty by State, Working-age Households with Children, 2016



Note: States are ordered by the proportion of working-age households with children who fall below the absolute poverty threshold when only including market sources of income. The bar represents the percentage point difference between the proportion of working-age households with children who are below the poverty threshold when only including market sources of income compared to the proportion who remain below the threshold after income from the four redistributive mechanisms (federal transfers, federal taxes, state transfers, state taxes) are added to their household income.

Figure 8. Average Poverty Reduction Attributed to Redistributive Mechanisms, Working-age Households with Children, 2016



Note: Values represent percentage point poverty reductions attributable to each redistributive mechanism on average (i.e. the average of the 16 possible orderings). In the figure, states are ordered from top to bottom by the proportion of working-age households with children who fall below the absolute poverty threshold when only including market sources of income. The symbols represent the average poverty reduction attributable to the four redistributive mechanisms (federal transfers, federal taxes, state transfers, state taxes). State transfer estimates use the TRIM3 corrected values.

Appendix

Geographic Cost-of-living Adjustments

In the social provision analyses, we use the Bureau of Economic Analysis (BEA) Regional Price Parities by State and Metro Area (RPP). The RPP's are annual price indexes that are designed to measure the geographic difference in cost-of-living using a weighted average of the price of goods and services for the average consumer in one geographic region compared to all other regions in the U.S. We use the RPP's to adjust the generosity indicators (dollar amount spent per recipient) for all programs. Specifically, we use the aggregate state-level "all items" RPPs which cover all consumption goods and services including housing rents, and apply the adjustment to the entire generosity value.[31]

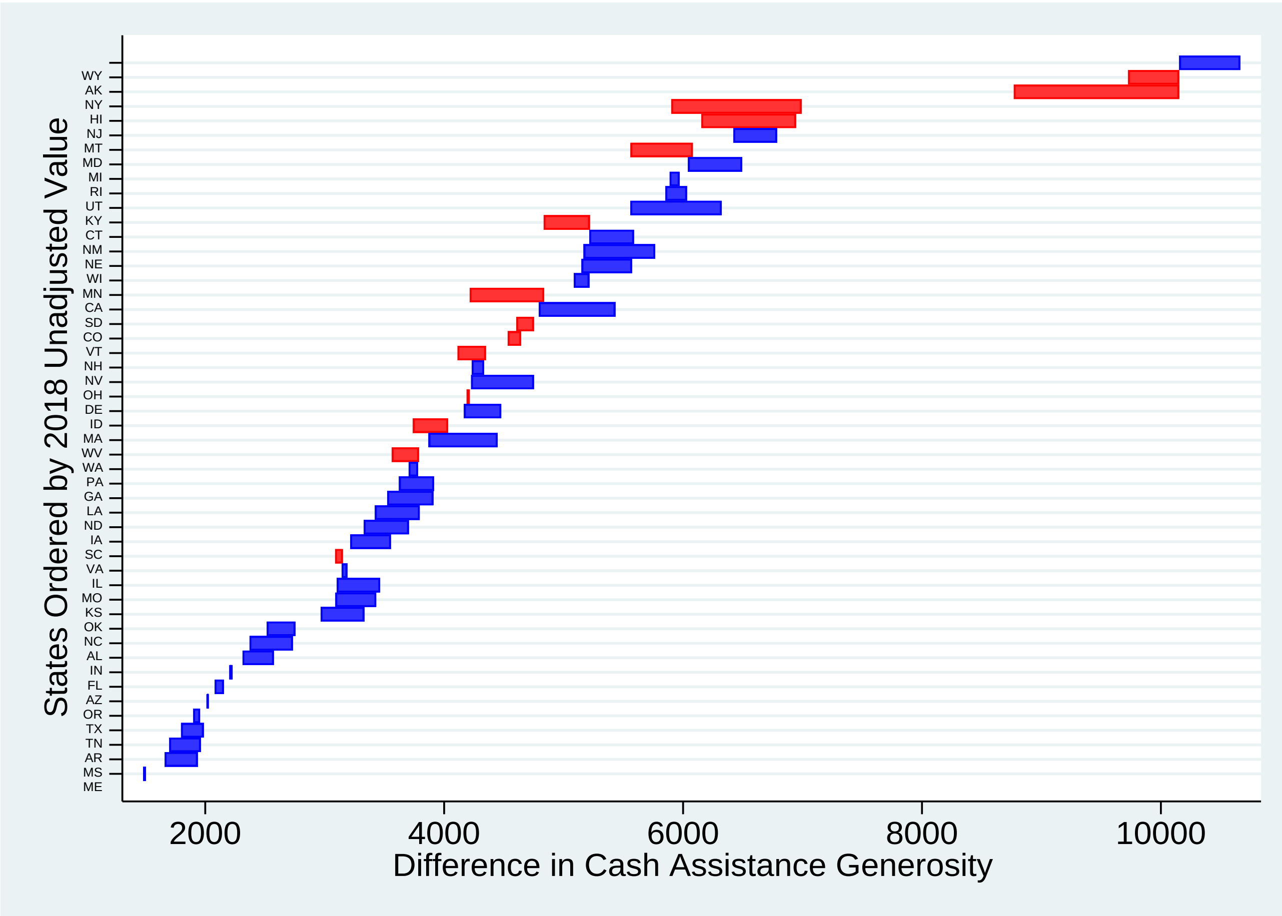
We use the BEA RPP cost-of-living adjustments for two primary reasons. First, the RPP adjustment is a full basket adjustment, incorporating state-level differences in costs beyond geographically-adjusted rents. Second, the state-level BEA RPP are at the same level of geography as the generosity policy indicators. This differs from the SPM adjustments which are based on primarily on Department of Health and Urban Development (HUD) Fair Market Rents (e.g. 40th percentile rent and utilities), which are applied to household survey data at the family level.[32]

Figure A1 compares the generosity indicator for cash assistance with and without the BEA RPP geographic cost-of-living adjustment (COLA). For the vast majority of states, applying the RPP COLA increases the value of the generosity indicator. In the graph, blue bars indicate an increase in value when comparing the adjusted and unadjusted values. The largest decreases in value are observed in states with more generous cash assistance benefits (represented by red bars). Applying the RPP COLA reduces the extent of cross-state variation (from a Gini coefficient of 0.253 without the adjustment to 0.234 with the adjustment).

[31] The BEA RPPs are available yearly beginning in 2008 through 2017. For years prior to 2008, we adjust the generosity indicators using the five year average of 2008-2012 RPPs. For 2018, we adjust using the 2017 value.

[32] For more information on geographic differences in the cost of living using the SPM, see Nolan et al. 2016.

Figure A1. Cost-of-living Adjusted (COLA) Compared to Non-COLA Cash Assistance Generosity, 2018



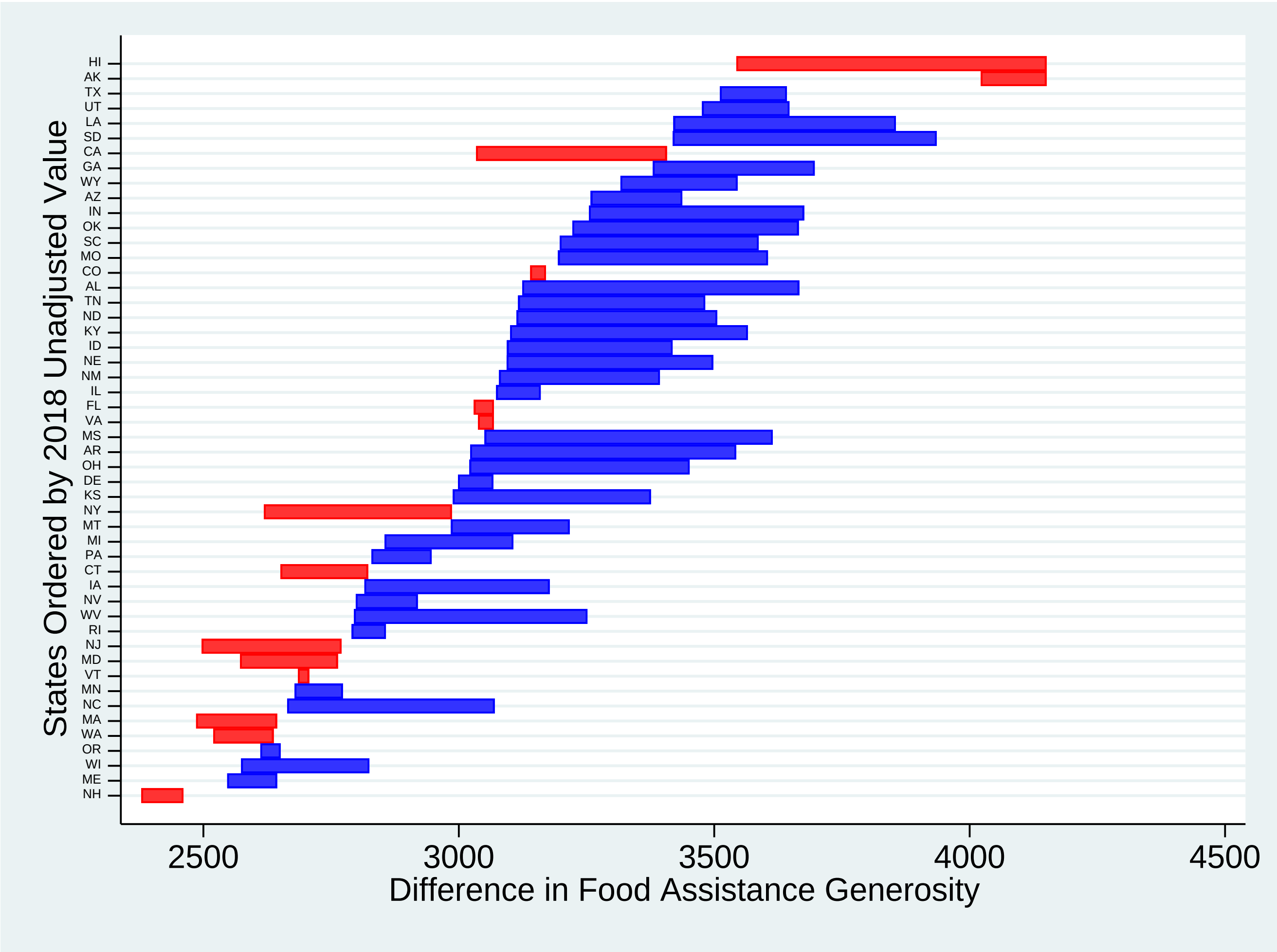
Note: The cost-of-living adjustment (COLA) uses the Bureau of Economic Analysis' Regional Price Parities by State and Metro Area (RPP). Red indicates a decrease in the generosity value for that state after applying the RPP COLA. Blue indicates an increase in the generosity value for that state after applying the RPP COLA.

The decrease in cross-state inequality observed for cash assistance is also observed in six of the ten programs (see Table A1). However, in four programs cross-state inequality is greater when using the COLA measures compared to the non-adjusted measures (food assistance, SSI, state income taxes, and cash assistance-based work assistance). To get a sense of why cross-state inequality is increased in some programs it is helpful to look at the difference between the indicators for individual states. Figure A2 displays the COLA and non-COLA adjusted generosity indicator for food assistance. As can be seen in the graph, many of the states that have values that are decreased with the application of the adjustment are states that have the lowest generosity value without the adjustment. This pattern results in pulling the bottom end of the distribution further down, and in so doing increases cross-state inequality.

Table A1. Cross-State Inequality in Generosity of Social Provision, Cost-of-living Adjusted (COLA) Compared to Non-COLA, 2018

	Generosity (Gini Coefficient)	
Program	Adjusted	Unadjusted
Cash Assistance	0.234	0.253
Child Support	0.082	0.101
Food Assistance	0.066	0.053
Unemployment Insurance	0.152	0.170
Supplemental Security Income	0.049	0.015
State Income Tax	0.886	0.874
Preschool and Early Education	0.139	0.146
Targeted Work Assistance	0.548	0.541
Child Health Insurance	0.139	0.143
Child Care	0.123	0.133

Figure A2. Cost-of-living Adjusted (COLA) Compared to Non-COLA Food Assistance Generosity, 2018



Averaged Decomposition Approach to Calculating Poverty Reduction

In order to overcome the sequential ordering limitation of the simple additive approach to the calculation of poverty reduction, we implement an averaged additive method that calculates the amount of poverty reduction attributable to each of our four redistributive mechanisms. To do this, we calculate all possible permutations of the four redistributive mechanisms. Though 24 permutations or orderings of the four mechanisms are possible, only 16 yield unique values.[33] These 16 unique values are the full set of poverty reduction estimates attributed to a specific mechanism. These values are then averaged together to create the "average" poverty reduction attributable to each mechanism.

TRIM3 Imputation Procedure and Parolin Correction Comparisons

The TRIM3 procedure developed and implemented by the Urban Institute, and employed by Parolin (2019), makes use of individual and household data from the CPS ASEC to model and correct for underreporting in TANF, SSI, and SNAP. This procedure first makes use of CPS ASEC data to identify households that have underreported these benefits, and then employs an algorithm to both predict whether the household or individual is likely to have received benefits (take up) and then calculate the amount of benefit the household or individual would receive. Importantly, the TRIM3 procedure does not identify and target solely individuals and households that underreport for correction, rather the model surveys all individuals and households and applies a general correction to eligible households, whether this entails an adjustment upward or downward in benefits. To model take up of benefits, TRIM3 does not assume a one hundred percent take up rate among underreporting households, and instead first identifies eligible households and individuals and utilizes an estimation method that predicts likelihood of receipt using a variety of demographic data including race, nativity, marital status, state of residence, income, as well as state policy rules, both available from the ASEC and from administrative data sources (for a more detailed explanation of the estimation procedure, see Zedlewski and Giannarelli 2015). Once TRIM3 has modeled take up for an individual or household, it assigns the unit the full amount of benefit for which the unit is eligible according to state-level guidelines. Importantly, while TRIM3 models the likelihood of take up, it does not model for likelihood that individual would receive more or less than the amount for which it is eligible. Put differently, the TRIM3 procedure assumes that the benefits an adjusted household or individual would receive are correct in their amount and therefore does not model individual error on the part of caseworkers or in reporting by individuals or households.[34]

In our analysis, we use the method of applying the TRIM3 underreporting corrections developed by Parolin (2019) to examine the effect of underreporting corrections on our decompositions in the CPS ASEC sample of working-age households with children. Differences in the raw amounts of the three means-tested benefits are compared in Table A2. The increases in the rate of

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[33] For example, federal transfers could be added first to the sequence, in which case we calculate the amount of poverty reduced from the poverty rate at market income only. The full possible permutation might be federal transfers, federal taxes, state taxes, then state transfers; however, the amount of poverty reduction attributable to federal transfers in this permutation is no different than if the permutation contained a different sequencing of the instruments following the federal transfers in the first position. The amount of poverty reduction attributable to an instrument is only unique when the instrument is added to the sequence, and in permutations when the instrument is preceded by other instruments, not in permutations where the instrument is followed by others.

[34] Linda Giannarelli, personal correspondence, February 2, 2020.

coverage across SNAP, TANF, and SSI are consistent with the findings of Parolin (2019) in his underreporting adjustments (see pg. 893). While Parolin (2019) found that the median value of SNAP, TANF, and SSI increased among households with children following the TRIM3 adjustments, we found a slight downward adjustment in benefits for TANF and SSI. Nevertheless, our estimates of the median value of SNAP, TANF, and SSI following the TRIM3 adjustment are generally consistent with the median values reported by Parolin (2019) within a margin of $35 to $150.

Table A2. Benefit Values and Coverage, Working-age Households with Children, CPS ASEC and TRIM3, 2015-2017

		CPS ASEC	TRIM3	Absolute Difference
SNAP				
	Median Value	$3,192	$3,401	$209
	Coverage Rate	16.7%	27.6%	10.9%
TANF				
	Median Value	$3,199	$3,000	- $199
	Coverage Rate	2.8%	3.9%	1.1%
SSI				
	Median Value	$8,676	$8,652	- $24
	Coverage Rate	3.3%	5.8%	2.5%

Note: The median value corresponds to the median benefit among working-age households with children receiving any amount of benefit greater than zero across 2015-2017. The coverage rate corresponds to the proportion of working-age households receiving any amount of benefit greater than zero across 2015-2017.