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Are We Providing Enough to Those Who Have Too Little? Measuring Poverty Relief

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Abstract

This manuscript presents a new measure of safety net program effectiveness—a “poverty relief ratio”—that is based on the estimated relationship between market income and social transfers, and reports the amount of income support provided, relative to the amount required to provide for all low-income households’ basic needs. In an important advance over the standard poverty reduction rate measures, the poverty relief ratio preserves the rank order of observations across varying poverty thresholds. In this paper, we introduce this measure and demonstrate its validity by tracking major changes in federal policy, and cross-state variation in safety net programs.

Keywords

Anti-poverty; welfare; social policy; inequality; low-income; poverty measurement

This manuscript presents a new measure of the effectiveness of social policy—a “poverty relief ratio”—that is based on the estimated relationship between market income and social transfers, and reports the amount of income support provided, relative to the amount required to provide for all low-income households’ basic needs. In an important advance over the standard poverty reduction rate measures, the poverty relief ratio preserves the rank order of observations across varying poverty thresholds. In this paper, we introduce this measure and demonstrate its validity by tracking major changes in federal policy, and cross-state variation in safety net programs. In estimating the poverty relief ratio, this paper also addresses three questions: How has the US fared over time in its commitment to provide baseline income support to those who are very poor (e.g., “baseline relief”)? How does income support change with small increases in earnings (e.g., “relief falloff”)? Finally, how effective are US safety net programs, on the whole, in raising the incomes of poor families to levels sufficient to meet basic needs (e.g., providing “poverty relief”)? Our research builds on recent work by Ben-Shalom, Moffitt & Scholz (2011) and others (e.g. Moffitt & Scholz 2010, Ziliak 2008), which use household-level survey data to assess the effectiveness of American safety net programs. Here, we propose a new measure of poverty relief, the *poverty relief ratio* ($\mathcal{R}$), which reports the amount of income support provided to low-

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income households, as a proportion of the support needed to bring all low-income households to a specified poverty threshold, and which offers several important features:

First, while like some other measures, our poverty relief ratio uses “normative” poverty threshold as a benchmark – that is, we assess the extent to which American safety net programs are successful in providing the income necessary “to maintain a living standard considered normatively minimally acceptable” (Ray 2006) – our measure maintains rank-order stability across different poverty thresholds. What this means is that the *actual* threshold specified matters only for the *magnitude* of measure (i.e., the proportion of relief supplied); systems that are most (or least) effective in providing poverty relief will be consistently ranked among the best (worst) of the sample being studied. Importantly, as this analysis will show, rank-order stability distinguishes the poverty relief ratio from other commonly used threshold-based measures of poverty reduction. In an example presented below, the state of Illinois ranks tenth or twenty-second, when the effectiveness of social policy is estimated using poverty rate reductions, and depending on the threshold used (i.e., 50 or 100 percent of the official US poverty line).¹ However, when poverty relief ratios are estimated instead, Illinois is ranked fourteenth, regardless of which poverty threshold is used. Differences in rankings for other states can be much more dramatic: Louisiana ranks either *twenty-eight* or *fiftieth* in poverty rate reductions, depending on the poverty threshold used (100 or 200 percent of the official US poverty line), but is characterized by a poverty relief ratio that ranks nineteenth, regardless of threshold. The ordering of other states similarly varies according to how “poverty” is defined, when current threshold-based measures of poverty are used.

Why is rank-order stability in a threshold-based measure important? In order to identify effective social policies, political science requires a measure that consistently identifies those observations that are more or less successful in their anti-poverty efforts. With existing threshold-based measures, the effectiveness of different policies must be seen as conditioned by the specific poverty threshold used in the analysis (i.e., usually some percentage of the official poverty line or, in Europe, of the median income). Worse still, when other measures are used, the substantive implications of analyses, as this discussion will show, may vary with the threshold used: Simply, whether a policy measure appears effective may vary with the income level that defines poverty. Maintaining a threshold-based approach, but with the advantage of rank-order stability, allows us to address our motivating question, “are we providing enough?,” and also provides an empirical basis for comparison across systems that may have very different programs. (Jusko 2008, for example, developed this measure for cross-national comparisons.)

The second distinguishing feature of this analysis lies in its parametric approach: We estimate the poverty relief ratio $\mathcal{R}$ using parameters that characterize the (negative exponential) relationship between market income and social transfers. This paper will show that the parameters, in fact, provide useful information about the characteristics of income support – information that cannot be easily recovered from other poverty reduction measures.² Therefore, in addition to the standard benefits of a parametric framework –

¹Similarly, Illinois’s rank varies between eleventh and seventeenth, when poverty gap measures are used.

including the rank-order stability, noted above, as well as ease of computation – the parameters that contribute to the poverty relief ratio provide additional measures of the effectiveness of social policy. Further, the parameters may better reflect policy intentions, rather than the idiosyncrasies of a particular sample.³

Here, our intention is to develop and validate this measure of poverty relief that, as we suggest, offers important advantages over other measures that are more commonly used in political science. While a full assessment of the American safety net is beyond the scope of this paper, we do track levels of poverty relief over time, and across states as a way to demonstrate our measure's validity. We use the Current Population Survey (CPS) from 1992 to 2015, to address the questions raised above, about the effectiveness of baseline relief, relief falloff, and the overall poverty relief provided by American safety net programs. Along the way, we demonstrate the reliability and merits of $\mathcal{R}$, by tracking major policy shifts, and tying cross-state variation in our poverty relief ratio to differences in unemployment insurance and welfare benefits.

In the end, we provide a new way to examine the (generally, quite limited) effectiveness of the American social safety net. We show that, although there have been some improvements in support for low-income families over the last 25 years, there is still work to be done: Even during the short-term expansion of poverty relief programs during the 2008 financial crisis, by our measure, American safety net programs provided only about half of the income support needed to raise the incomes of poor households to levels that provide for basic needs. The long-term improvements in income support, however, come not for those in deep poverty: Until the Great Recession, in which there was a temporary increase in support, baseline relief steadily declined. Instead, we observe important changes in the rate at which transfers decline with small increases in market earnings – what we term relief falloff. As Moffitt & Scholz (2010) suggest, this reflects the expansion of EITC and increased support for low-incoming working families.

In the next section, we outline standard measures of poverty reduction, and identify how they differ from our poverty relief ratio. Then, using the household-level relationship between market income and social transfers, we justify a “total income” approach to evaluating safety net programs and build on earlier work to derive our poverty relief ratio. Finally, we provide some evidence of the validity of our measure by linking the poverty relief ratio to cross-state differences in unemployment and welfare benefits, and by tracking major shifts in federal antipoverty policy.

²Note, for example, that while $\mathcal{R}$, like other threshold-based measures (e.g., Ray 2006), provides an estimate of the proportion of support provided through social transfers, baseline relief and relief falloff are measured in standard currency. While one could estimate the quantities equivalent to our baseline relief and relief falloff using a poverty gap measure, estimated over a range of thresholds, the parameters estimated here make quick work of these calculations.

Of course, a parametric set-up also facilitates hierarchical analysis, in which the “first stage” parameters become outcomes in a higher level, explanatory model. Analysts, for example, are often interested in determinants of levels of baseline support, and use legislated, rather than realized, maximum monthly TANF benefits as a best proxy (e.g., Reingold & Smith 2012, Hero & Preuhs 2007).

³Of course, the parametric framework presents challenges, as well, notably parameter instability in small samples. In fact, with large income surveys, available through the Luxembourg Income Study, or the Current Population survey, this concern rarely applies.

1 Standard Measures of Poverty Relief

Political science has traditionally relied on four broad types of measures to characterize social policy: fiscal measures, behavioral measures, distributional measures, and threshold-based measures. Each type of measure offers analytic advantages but these existing measures also make assumptions or obscure the effects of antipoverty policy in ways that complicate their interpretation and comparative analysis. This paper begins by briefly describing each type of conventional measure, and their insufficiencies. We focus more intently on the poverty reductions measures which are most closely related to our own poverty relief ratio, and we then use this discussion to motivate proposed poverty relief measure.

Fiscal measures focus on government spending directed toward social problems. This group of measures give a summary measure of policy decisions. Safety net expenditures, usually as a percent of GDP, are the most prominent of these fiscal measures, and scholars that use fiscal measures often implicitly assume that government spending directly, or at least disproportionately, benefits low-income households. However, there is evidence that fiscal measures do not straightforwardly measure redistribution, or safety net program effectiveness (see Milanovic 2000): For example, Moffitt & Sholz (2009) find that in spite of increased social spending between 1984 and 2004, support for very poor families declined during this period. This likely reflects Okun's (1975) "leaky bucket." Some of the money transferred from rich to poor "will simply disappear in transit" (quoted in Boadway & Keen 2000). In general, fiscal measures are "input-oriented" and insufficiently address the effects of social policy—who benefits and how much.

Distributional measures improve on fiscal measures by assessing how the income distribution of a population changes after tax and transfers take place, and can take on a variety of forms: Most often, the Gini coefficient measures the relationship between the cumulative income distribution and the cumulative population distribution, and the effects of redistribution can be measured by evaluating the difference in the pre-tax income and the post-tax, post-transfer levels of income inequality. Similar analyses use differences in the ratios of, for example, income at different percentiles of the distribution. Notice, however, that distributional measures fail to provide information about the well-being of low-income households: What do distributional measures imply about the ability of low-income households to meet basic needs? Thompson & Smeeding (2013), for example, combine their analysis of income inequality following the Great Recession, with a separate analysis of poverty rates—both parts necessary to provide a comprehensive picture of the implications of the financial crisis. Distributional measures, by focusing in the whole income distribution, therefore, may provide limited information about the effects of policies for those at the low end of national income distributions.

Behavioral Measures tie safety net program effectiveness to changes in, for example, changes in program caseload, or the labor force participation rates of (former) safety net program participants (see, e.g., Blank 2002). Probably because of the work requirements incorporated in the Personal Responsibility and Work Opportunity Act of 1996, analysis of the mid-1990s welfare reform has generally focused on behavioral measures, and often track

change in behavioral outcomes within one state. While behavioral measures have the advantage of tying program outcomes to specific program goals, there are at least two significant shortcomings: First, the relationship between behavioral outcomes and policy measures may be complicated by general economic conditions. Of the dramatic reduction in caseloads following welfare reform, for example, MLA Lichter & Jayakody (2002, 119) ask, “Is the decline in caseloads mostly due to the new welfare reform legislation or to a robust economy?” Second, the relationship between specific behaviors and economic well-being may be ambiguous. There is some evidence that suggests that while TANF programs increase employment among low-income women, for example, significant proportions of welfare-to-work program participants have maintained incomes below the official poverty line (see, e.g., Danziger, Heflin, Corcoran, Olthmans & Wang 2002, Bavier 2001, Schoeni & Blank 2000). Further, as Shaefer & Edin (2015) report, a focus on declining caseloads may obscure the ways in which TANF restrictions have forced increasing numbers of low-income households, particularly those with only tenuous connections to the labor market, into extreme poverty (see also Tach & Edin 2017). For these reasons—complex relationships between policy and behavior, and ambiguous relationships between behavior and economic well-being—behavioral measures may provide limited or misleading information about antipoverty policy effectiveness.

Finally, the most commonly used measures for the analysis of social policy are *threshold-based measures*. As suggested in the introduction to this analysis, threshold based measures examine the frequency and income distributions of individuals or households earning less than the amount necessary meet basic needs (Ray 2006). Of course, there is a large literature devoted to the identification of this threshold, and the development of alternatives (for a recent summary, see Meyer & Sullivan 2012).⁴ Nevertheless, empirical research on the US typically uses (sometimes, percentages of) the official poverty line, or a relative proportion (e.g., 65 percent) of the median income as the poverty threshold. Then, this class of measures is based estimates of the frequency or extent of deviations from the poverty threshold. In their original formulation, (Foster, Greer & Thorbecke 1984), for example, present the poverty measure,

$$P_{\gamma} = \frac{1}{n} \sum_{i=1}^q \left(\frac{\psi - y_i}{\psi} \right)^{\gamma} \quad (1)$$

Here, ψ is the poverty threshold, y_i is an individual’s income (ranked in increasing order of i), n is the total population, and q is the number of individuals with incomes less than ψ . The parameter $\gamma \geq 0$ has been characterized as a “poverty aversion” parameter: Specifically, a larger value of γ “gives greater emphasis to the poorest poor. As $[\gamma]$ becomes very large P_{γ} approaches a ‘Rawlsian’ measure which considers only the position of the poorest household.” Notice that P_0 gives the poverty rate, or the frequency with which individuals or households have incomes less than the poverty threshold. Further, P_1 provides what is

⁴Although we use the official poverty line here, we understand and agree with many of the criticisms that have been offered by Brady (2005), Citro & Michael (1995), and others.

referred to as the poverty “gap,” or the average deviation of incomes from the poverty threshold (expressed as percentage of the poverty line), among low-income individuals or households. Within this “FGT” framework, the impact of policy interventions is evaluated through the calculation of differences in P_γ usually for $\gamma = 0, 1, 2$. To be sure, the FGT class of measures offers important analytic advantages (e.g., additive subgroup decomposition), as reflected by substantial, cumulative research building from the initial analysis (for a discussion of this literature, see Foster, Greer & Thorbecke 2010). However, as suggested above, and as should be obvious from Eq. (1), the comparisons across units or policies will be complicated by the relationship between q and ψ . That is, because the number of low-income households (q) will vary with poverty threshold (ψ), in ways that likely vary across observations, rankings of observations over P_γ will also vary with the poverty threshold, especially when $\gamma = 0$ (i.e., poverty rates).⁵ More extensive comparisons between the poverty relief ratio, R , and the FGT poverty gap measure will be made below; this brief discussion serves as an introduction to one of the key challenges associated with more standard threshold-based measures, and an important justification for a new approach measuring the effectiveness of social policy.

The next section of this paper offers some descriptive analysis of the relationship between social transfers and market income that provides the foundation for our analysis of poverty relief, and provides some justification of dataprocessing decisions. Then, this paper will offer a formal presentation of the poverty relief ratio, that will include an explicit comparison to more standard measures.

2 Measuring Poverty Relief

Low-income households in the US benefit from a portfolio (or “patchwork,” see Moffitt & Scholz 2010) of safety net programs, often administered at several different levels of government. The composition of income support varies with income level, even among low-income households. Further, because participation for some programs limits eligibility for others, a focus on the antipoverty effectiveness of specific programs may be difficult to assess. Therefore, to understand the effectiveness of the American safety net, we examine the total amount of transfers to low-income households.⁶ Specifically, we use the relationship between total social transfers and total market income to derive summary statistics that characterize dimensions of safety net support in the US. This section provides an overview of these how these data are measured, and some basic descriptive analysis; Appendix A reports the more technical details.

Figure 1 uses the CPS Annual Social and Economic (March) Supplement (ASEC) – our primary data source, and the best resource for cross-state analysis of household income

⁵As Zheng (2000) reports, a major thread in the literature that builds from Foster, Greer & Thorbecke’s (1984) original analysis, devotes attention to “poverty-line orderings.”

⁶Of course, we recognize the challenges associated with measuring income, that are well-documented by Meyer & Sullivan (2003), for example. To the extent that low-income populations are likely to under-report both market income and income from social programs, we under-estimate overall levels of poverty relief (Wheaton 2007). Nevertheless, income remains the primary determinant of eligibility for safety net programs, and for this reason, we focus on differences in levels of support across income groups. Further, by focusing on income security, we also recognize that some other indicators of well-being (i.e., food insufficiency, material hardship, and social isolation), often used in sociology literature, can be addressed with more generous income support (e.g. Gundersen, Kreider & Pepper 2011)

dynamics – to estimate levels of social transfers, by program type, and market earnings. Here, we group social transfers into three program categories: social insurance, social assistance benefits, and refundable tax credits. (While low-income households may receive benefits in any of these categories from federal, state, or sometimes local programs, the CPS reports sum totals in various program categories.) Social insurance benefits include unemployment insurance and workers' compensation. Social assistance benefits include traditional welfare benefits, as well as near cash food and energy supplements. Finally, refundable tax credits include EITC and children's tax credits (CTC), which are calculated by the US Census Bureau on the basis of the information provided by respondents. The total working-aged household amounts of these social transfers – social insurance, social assistance, EITC, and CTC – are reported on the vertical axis of Figure 1. The horizontal axis reports working-aged household levels of market income, which includes wages and salaries, and income from self employment, farm, interest and dividends, rent, child support, alimony, veteran's benefits, pension and retirement benefits (excluding social security), and assistance from friends and family members.⁷

Notice, in Figure 1, three dimensions of variation across income levels: First, income groups vary in *total amount* of income support they receive, with those with no market earnings receiving the largest amounts. Second, income groups vary in the programs they participate in: By design, households without market earnings do not receive EITC+CTC support. Third, low-income households vary in the *composition* of support they receive from each program type: Compare, for example, the income groups at the very low end of the income distribution. Those with no market earnings receive substantially more support from social assistance programs, than do those households with slightly higher – but still very low – levels of market earnings. Here, we refer to the extent to which income support levels drop off with small differences in earnings as “relief falloff.”⁸ When estimates of relief falloff are very high, this indicates that safety net support drops dramatically with small increases in earnings, and increased earnings may be associated with less income, overall. (Of course, the extent to which this is true will depend on local labor market conditions.) As we suggest above, differences in “baseline relief,” or support provided to those with no market earnings, and relief falloff contribute in important, different ways to the overall effectiveness of safety net programs.⁹ Finally, what Figure 1 demonstrates most clearly is that attention to any one program, or even one type of program, would provide an incomplete, and potentially misleading impression of poverty relief in the US. A focus on the effects of EITC, for example, would ignore those households with no earnings. Similarly, an exclusive focus on

⁷While we used “as reported” household income amounts in this analysis, we recognize that these income amounts could also be estimated for equivalent-households – that is, in amounts adjusted for the composition of households. Appendix F reports the strong relationship between estimates of poverty relief for “as reported” and equivalent households (i.e., the cross-state relationship is characterized with correlation coefficient 0.94). The analysis presented here relies on “as reported” households, following the advice of an earlier reviewer for this manuscript: cross-state differences in household composition are likely small (confirmed by an analysis of cross-state variance in the size of households: differences in the size of average low-income households, are very small, and often indistinguishable), and taken into account in the amount of transfers.

⁸“Relief falloff” is similar to the “effective tax rate” concept used in the economic literature. Here, I use the alternate term to refer explicitly to the distribution of benefits. Also, we wish to “relief falloff” to distinguish the change in total income support, from “benefit reduction rates,” which typically measure the decline in support received from a specific program (e.g., Supplemental Nutrition Assistance Program, or SNAP Smeeding, Jolliffe & Tiehen 2013). Similarly, we use “baseline relief” to refer to the total amount of support no-income households receive from social assistance, social insurance, and tax credit programs.

⁹This coincides with the “benefit guarantee” concept used in economics.

TANF would miss the antipoverty relief the EITC provides to those who earn very little. Instead, we argue that comparative analysis of poverty relief ought to take a total income approach, that recognize the varying structure of low-income households' portfolios of support. The next section of this discussion uses the general relationship between social transfers and market income to derive a measure of poverty relief ratio, and then demonstrates how its component parameters provide new, useful insight into American safety programs.

In fact, the negative curvilinear relationship between social transfers and markets, that we observe in Figure 1, is quite general [see Appendix B and our earlier work]. We see similar relationships in Figure 2, for example, which reports the relationships between social transfers and market earnings in California, Florida, and Texas. In each panel, each data point represents one percent of the 2010–2014 pooled state sample; the error bars denote the interquartile range of social transfers for each group.¹⁰ The diagonal, dashed line in each panel reports the amount of income needed at each income level to meet the poverty threshold, here, the 2014 official US poverty line (for a family of four, used here for consistency with later analysis), of \$19,790.

There are, however, important differences in the relationships between social transfers and market income for these states: California provides generally higher levels of baseline relief to those with no market income (almost seven thousand dollars), than does Florida or Texas (less than five thousand). Second, the rate at which benefits falloff is slightly lower in Texas, than in the other two states. (Compare, for example, where the curved line intersects the dashed line.) Finally, although we won't consider these differences extensively here, notice that the states differ in levels of support provided to those with relatively high incomes, at the right hand side of each panel. (This, of course, is not surprising: Most of the income support received by those in households earning more than twenty thousand is provided through social insurance programs, which are often administered by the states. In later analysis, we will use state unemployment benefits to validate our overall measure of poverty relief).

Note that the solid line in Figure 2 fits the relationship between market income and social transfers in each state quite well. This solid line reports predicted values from the following non-linear expression:

$$ST_{ij} = \alpha_j + \beta_1 \exp(\beta_2 MI_{ij}) + e_{ij}. \quad (2)$$

Here, ST_{ij} denotes social transfer amounts, and MI_{ij} denotes market income, for individuals $i = 1 \dots n$ in states $j = 1 \dots J$. The parameters $\alpha_j > 0$, $\beta_1 > 0$, and $\beta_2 < 0$ describe the bi-variate relationship within each state, and e_{ij} is a stochastic residual term.¹¹ As suggested above, the dashed line in Figure 2

¹⁰Notice that this range almost always includes zero: Even very low-income households may be ineligible for transfers, or may under-report the amount of support they receive.

¹¹This function is identified with the restriction that β_1 and β_2 do not equal zero.

$$ST_{ij} = \psi - MI_{ij}, \quad (3)$$

reports the amount of income support that would bring all low-income families up to a poverty threshold, ψ , and will be important to our analysis later in this discussion.

One important advantage of using Eq. (2) to characterize the relationship between market income and social transfers is that the parameters have accessible, substantive interpretations. Notice that, when $\beta_{2j} < 0$,¹² individuals who have no market income receive social transfers in the amount of $\alpha_j + \beta_{1j}$ —our measure of “baseline relief”. Similarly, for very high levels of MI_{ij} , ST_{ij} is expected to take on the value α_j . In the US, this level corresponds to average social insurance benefits; outside the US, this amount might include universal, non-means-tested non-contributory benefits like Germany’s *kindergeld*. Finally, the expression $\beta_{1j} \times (1 - \exp(\beta_{2j}))$ can be used to estimate the rate at which benefit levels falloff, with increased market earnings, or the amount income support decreases with an increase from no market earnings to \$1000. The parameters α_j , β_{1j} , and β_{2j} , therefore, jointly describe income support provided through a specific state’s safety net programs, and can be used as the basis for a comparison of poverty relief within a society over time, or across societies more generally.

Figure 3 plots these estimates of baseline relief ($\alpha_j + \beta_{1j}$) against relief falloff ($\beta_{1j}(1 - \exp(\beta_{2j}))$)—for the US states, for pooled 2010–2014 state samples. The vertical axis reports the average amount of support provided to those with no market earnings, in each state. The horizontal axis reports estimates relief falloff, specifically the amount that income support will decrease, with an increase of \$1000 in earnings. For example, households earning \$1,000 in California can expect to receive about \$150 less in income support, than households with no market income. Differences in income support for households with no market income, and those with very little market income increase along the horizontal axis: As we observed above, although Texas provides considerably less baseline relief, the amount of relief falloff is also low, relative to relief falloff in California.¹³

The relationship between baseline relief and relief falloff, therefore, can be used to classify state safety programs: Those states in the upper left quadrant, like Connecticut, provide relatively high levels of baseline support, with comparatively rates of low rates of relief falloff. Those state in the upper right quadrant, like California and Washington, also provide high levels of baseline relief, but the rate at which benefits falloff is quite high. States in the lower quadrants provide more limited baseline relief, but those on the right (e.g., Louisiana) have relatively high relief falloff, compared to those in the lower left quadrant (e.g., Texas).

Of course, a cross-state or time series comparison based on only one of the dimensions in Figure 3 would be an incomplete, and potentially misleading, measure of poverty relief in the US states. There are many examples of states with similar levels of baseline relief, for

¹²This restriction ensures that the parameters are identified.

¹³Note that our concept of relief falloff reports how *benefit* levels change with increases in earnings; a full discussion of how heterogenous labor markets might condition an individual’s participation incentives is beyond the scope of this analysis.

example, but quite different rates of relief falloff.¹⁴ Nevertheless, we can use the relationship between market income and social transfers to develop a summary measure of poverty relief. Recall, the dashed line in Figure 2, Eq. (3), reports the amount of income support that would bring all low-income families up to a poverty threshold, ψ .¹⁵ Then, the ratio of the area under the curve defined by the observed relationship between market income and social transfers (Eq. 2), to the triangular area defined by Eq. (3) provides an estimate of the amount of income support that is provided, relative to the total amount that would provide all low-income households with sufficient income to meet basic needs.¹⁶ The poverty relief ratio $\mathcal{R}$, then, can be estimated according to the following expression:

$$\mathcal{R} = \frac{\int_0^{\tau} (\alpha + \beta_1 \cdot \exp(\beta_2 \cdot MI)) \partial MI + \int_{\tau}^{\psi} (\psi - MI) \partial MI}{\int_0^{\psi} (\psi - MI) \partial MI} \quad (4)$$

Here, τ reports the point of intersection for Eqs. (2) and (3).¹⁷ After integrating over the region of 0 to ψ , it can be shown that the poverty relief ratio $\mathcal{R}$ increases with baseline relief, and as relief falloff decreases. Specifically,

$$\frac{\partial \mathcal{R}}{\partial \alpha}, \frac{\partial \mathcal{R}}{\partial \beta_1} \text{ and } \frac{\partial \mathcal{R}}{\partial \beta_2} > 0 \quad (5)$$

Thus, for fixed ψ , the poverty relief ratio $\mathcal{R}$ provides a useful summary of safety net program support, with a meaningful substantive interpretation: $\mathcal{R}$ reports the average percentage of income support received by low-income households, of the support needed to have a total income equal to a specified poverty threshold.¹⁸

To see how the poverty relief ratio is different from more standard poverty rate and poverty gap measures, compare Eq. (1) to Eq. (4). Foster, Greer & Thorbecke (2010) recall the following example, given by Morduch (1999, 99), that helpfully demonstrates an important difference between the poverty relief ratio, and more commonly used FGT measures:

¹⁴Compare, for example, Pennsylvania, Massachusetts, California and Oregon. In each case, these states provide approximately \$7,000 in baseline relief. However, relief falloff is estimated to be \$202, in Pennsylvania, \$161 in Massachusetts, \$147 in California, and \$124 in Oregon. Connecticut and South Carolina also provide similar levels of baseline relief (slightly more than the median, about \$5,650), but different levels of relief falloff (\$90 in Connecticut, and \$170 in South Carolina).

¹⁵Here, we follow the Census Bureau and use a single, national poverty threshold. Of course, cost-of-living adjustments could be incorporated in varying values of ψ .

¹⁶The relationship between social transfers and market income is reminiscent of Jenkins & Lambert's (1997) "three I's of poverty" curve, in which the cumulative sum of poverty gaps is plotted against the cumulative population share. In their analysis, Jenkins & Lambert draw attention to the incidence, inequality, and intensity (magnitude) of poverty gaps. Although Jenkins & Lambert do not anticipate the use of TIP curves for the evaluation of income support programs – instead, they consider cross-sectional and temporal comparisons – Ziliak (2006) shows how TIP curves might incorporate social transfers, and facilitate analysis of changes in income support programs. This analysis departs from this important earlier work by estimating the relationship between social transfers and market income in a flexible but appropriate parameterized individual-level model, and uses the parameters as the basis of a summary measure: $\mathcal{R}$ gives the average intensity of the post-transfer poverty gap, as a proportion of the poverty threshold.

¹⁷The parameter τ was identified by searching for the value that equated Eqs. (2) and (3).

¹⁸Of course, this measure does not provide an estimate of the efficiency of social spending: It does not, for example, estimate the proportion of total funds targeted to those households below the poverty threshold. Rather, for a given poverty threshold, $\mathcal{R}$ simply compares the amount of transfers provided to households with incomes below that threshold, to the total amount need so that all households have gross incomes equal to that threshold. Note that $\mathcal{R}$ exceed one if a (very low) threshold is chosen such that households receive transfers in excess of the amount needed to meet that threshold.

Suppose, for example, a social program is able to target only relatively well-off low-income households (but not sufficiently to increase their incomes above the poverty line), while another provides benefits (in the same amount) to the very poor. Note that the poverty rate measure, P_0 would be unable to distinguish between these policies: the number of low-income households remains unchanged. Further, the poverty gap measure (P_1) would report that the policies are equally effective. (Only for $\gamma > 1$ would differences in the implications of the policy be apparent.) Calculating the poverty relief ratio, however, draws attention to the important differences in the distribution of benefits: In the first case, the rate of relief falloff would likely be reduced; the second case would likely generate higher estimates of baseline relief. (The second program would be located higher, on both dimensions presented in Figure 3.) Overall levels of poverty relief are also likely to be higher in the second case.

Figure 4 reports estimates of the poverty relief ratio for each state, with states grouped by quartile. (Appendix B reports estimates of the parameters α, β_1, β_2 , and τ for each state, as well as estimates of the poverty relief ratio, $\mathcal{R}$; ψ is fixed at \$19,790, the 2014 official poverty line). On average, states provide about 46 percent of the poverty relief needed during this period, with some evidence of regional variation: Western states are over-represented in the highest quartile; all but two Southern states provided below-the-median levels of poverty relief.

Notice, as well, that the poverty relief ratio $\mathcal{R}$ essentially orders the states as they appear in Figure 3, but distinguishes between states that offer similar levels of baseline benefits, but have different levels of relief falloff: For example, notice that in Figure 3, Connecticut and Louisiana provide approximately equal levels of baseline relief (about the median level), but rates of relief falloff are quite different in these states. Estimates of $\mathcal{R}$ take these differences into account, and report higher values for those states (i.e., in this case, Connecticut) with lower rates of relief falloff. As Appendix C reports, average levels of poverty relief are estimated to be about 44 percent of the federal poverty line in Connecticut, and 38 percent in Louisiana, a difference that represents approximately 23 percent of the entire range of $\mathcal{R}$ values. Therefore, $\mathcal{R}$ provides an effective summary statistic for the two key dimensions of safety net programs, baseline relief and relief falloff, and provides a substantively meaningful estimate of poverty relief in each state.

3 The Poverty Relief Ratio and Policy

Does $\mathcal{R}$ reflect meaning differences (or changes) in safety net policy? Of course, there should be some evidence of a positive relationship between our poverty relief ratio, $\mathcal{R}$, and more generous safety net policy intentions. However, because $\mathcal{R}$ captures the multidimensionality of income support for low-income households, it likely correlates imperfectly with any given measure of policy.

Indeed, as we see in Figure 5, there is evidence that $\mathcal{R}$ is positively correlated with both state average unemployment benefits, and with maximum TANF benefits. For example, those states that we observe with the highest levels of unemployment benefits typically are in the highest quartile of the $\mathcal{R}$ distribution. Similarly, not surprisingly, states with relatively

high maximum TANF benefit levels are typically associated with high estimates of poverty relief, although there is more variance in this bivariate relationship.

Note, as Table 2 reports, unemployment benefits and TANF benefits contribute independently to cross-state variation in poverty relief ratios. Even with the inclusion of TANF benefits, an increase in \$100 in average monthly unemployment benefits is associated with about a 2 percent increase in poverty relief. Although estimated with more variance, the coefficients in Table 2 suggest that an \$100 increase in monthly TANF benefits would be associated with about a 1 percent increase in poverty relief. Therefore, there is some evidence to suggest that Finally, while a full analysis of changes in American social policy is beyond the scope of this analysis, that national estimates for $\mathcal{R}$ track major policy changes provides further evidence of the validity of our measure: Figure 6 reports estimates of the poverty relief ratio (top panel), and baseline relief (middle panel) and relief falloff (bottom panel), for the entire US over the 1991 to 2013 period. At the end of this time series, only about 34 percent of the relief needed to bring an average low-income household's income to the official poverty line is provided. While important shifts in safety net policy have changed levels of income support over this period, we observe a steady erosion of benefits following the Clinton-era welfare reform, with brief interruptions in the early 2000s, and following the 2008 financial crisis. The middle panel demonstrates that most of this erosion comes from a dramatic decline in baseline relief – that is, support for those in deep poverty. The decline and leveling of relief falloff (seen in the bottom panel) reflects the expansion of EITC and increase in support for low-income working families.

Importantly, each major shift in policy corresponds to expected changes in $\mathcal{R}$: For example, the initial increase in poverty relief that we observe in the top panel resulted from the Bush and then the Clinton administration's expansions of EITC (instituted by the Omnibus Budget Reconciliation Acts of 1990 and 1993), which dramatically decreased rates of relief falloff, as we observe in the bottom panel. Then, following the implementation of mid-1990s major welfare reform (Personal Responsibility and Work Opportunity Act, PRWOA), we observe a significant decrease in baseline relief, and a corresponding decline in overall poverty relief. Although we observe some safety net expansion following the Bush administration's post-9/11 economic stimulus, levels of poverty relief remained steady until the major expansion implemented by President Obama in the American Recovery and Reinvestment Act of 2009 (ARRA), which temporarily expanded federal unemployment benefits, near-cash food and energy benefits.

Earlier in this discussion, we suggested that one important advantage of $\mathcal{R}$, compared to the more standard threshold-based measures, is that it generally preserves the rank order of observations, across different poverty thresholds (here, values of ψ). This feature is important because it allows the effects of policy to be examined in a consistent and reliable way. Before considering the implications of this analysis, here, we briefly demonstrate how, with other threshold-based measures, rank order varies with the poverty threshold, and how this might affect understanding of the impact of various policy measures.

The right panel of Figure 7 plots estimates of $\mathcal{R}$, for each state against estimates using the 50 percent, 150 percent, and 200 percent of the threshold original threshold, against the

original poverty threshold (i.e., the original poverty line). For comparison, the left and middle panels of Figure 7 repeats this analysis, with the same data, but using the more common proportional reduction in poverty rate and gap measures (the most commonly used measures of social policy outcomes). The advantage of $\mathcal{R}$ over the poverty rate and gap measures is especially clear when we compare relative ranking of North Dakota for each measure and threshold: When the effectiveness of safety net programs is measured using the poverty reduction rate measure, North Dakota ranks second, second, tenth, and fourth, for threshold equals 50%, 100%, 150%, and 200% of the official poverty line, respectively, and tenth, third, fifth, and second, for the poverty gap measures. Regardless of threshold, however, North Dakota always ranks first (i.e., least effective) when $\mathcal{R}$ is used, instead. More generally, spearman rank order correlation coefficients range from 0.38 to 0.52 for the poverty reduction rate measures estimated using different thresholds. Rankings using the poverty gap measure are more stable, with spearman rank order correlation coefficients ranging from 0.58 to 0.79, but still less than similar coefficients estimated for $\mathcal{R}$, which exceed 0.96, across all of the various thresholds.

Table 3 demonstrates the importance of rank order stability with a simple example, and reports the estimated relationship between the poverty relief ratio, proportional reduction in the poverty rates and gaps, and maximum TANF benefits. We might reasonably expect that, as a proximate measure of the generosity of transfers in each state, maximum TANF benefits will be strongly and consistently related to levels of poverty relief, overall. In fact, this is the case when the poverty relief ratio is used as a measure of the effectiveness of anti-poverty policy. However, when alternate threshold based measures of poverty reduction are used, instead, this expected relationship is estimated with considerably more variance, that because of field conventions dictating minimally-accepted t-statistics (i.e., the ratio of coefficients to standards ought to be at least 1.96 for a coefficient to be considered “statistically significant”), would lead to conflicting substantive conclusions. (Notice, for example, that when the official poverty line is used, the generosity of TANF benefits has an ambiguous effect on the reduction of poverty rates or gaps!) In this case, when the effectiveness of anti-poverty policy is measured using existing measures of poverty reduction, conclusions about whether the size of TANF benefits matters for policy effectiveness depends on which poverty threshold is used.

4 Implications

In this discussion, we have offered a measure of poverty relief that offers several important advantages over standard measures used in the literature. Specifically, this measure uses a total income approach that readily accommodates the portfolios of support on which low-income households rely. In combination with a poverty threshold, we have shown that the parameters that describe the relationship between market income and social transfers provide a useful way to distinguish social policy, and can be used to generate a ratio estimate that reports the proportion of income support that is provided, relative to the account of support needed to raise all poor families’ incomes to a specified threshold. Thus, the poverty relief ratio incorporates explicit policy goals.

We anticipate three sets of concerns about the general utility of $\mathcal{R}$:

First, some readers may question the utility of a parameterized model of poverty relief. Because the model generally fits the data well and can be easily estimated, we believe that there is little information lost through its estimation. Further, the parameters α , β_1 , and β_2 provide important, substantively meaningful insight into the nature of poverty relief and, as we have shown, can be used as the basis of comparative analysis. Finally, as suggested above, the non-linear set-up used here can easily accommodate a hierarchical model, in which levels of baseline relief, or relief falloff are predicted by political and economic characteristics of each state.

Second, other readers may point out that $\mathcal{R}$ provides no information about the rate of poverty. This is undoubtedly true: we focus instead on levels of income support, and the distribution of benefits among low-income households.

Finally, like other measures of safety net program effectiveness that rely on individual-level surveys (i.e., the distributional and poverty reduction rate measures), $\mathcal{R}$ is susceptible to the bias introduced by the under-reporting of benefits, and limited by available survey measures. To the extent that especially those with no market income, understate the amount of support they receive, $\mathcal{R}$ may underestimate levels of poverty relief. Wheaton (2007) suggests that the CPS data may be especially problematic, although other income and labor force surveys also under-reports safety net program participation. To provide some confidence in the substantive interpretation of the results presented here, Appendix D replicates the time series analysis of national trends in poverty relief using SIPP data, and as closely as possible. (SIPP data are not well-suited for cross-state comparisons.) While there are some differences in the annual estimates of $\mathcal{R}$, for example, they are very small, and the bias introduced by the under-reporting of benefits does not complicate the substantive interpretation of the over-time analyses presented here. Readers may also be interested in the relative relief provided by federal and state programs; to the extent that surveys measure support for different programs, the poverty relief measure can facilitate this sort of analysis. This new measure of poverty relief, therefore, and its component parameters, provide a new way to characterize and evaluate safety net programs in the US. Here, we find substantial cross-state variation in the effectiveness of safety net programs: Some states, like Alabama and Wyoming, provide only about a third of the income support needed to raise incomes up to the poverty threshold. Other states, including Washington and Massachusetts provide about 60 percent of this needed income support. While most of the cross-state variation in poverty relief is attributable to differences in baseline relief (a bivariate regression generates estimates of $R^2 = 0.98$), $\mathcal{R}$ usefully distinguishes between states with different rates of relief falloff. In tracking federal policy from 1991 to 2013, we find that even at its most expansive level during this period, the American safety net provided only about half of the support required to meet basic needs. The declining levels of support to those with no market income (our baseline relief) is especially concerning. To the extent that the official poverty line underestimates the amount needed, and because our estimates here includes near-cash transfers, as well as cash transfers, this analysis presents a particularly dire impression of the American social safety net.

What sets this analysis apart from existing work, importantly, is a strategy for evaluating the effectiveness of different anti-poverty policies, in a way that is invariant to how poverty is

defined. The poverty relief ratio, therefore, provides both a reliable means of examining the impact of different policies, as well a measurement that can be used for comparison across quite different systems.

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Appendix A.: Data Processing Notes

- All income amounts are reported in thousands of 2016 US dollars.
- In an effort to generate the most inclusive measure of poverty relief, we follow the example of Smeeding, Jolliffe & Tiehen (2013), and treat Supplemental Nutrition Assistance Program benefits (i.e., food stamps), and other near-cash benefits (energy assistance), as income support.
- We restrict the analysis to households in which the head of the household is over the age of 25, and under the age of 60, to avoid the inclusion of households whose low levels of market income may not reflect their true levels of resources (i.e., students, seniors). We also exclude social security income, SSI, disability insurance, and education assistance.
- We use reported, simulated estimates of EITC and CTC payments.
- The parameters α , β_1 , and β_2 are estimated using Stata SE 12.1's `n1` program with starting values of $\alpha = 1$, $\beta_1 = 2$, and $\beta_2 = -.1$. The parameter τ is estimated using a line-search strategy. Standard errors for τ and $\mathcal{R}$ are calculated from simulated draws, based on the parameters and variances of α , β_1 , and β_2 .

Appendix B.: The General Relationship between Market Income and Social Transfers

NOTE. In the following panels, each data point represents one percent of the pooled 2010-2014 state sample. Error bars report the interquartile distribution at each income level. All currency amounts are reported in thousands of 2016 US dollars. The solid line reports predicted values for Eq. (2). The dashed line reports predicted values for Eq. (3).

Appendix C.: State Level Analysis

Table 4:

Estimates of α , β_1 , β_2 , τ , and $\mathcal{R}$

	N	α	β_1	β_2	τ	$\mathcal{R}$
Alabama	2,881	0.6755 (0.1502)	3.9319 (0.2204)	-0.0260 (0.0035)	16.5003 (0.1044)	0.3540 (0.0000)
Alaska	3,041	0.6040 (0.1956)	4.4973 (0.2607)	-0.0184 (0.0027)	15.7673 (0.1488)	0.4044 (0.0001)
Arizona	3,199	0.4150 (0.1581)	4.9993 (0.2143)	-0.0224 (0.0024)	15.8168 (0.1093)	0.4138 (0.0000)
Arkansas	2,581	0.3573 (0.2200)	4.3021 (0.2327)	-0.0187 (0.0027)	16.2018 (0.1078)	0.3694 (0.0000)
California	22,557	0.7857 (0.0663)	6.1945 (0.1157)	-0.0241 (0.0010)	14.5895 (0.0681)	0.5168 (0.0000)
Colorado	5,402	0.6364 (0.1013)	5.1439 (0.2103)	-0.0258 (0.0021)	15.6654 (0.1096)	0.4330 (0.0000)
Connecticut	5,132	0.4958 (0.1428)	5.1566 (0.2261)	-0.0175 (0.0018)	15.2967 (0.1389)	0.4437 (0.0001)
Delaware	3,554	0.5028 (0.1519)	5.2506 (0.2229)	-0.0217 (0.0022)	15.4789 (0.1215)	0.4398 (0.0001)
Florida	9,904	0.4264 (0.0797)	4.4184 (0.1255)	-0.0249 (0.0016)	16.3747 (0.0658)	0.3688 (0.0000)
Georgia	5,653	0.6250 (0.0988)	5.0683 (0.1677)	-0.0279 (0.0020)	15.8585 (0.0857)	0.4217 (0.0000)
Hawaii	3,463	0.7229 (0.1773)	6.9535 (0.3493)	-0.0250 (0.0026)	14.1322 (0.1949)	0.5569 (0.0001)
Idaho	2,766	0.5384 (0.2462)	5.7189 (0.2968)	-0.0198 (0.0026)	14.9416 (0.1601)	0.4789 (0.0001)
Illinois	7,642	0.7229 (0.1048)	5.5421 (0.1817)	-0.0246 (0.0018)	15.2032 (0.0972)	0.4687 (0.0000)
Indiana	3,675	0.7098 (0.1521)	4.9282 (0.2230)	-0.0245 (0.0026)	15.6723 (0.1133)	0.4276 (0.0001)
Iowa	4,256	0.5571 (0.1559)	4.7614 (0.2104)	-0.0202 (0.0022)	15.7139 (0.1173)	0.4145 (0.0001)
Kansas	3,358	0.5471 (0.1855)	4.4922 (0.2441)	-0.0202 (0.0027)	15.9349 (0.1292)	0.3951 (0.0001)
Kentucky	3,298	0.6334 (0.1735)	4.3516 (0.2174)	-0.0229 (0.0029)	16.0928 (0.1060)	0.3860 (0.0000)
Louisiana	2,870	0.6054 (0.1241)	4.7054 (0.2226)	-0.0307 (0.0032)	16.2746 (0.1031)	0.3898 (0.0000)
Maine	3,545	0.5357 (0.1647)	5.8336 (0.2539)	-0.0233 (0.0023)	15.0981 (0.1392)	0.4767 (0.0001)
Maryland	5,617	0.5126 (0.1049)	4.7374 (0.2064)	-0.0214 (0.0019)	15.8545 (0.1177)	0.4062 (0.0001)
Massachusetts	3,552	0.8317 (0.1276)	6.0258 (0.3126)	-0.0272 (0.0028)	14.8859 (0.1694)	0.5014 (0.0001)
Michigan	5,268	0.9214 (0.1086)	5.7966 (0.2084)	-0.0301 (0.0023)	15.1386 (0.1108)	0.4865 (0.0001)
Minnesota	5,560	0.5435 (0.1272)	4.7811 (0.1894)	-0.0193 (0.0018)	15.6610 (0.1127)	0.4170 (0.0001)
Mississippi	2,417	0.4971 (0.2272)	4.1510 (0.2491)	-0.0210 (0.0033)	16.2892 (0.1123)	0.3650 (0.0001)
Missouri	3,741	0.5642 (0.1332)	4.1491 (0.1857)	-0.0214 (0.0023)	16.2460 (0.0991)	0.3696 (0.0000)

	N	α	β_1	β_2	τ	$\mathcal{R}$
Montana	2,390	0.5254 (0.2208)	3.9018 (0.2540)	-0.0194 (0.0033)	16.3710 (0.1222)	0.3532 (0.0001)
Nebraska	3,629	0.8885 (0.0882)	4.5785 (0.2503)	-0.0335 (0.0032)	16.1872 (0.1107)	0.3987 (0.0000)
Nevada	3,772	0.9611 (0.1444)	5.8230 (0.2774)	-0.0314 (0.0031)	15.1588 (0.1371)	0.4878 (0.0001)
New Hampshire	4,475	0.2066 (0.1914)	3.9135 (0.2194)	-0.0134 (0.0020)	16.3896 (0.1368)	0.3408 (0.0001)
New Jersey	4,788	1.1782 (0.1237)	6.0678 (0.3245)	-0.0303 (0.0030)	14.6742 (0.1713)	0.5221 (0.0001)
New Mexico	2,555	0.5772 (0.2163)	4.1854 (0.2553)	-0.0203 (0.0032)	16.1433 (0.1208)	0.3758 (0.0001)
New York	10,212	0.6615 (0.0905)	5.1450 (0.1497)	-0.0242 (0.0016)	15.5424 (0.0832)	0.4390 (0.0000)
North Carolina	4,890	0.5976 (0.1086)	5.0892 (0.1929)	-0.0283 (0.0023)	15.8906 (0.0935)	0.4201 (0.0000)
North Dakota	3,195	0.5313 (0.1516)	2.8481 (0.1877)	-0.0173 (0.0029)	17.0854 (0.1024)	0.2802 (0.0000)
Ohio	6,100	0.5236 (0.1416)	5.0279 (0.1837)	-0.0210 (0.0019)	15.5863 (0.0980)	0.4282 (0.0000)
Oklahoma	3,058	0.4032 (0.1759)	4.2722 (0.2146)	-0.0202 (0.0026)	16.2567 (0.1081)	0.3677 (0.0000)
Oregon	3,326	0.3368 (0.2414)	6.6717 (0.2932)	-0.0188 (0.0021)	14.3000 (0.1669)	0.5288 (0.0001)
Pennsylvania	6,830	1.0909 (0.0888)	5.8957 (0.2225)	-0.0349 (0.0025)	15.1747 (0.1149)	0.4936 (0.0001)
Rhode Island	3,554	1.0728 (0.1543)	6.2746 (0.3163)	-0.0282 (0.0029)	14.4951 (0.1700)	0.5323 (0.0001)
South Carolina	3,189	0.7247 (0.1193)	4.9225 (0.2357)	-0.0353 (0.0035)	16.2349 (0.1085)	0.4031 (0.0001)
South Dakota	3,428	0.7914 (0.1168)	3.8131 (0.2009)	-0.0256 (0.0029)	16.4441 (0.1007)	0.3565 (0.0000)
Tennessee	3,335	0.3321 (0.2227)	4.3413 (0.2442)	-0.0188 (0.0028)	16.2040 (0.1162)	0.3699 (0.0001)
Texas	14,736	0.3660 (0.0872)	4.7249 (0.1064)	-0.0188 (0.0011)	15.8687 (0.0612)	0.3999 (0.0000)
Utah	2,982	0.8269 (0.1729)	5.5248 (0.2745)	-0.0209 (0.0023)	14.8609 (0.1618)	0.4852 (0.0001)
Vermont	3,131	0.5190 (0.1673)	5.4015 (0.2709)	-0.0230 (0.0026)	15.4289 (0.1496)	0.4478 (0.0001)
Virginia	5,257	0.5043 (0.0797)	4.0800 (0.1634)	-0.0227 (0.0018)	16.4257 (0.0905)	0.3568 (0.0000)
Washington	4,261	0.7645 (0.1634)	6.7686 (0.2990)	-0.0237 (0.0022)	14.1312 (0.1672)	0.5522 (0.0001)
West Virginia	2,530	0.5434 (0.2667)	4.1802 (0.2816)	-0.0183 (0.0032)	16.0740 (0.1311)	0.3772 (0.0001)
Wisconsin	4,467	0.5867 (0.1413)	5.2586 (0.2129)	-0.0218 (0.0020)	15.3866 (0.1194)	0.4467 (0.0001)
Wyoming	3,251	0.4427 (0.2084)	3.6522 (0.2286)	-0.0163 (0.0027)	16.5002 (0.1243)	0.3348 (0.0001)

NOTE. This Table reports estimated parameters for pooled 2010–2014 state samples, for Eq. (2). See Appendix A for more information.

Appendix D.: SIPP Replication

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Figure 8:

National poverty relief (SIPP; 1991–2014)

NOTE. This Figure replicates Figure 6, but uses Survey of Income and Program Participation data, instead (the original CPS estimates are shown in grey). Estimates are weighted using calendar year weights. See Appendix A for other data-processing notes.

Appendix E.: Replication with Equivalent Households

Figure 9:

Poverty Relief in Equivalent Households

NOTE. This Figure offers a comparison of estimates of the poverty relief ratio, estimated “as reported” to estimates of poverty relief for equivalent households. To generate equivalent household estimates, market income and social transfer amounts are divided by the squareroot of the number of people in each household.

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Figure 1:

Social transfers, by type and level of market earnings (2010–2014)

NOTE. Figure 1 reports the relationship between social transfers by type and market income for the United States (2010–2014). Each bar represents the mean amount of social transfers for one percent of the pooled 2010–2014 sample. The main text provides details of program categories. All currency amounts are reported in thousands of 2014 US dollars.

Figure 2:
Social transfers, by market earnings, and states (2010–2014)

NOTE. Figure 2 reports the relationship between social transfers by type and market income for California, New York, and Texas (2010–2014). Each data point represents one percent of the pooled 2010–2014 sample; error bars report the interquartile distribution at each income level. All currency amounts are reported in thousands of 2016 US dollars. The solid line reports predicted values for Eq. (2). The dashed line reports predicted values for Eq. (3).

Figure 3:

Baseline relief and relief falloff, by state (2010–2014)

NOTE. Figure 3 plots estimates of baseline relief (vertical axis) – $\alpha_j + \beta_{1j}$ – against relief falloff (horizontal axis) – $\beta_{1j} \times (1 - \exp(\beta_{2j}))$ – for the US states, for pooled 2009–2013 state samples. Parameters are estimated for Eq. (2). All currency amounts are reported in 2016 US dollars, for households. The solid lines report median values on each dimensions (2). Error bars report 95 percent confidence intervals.

Figure 4:

Poverty relief, by state (2010–2014)

NOTE. Figure 4 reports estimates of the poverty relief ratio for each state, with states grouped by quartile. See the appendices for estimation details.

Figure 5:

Poverty relief and policy (2010–2014)

NOTE. Figure 5 plots estimates of the poverty relief ratio for each state, against measure of the average monthly unemployment insurance benefit (for 2009–2013, left panel) and maximum TANF benefit (for 2009–2013, right panel). Solid grey lines denote the median values on each dimension, and the darker line reports predicted values from bivariate linear regression models (see Table 2).

SOURCES. UI: *Monthly Program and Financial Data: SUMMARY DATA FOR STATE PROGRAMS, BY STATE, REPORT PERIOD FOR 01/2012* (2008–2012). TANF: *Welfare Rules Database* (2008–2011).

Figure 6:

National poverty relief (1988–2014)

Figure 6 plots national estimates of the poverty relief ratio, baseline relief, and relief falloff, for the 1988–2012 period.

Figure 7:

Rank Order with Varying Poverty Thresholds

NOTE. Figure 7 compares proportional reduction in poverty rate and gap estimates, calculated for different poverty thresholds (50, 150, and 200 percent of the official poverty line), against estimates of $\mathcal{R}$, calculated for the same thresholds.

Table 1:

Standard Measures of Poverty Relief in the Social Science Literature (2000–2012)

Type of Measure	Frequency
Fiscal Measures	11
Distributional Measures	54
Behavioral Measures	56
Threshold-Based Measures	81
TOTAL	202

NOTE. This Table reports the type of measure used in the 68 articles assessing outcomes of social policy, published in the social sciences between 2000 and 2012, and on JSTOR.

Table 2:

Poverty relief and policy (2010–2014)

	(1)	(2)
Average Monthly UI Amount	0.0131 (0.0040)	
Maximum Monthly TANF		0.0134 (0.0056)
Intercept	26.5439 (4.8375)	36.5722 (2.5273)
N	50	50
Adjusted R^2	0.1715	0.0876

NOTE. This Table reports OLS regression estimates of the relationship between poverty relief ($\mathcal{R} \times 100$) and average monthly unemployment insurance and maximum TANF benefits. Standard errors are reported in parentheses.

SOURCES. UI: *Monthly Program and Financial Data: SUMMARY DATA FOR STATE PROGRAMS, BY STATE, REPORT PERIOD FOR 01/2012* (2008–2012). TANF: *Welfare Rules Database* (2008–2011).

Table 3:

Regression Analysis Using Different Poverty Thresholds

	Percent of Poverty Line			
	50%	100%	150%	200%
<i>(A) Poverty Relief Ratio ($\mathcal{R} \times 100$)</i>				
Maximum Monthly TANF Benefit (in \$1000s)	21.328 [*] (10.680)	11.687 [*] (5.235)	8.462 [*] (3.383)	6.361 [*] (2.341)
Intercept	73.2727 ^{**} (4.936)	37.349 [*] (2.420)	23.418 ^{**} (1.564)	16.279 ^{**} (1.082)
<i>(B) Proportional Reduction in Poverty Rate ($\times 100$)</i>				
Maximum Monthly TANF Benefit (in \$1000s)	6.585 (4.109)	3.619 (3.443)	5.681 [*] (5.466)	6.133 ^{**} (1.546)
Intercept	34.548 ^{**} (1.899)	21.338 ^{**} (1.754)	12.750 ^{**} (1.044)	5.466 ^{**} (0.713)
<i>(C) Proportional Reduction in Poverty Gap ($\times 100$)</i>				
Maximum Monthly TANF Benefit (in \$1000s)	1.783 (4.808)	5.542 (3.499)	5.665 [*] (2.763)	5.598 ^{**} (2.154)
Intercept	48.262 ^{**} (4.808)	31.603 ^{**} (1.754)	23.144 ^{**} (1.277)	16.552 ^{**} (0.996)

^{**} NOTE. $p < 0.01$;

^{*} $p < 0.05$.

This Table reports the results of a simple experiment, in which several versions of the poverty relief ratio and the proportional reduction in poverty rates and gaps, estimated using several poverty thresholds, are regressed on maximum monthly TANF benefits.