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Applying Augmented Survey Data to Produce More Accurate, Precise, and Internationally Comparable Estimates of Poverty within the 50 United States

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Applying Augmented Survey Data to Produce More Accurate, Precise, and Internationally Comparable Estimates of Poverty within the 50 United States

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Abstract: This paper introduces a series of augmentations to the Current Population Survey to allow for more accurate estimations of American poverty outcomes and a more fruitful integration of the U.S. into comparative research. The augmentations address three shortcomings in recent poverty research, including (1) severe measurement error in the data from which U.S. poverty estimates are most often derived, (2) the conceptualizations of poverty adopted within U.S.-centric research, and (3) the masking of substantial cross-state variation in poverty outcomes across the 50 United States. Specifically, the augmentations, made public for future researchers to apply, partially correct for the underreporting of four means-tested transfers, establish an internationally comparable conceptualization of poverty, and increase sample sizes for more-precise state-level estimates. The findings illustrate the extent to which prior studies have overestimated the incidence of poverty within the U.S. and have conceptually undervalued the immense heterogeneity of poverty outcomes across the 50 states.

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1. Introduction

The practice of comparative social policy research has been of historical importance in producing theoretical perspectives on the development of welfare states and empirical evidence on how certain components of welfare states have influenced social outcomes across time and place. As it relates to the integration of the United States into comparative social policy research, however, conceptual, empirical, and theoretical shortcomings abound in historical and contemporary academic literature. This is particularly true with respect to comparative analyses of poverty outcomes.

As this paper details, three common shortcomings can be identified in poverty research that focuses on, or includes, the United States. These shortcomings regularly inhibit (a) more accurate and precise estimates of American poverty outcomes and (b) a more fruitful integration of the United States into comparative poverty research. After detailing these three practices, this paper presents resolutions to address each and demonstrates the necessity of doing do.

The first of the three shortcomings refers to the common practice of deriving American poverty estimates from datasets that substantially underreport the real sum of mean-tested transfers. An ample amount of evidence demonstrates, for example, that measurement error within the survey data most often used to produce U.S. poverty estimates severely underestimates the extent of cash or near-cash transfers to low-income households and, thus, is likely to overestimate the incidence and severity of poverty within the U.S. (Meyer & Mittag, 2015; Wheaton, 2007).

The second shortcoming is the conceptualizations of poverty used to produce the estimates of the phenomenon within much U.S.-centric research. Critiques of the U.S. Official Poverty Measure are widely documented; nonetheless, much of the country's academic literature still relies on it (Brady & Destro, 2014; Citro & Michael, 1995; Foster, 1998; Fox et al., 2014). The U.S. Supplemental Poverty Measure, meanwhile, does not directly avail itself for cross-national comparative analysis, but does overlap closely, in concept and outcomes, with an alternative measure commonly applied in cross-national poverty analyses.

The third issue involves the tendency to mask the substantial interstate variation in poverty outcomes across the U.S. Specifically, this refers to the aggregation of income and poverty estimates for each of the 50 states and the country's 320 million residents into a single indicator. Recent evidence points to increasing state-level divergence in policy design and social outcomes, suggesting that poverty trends may vary considerably across the 50 United States (Bruch, Meyers, & Gornick, 2016; Caughey & Warshaw, 2016; Parolin, 2016). This paper evaluates that possibility and its potential implications for both (a) cross-state research among the 50 United States and (b) cross-national research that produces or operationalizes measures of U.S. poverty outcomes.

In resolving these shortcomings, this paper envisions and addresses two audiences. The first is U.S.-focused scholars who wish to evaluate income and poverty estimates on the state- or federal-level with more accurate survey data and a conceptualization of poverty that aligns with international practices. The second is international comparativists who wish to account for measurement error and state-level heterogeneity when embedding the U.S. into comparative research, while still using income concepts that align with those developed by LIS, the Cross-National Data Center in Luxembourg, in order to compare across countries. Part of the broader aim of this paper, however, is to facilitate the overlap of the two groups' research practices.

After a review of evidence on the three identified shortcomings (Section 2), a set of augmentations to the U.S. Current Population Survey (CPS) dataset is introduced to correct for the underreporting of several means-tested benefits, to establish an internationally comparable conceptualization of poverty, and to allow for more-precise state-level estimates (Sections 3 & 4). As the paper details, these augmentations enable comparisons of income and poverty dynamics in each of the 50 United States to the more than 40 countries present with the Luxembourg Income Study (LIS) cross-national database.

After introducing these augmentations, Section 5 then applies them to illustrate the extent to which prior studies relying on the uncorrected CPS data may have overestimated the incidence of poverty within the U.S. The theoretical and empirical implications of moving away from the U.S. Official Poverty Measure and Supplemental Poverty Measure to an internationally comparable measure are explored. As a final step, the diversity of poverty outcomes across each of the 50 states is highlighted to demonstrate (a) the conceptual weakness of aggregating the country's poverty estimates into a single indicator for the purpose of cross-national comparison and (b) the need for an expanded research agenda on the causes and consequences of the immense cross-state diversity in American poverty outcomes.

2. Shortcomings in the Estimation of American Poverty Outcomes

As detailed in the Introduction, three shortcomings of poverty analysis that focus on or include the U.S. are highlighted and addressed within this paper. In broad terms, these include (1) measurement error in the data from which U.S. poverty estimates are most often derived, (2) the concept and measure of poverty used to produce the estimates in U.S.-centric research, and (3) the aggregation of the poverty estimates into a single indicator to represent the country as a whole. Reconciling these issues is relevant for producing better poverty research for at least two sets of reasons, which are highlighted here and elaborated on throughout this paper.

The first reason is self-evident: deriving income-based poverty rates from a dataset that sizably underestimates relevant components of income is bound to lead to bias in the poverty estimates.

Among nationally-representative and publically-available surveys of American households' financial details, the Annual Social and Economic Supplement to U.S. Current Population Survey (CPS ASEC) provides the most detailed information regarding income, transfers, and tax liabilities, and is the source of data most commonly used to produce U.S. poverty estimates. The CPS ASEC also serves as the input data for LIS, the Cross-National Data Center in Luxembourg, from which estimates of U.S. poverty rates are often derived for the purpose of cross-national research.

Severe underreporting of transfer income, however, inhibits the CPS ASEC from producing accurate estimates of disposable income among many households in the bottom half of the income distribution (Meyer & Mittag, 2015; Wheaton, 2007; Winship, 2016). Plotting the CPS ASEC data against administrative records, for example, Meyer & Mittag (2015) find that the survey data underestimates the quantity of housing assistance recipients in New York by more than 33 percent, SNAP (the Supplemental Nutrition Assistance Program, formerly known as the Food Stamp Program) recipients by more than 40 percent, and TANF (Temporary Assistance for Needy Families, a cash assistance program) recipients by more than 60 percent. As a result, incomes toward the lower end of the distribution tend to be "substantially understated" in the survey data (p. 4).

Similarly, Wheaton (2007) finds that the proportion of real TANF, SNAP, and SSI (Supplemental Security Income, a means-tested disability assistance program) caseloads captured in the CPS ASEC declined relative to the values reported in administrative data between 1997 and 2002. In the latter year, about half of TANF benefits were missing in CPS ASEC, while 40 percent of SNAP and 30 percent of SSI benefits were likewise absent.

Several factors are hypothesized to contribute to the underreporting among survey respondents, including stigmatization of benefit receipt, respondent errors, confusion over particular program names, and under-coverage or under-count corrections (Wheaton, 2007). Regardless of precise determinants, matching administrative records with CPS ASEC data reveals clear discrepancies in the levels of means-tested benefits reported.

Despite the ample evidence of underreported transfers, this limitation is not addressed in much of contemporary poverty research derived from the CPS ASEC. This is surprising for at least two reasons: first, the underreporting of these transfer programs has large ramifications for analyses that focus on the bottom half of the household income distribution (as will be shown); and second, publically available resources exist for researchers to access and apply benefit imputations that aim to partially correct for underreporting in the CPS ASEC.

An additional drawback of the CPS ASEC is that it is not designed to provide adequate state-level sample sizes for reasonably-precise estimates of income or poverty at the subnational level. This may inhibit evaluations of state-level diversity in poverty outcomes, which this paper will demonstrate is an increasingly relevant source of inquiry.

To address these issues, Section 3 introduces a series of augmentations to the CPS ASEC dataset that partially correct for the underreporting of transfer benefits and works past the issue of state-level sample sizes. The implications of the benefit corrections on income and poverty estimates for four demographic groups – working-age adults, pensioners, children in lone-parent households, and children in two-parent households – are then illustrated.

Aside from the aim of producing more accurate estimates of poverty, a second set of reasons for addressing the identified shortcomings is to advance the practice of comparative social policy research, both within an intra-U.S. and international context.

Internationally comparative poverty research had shed light on the efficacy of different policy strategies in reducing poverty rates across different demographics (Bradshaw & Finch, 2010; Hinrichs & Lynch, 2010); the influence of macroeconomic conditions on poverty outcomes (Mares, 2010; Swank, 2010); the role of inputs and actors in shaping policy systems conducive to the reduction of poverty (Brady & Destro, 2014; Ebbinghaus, 2010; Immergut, 2010; Iversen, 2010); the relationship of social spending to poverty outcomes (Korpi & Palme, 1998; H. Obinger & Wagschal, 2010); approaches to defining and measuring poverty (Corak, 2005); how personal characteristics relate to the likelihood of living in poverty (Busemeyer & Nikolai, 2010; Kangas, 2010); and a range of additional inquiries.

Though many exceptions exist, a substantial portion of U.S.-based poverty research tends to eschew internationally comparative research, electing instead to limit the scope of analysis to policies and social outcomes occurring within the country (Brady & Destro, 2014; Smeeding, Rainwater, & Burtles, 2001). Brady & Destro (2014, p. 596) write that the "main limitation" of American social policy

literature is that it "concentrates exclusively on the United States". As the U.S. is generally recognized as an outlier with respect to poverty and inequality outcomes, the authors argue that attempts to explain or improve such outcomes without expanding the case selection beyond the country itself may lead to a narrower set of conclusions.

One example of this is the American literature's emphasis on family structure (such as single motherhood) and individual characteristics of the impoverished to attempt to explain the incidence of poverty; as Brady, Finnigan, and Hübgen (forthcoming) demonstrate in a cross-national analysis, however, the probability of a single mother living in poverty is uniquely high in the U.S., and the prevalence of single parents hardly explains cross-national differences in poverty rates. American policymaking often mirrors this bias toward individualism: during the years of the Great Recession, the state of Arkansas, as one example, allocated 40 percent of its total TANF budget toward the promotion of two-parent families and prevention of pre-marital pregnancy, while spending only 7 percent on direct cash assistance to low-income families (CBPP, 2015).

When performed adequately, the integration of the U.S. into internationally comparative research can advance (and has advanced) our understanding of social and labour market outcomes within the U.S. and provide a larger, more representative evidence base to inform future policy decisions. However, conceptual flaws and a lack of comparability in the measurement of poverty applied within much U.S.-centric research – the second shortcoming identified in this paper – reflects and may further inhibit the lack of integration between American and cross-national poverty research.

The U.S. is unique among its OECD counterparts in the way that its federal government (and, consequently, much of the country's academic research) measures the phenomenon of poverty. The U.S. Official Poverty Measure (OPM) relies on what is generally regarded as an 'absolute' determination of the poverty cutoff based on a calculation from the 1960s as to how much a typical family's budget is allocated to what was deemed to be a basic food plan (Ruggles, 1990). Moreover, the OPM relies on a pre-tax measure of income to evaluate a family's economic wellbeing that does not take into account near-cash benefits, meaning that neither food stamps nor refundable tax credits are included in the calculation.

This measure was deemed archaic enough that it was supplemented with a more-comprehensive Supplemental Poverty Measure (SPM) beginning in 2010 (Short, 2012). The SPM comes closer to measuring *net* income, factoring in any gains from tax credits, housing subsidies, and other means-tested benefits. Indeed, this approach to measuring income is similar to the post-tax and post-transfer income concept used in the primary statistical agencies within the EU and OECD (Eurostat, 2016; OECD, 2016) and more accurately assesses a household's economic wellbeing (Notten & De Neubourg, 2011). This is especially true among households earning low or no market wages within the U.S., as many of these households would be likelier to receive some form of non-cash or tax-based income support.

Calculating the design of family income support packages across the United States in 2014, for example, Parolin (2016) demonstrates that near-cash transfers in the form of SNAP (food stamps) made up more than 50 percent of the intended 'social floor' for jobless lone-parent families across a majority of states. For lone parents working full-time at minimum wage, the combination of SNAP and refundable tax credits were designed to increase gross-to-net incomes by up to 55 percent (approximately $18,000 to $28,000 in the case of Vermont). Failing to capture these tax-based or non-cash benefits is clearly likely to underestimate a household's consumption power.

While the income definition that the SPM applies is certainly an improvement over that of the OPM, it still does not avail itself for cross-national comparison, as its poverty threshold varies according to metropolitan region, home ownership, and price changes of a specific bundle of goods, which cannot be straightforwardly reproduced in other countries (Short, 2012). Conceptually, however, the SPM is similar to the 'relative' measure of poverty employed through most OECD and European Union Member States and, consequently, produces estimates of poverty that overlap closely with these 'relative' concepts.

To address this issue of comparability, Section 3 converts the CPS ASEC variables into an income definition that captures what LIS refers to as "disposable income", or a post-tax and post-transfer measure of a household's resources (LIS, 2016), while Section 4 outlines a framework for estimating state-level poverty rates in a manner comparable with OECD and EU Member States.

Finally, one commonality in internationally comparative and U.S.-centric poverty research is a tendency to aggregate poverty rates or other socioeconomic indicators from each of the 50 states into a single index to represent the country as a whole. This focus on federal-level trends also applies to research on policy inputs and the historical trajectories of social policy institutions within the country. While exceptions certainly exist, these practices appear to be dominant within policy and poverty literature (Smeeding & Rainwater, 2001).

Recent research, however, challenges this unitary understanding of the country's social policy landscape. Bruch, Meyers & Gornick (2016, p. 6) find that, since the 'devolution revolution' of the mid-1990s, the decentralization of policies designed to promote work and support low-income families has widened the inequities of family income support across the 50 United States. The authors write that this imbalance "has important but largely overlooked distributional consequences for economically-vulnerable families". Similarly, Parolin (2016) highlights state-level divergence in family income protections for lone-parent households. Again tracing policy developments from the mid-1990s, the study finds that state-level variation in statutory minimum wage levels, supplements to federal tax credits, and cash assistance for low-income families continues to grow more diverse.

Though these studies suggest that states are an increasingly important domain for understanding policymaking processes in the U.S. and the social outcomes to which they lead, they are far from the first to recognize the importance of identifying regional variance in poverty estimates.

In an analysis of within-nation differences in regional poverty outcomes in the EU, Kangas and Ritakallio (2007, p. 1) observe that, with respect to estimates of the prevalence of poverty, "conclusions based on national means may be misleading" and that "national means obscure more than they reveal." Similarly, Jesuit (2008, p. 5) finds in his subnational analyses that "studies at the national level of analysis mask intracountry variance in the rate of poverty".

Unmasking this variance not only adds an important layer of understanding to the national aggregates, but also allows us to move beyond an assumption of homogeneity within the U.S to enable more parsimonious analysis that may appropriately track, say, the differing political forces, cultural legacies, and historical processes that have influenced social outcomes in states like Texas

and New York.[2] Indeed, state-level research provides fertile grounds for the testing of theories related to this subject. How do states' levels of union membership influence the likelihood of income poverty among full-time, part-time, and/or jobless households? How do family leave policies shape gender-based wage inequities? These types of questions are often explored in cross-national comparative research, but less so among the American states.

Of course, the extent to which an aggregation of the American states overlooks relevant heterogeneities at the state level will depend on the research agenda at hand. There are many instances where a disaggregation would be an unfruitful exercise. As this paper aims to show, though, state-level analyses of income trends and poverty outcomes are one area where aggregation often hides meaningful differences beneath the surface.

Might there be other countries where a regional rather than federal focus would be of greater value? The U.S. is, after all, one of many federalist states that tends to be compressed for more expedient socioeconomic analysis. The United Kingdom, Belgium, Canada, Australia, Switzerland, Germany, and Italy, among others, each devolve some policymaking authority from the federal to regional level. An analysis of regional heterogeneity in each of these countries is beyond the scope of this paper. However, the literature on welfare states in federalist countries suggests that the extent of social policy decentralization is greater in the U.S. and Canada relative to the European states (Herbert Obinger, Leibfried, & Castles, 2005). Moreover, the evidence that does exist on cross-state variation within the U.S. points to greater diversity among the Americans states relative to the regional diversity in other federalist nations (Smeeding & Rainwater, 2001).

In sum, resolving the identified shortcomings – measurement error within survey data, the conceptualization and measurement of U.S. poverty, and the masking of regional variation – is important not only for producing more accurate estimates of income and poverty within the U.S., but also for advancing the practice of intra-U.S. and cross-national comparative poverty research. The remainder of this paper focuses on the resolutions to these shortcomings and illustrating the broader ramifications of producing more accurate, precise, and internationally comparable estimates of state-level poverty outcomes.

3. Augmenting U.S. Survey Data for Accurate & Comparable State-Level Income Estimates

The first objective in resolving the shortcomings is to augment the CPS ASEC so that it can provide more-accurate and internationally comparable estimates of income trends at the state level. This process includes (1) defining a comprehensive and comparable measure of income, (2) correcting for the underreporting of means-tested benefits in the survey data, and (3) ensuring adequate state-level sample sizes to reduce sample variance. Addressing these issues is necessary before moving to conceptualizations of poverty measurements, which are discussed in the next section.

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[2] As one example, case-oriented research that hypothesizes a 'power relations' theory of the influence of union membership on social policy outcomes might be wise not to adopt the U.S. as one case, but instead to recognize that the context and state-level policy outcomes may be vastly different in New York, where union density topped 25 percent in 2014, as opposed to Texas, where fewer than 5 percent of workers were unionized.

3.1. Establishing an Internationally Comparable Measure of Income

Determining which resources should count toward an individual's level of income is a first step toward producing estimates of income-based poverty or inequality. As detailed in the prior section, the U.S. Official Poverty Measure is flawed in that it does not take into account near-cash or tax-based transfers, which greatly increases the annual consumption capabilities of many low-income households (Parolin, 2016).

Demanding a more comprehensive measure of income can complicate comparability across countries with different systems of tax and transfer support. Several resources exist, however, to harmonize income concepts for this exact purpose. Perhaps the most accessible and widely-used resource of this type is LIS, the Cross-National Data Center in Luxembourg, which provides harmonized measures of net income in datasets that span more than 40 countries and, for some cases, more than 40 years.[3]

"Disposable income" (DI) is the most comprehensive indicator of economic wellbeing that LIS produces for each country-year. This definition of income includes the "sum of monetary and non-monetary income from labour, monetary income from capital, monetary social security transfers (including work-related insurance transfers, universal transfers, and assistance transfers), and non-monetary social assistance transfers, as well as monetary and non-monetary private transfers, less the amount of income taxes and social contributions paid" (LIS, 2016). This measure does not include non-monetary gains from capital or non-monetary universal transfers, such as freely-available education or healthcare.

In the case of the U.S., LIS uses the CPS ASEC as its input data. The calculation for DI includes refundable tax credits (such as the Earned Income Tax Credit and Additional Child Tax Credit), Section 8 housing vouchers, and SNAP benefits (food stamps), in addition to cash from market wages, unemployment benefits, child support payments, and other sources (the full income definition is detailed in the *Appendix*, while the program for converting the CPS ASEC to this measure of disposable income is available for download on the author's website, as listed in the *Appendix*).

The augmentations to the CPS ASEC data introduced here 'Lissify' the income definitions to match those used within LIS, meaning that a comprehensive definition of income (DI) can be compared across U.S. states and the 40+ countries within the LIS data framework, as will be demonstrated in Section 5.

Despite the comprehensive and harmonised measures of income that the 'Lissification' provides, two challenges still remain in using the CPS ASEC data to derive accurate and comparable state-level estimates of income and poverty: the underreporting of means-tested benefits within the dataset leaves out a substantial portion of cash transfers, while inadequate sample sizes among many of the U.S. states in the single-year CPS dataset disallow for estimations with reasonably small confidence intervals. These are now addressed in turn.

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[3] LIS does not provide datasets for each year; instead, it publishes in "waves" of years, which typically span three to four years. The three most recent harmonized U.S. datasets, for example, cover the years 2014, 2010, and 2007.

3.2. Correcting for the Underreporting of Means-Tested Benefits

As noted, one major limitation of CPS ASEC data[4] is the extent to which it underestimates the amount of means-tested transfers among low-income individuals and households. As detailed in Section 2, a comparison of administrative records to CPS ASEC data suggests that the survey data substantially underreports the transfer of means-tested benefits; thus, analyses of low-income households based on uncorrected CPS ASEC data are likely to overestimate the incidence and severity of economic deprivation (Meyer & Mittag, 2015; Wheaton, 2007).

The Urban Institute's Transfer Income Model, Version 3 (TRIM3), offers a series of imputations to address the underreporting of several means-tested transfers including TANF, SNAP, SSI, and housing subsidies; this paper examines and applies these imputations to the CPS ASEC to produce more accurate poverty estimates.

The TRIM3 simulations are aligned to match the participant and benefit levels in administrative data so that the simulated data may be used in place of reported values to correct for under-reporting within the CPS ASEC. As will be detailed, these benefit corrections come much closer than the standard CPS ASEC data in reflecting the administrative data on the real level of means-tested benefits appropriated.

TRIM3 benefit imputations for four of these transfers – TANF, SNAP, SSI, and housing subsidies – are applied to the augmented CPS ASEC data introduced in this study. State-specific eligibility rules and variance in state-level take-up of each of these benefits are factored into the imputations (TRIM, 2012).

Imputations for TANF benefits only concern the allocation of direct cash assistance (through the "Basic Assistance" spending category and not, for example, refundable tax credits that some states use the TANF block grant to fund). The housing subsidies include Section 8 Housing Choice Voucher Program and Project-Based Rental Assistance.

As will be shown, the levels of imputed benefits do not align perfectly with the administrative data (imputed SNAP benefits, for example, differ from administrative data by an estimated 1.9 percent), but do offer a substantial improvement over the uncorrected CPS ASEC in capturing the real incomes of households receiving any of these forms of social assistance.

TRIM3 also offers benefit imputations for other programs, such as Unemployment Insurance, income tax liabilities, child support, and the Special Supplemental Nutrition Program for Women, Infants and Children (WIC), but these imputations are not included into the analysis presented here. Instead, this paper only imputes benefit values for programs in which TRIM3 data is available in each survey year and in which evidence of underreporting has consistently been demonstrated.

The simulation of the transfer benefits follows a comparable process for each program before they are imputed into the public-facing version of the CPS ASEC: the appropriate filing unit is identified, eligibility checks are performed taking into account any applicable state-level restrictions, income

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[4] Other commonly used datasets in the U.S., such as the American Community Survey, also suffer from this issue, albeit to varying extents (Wheaton, 2007).

counting toward the means-test is compiled, the benefit computation is conducted, and a 'participation decision' is predicted based on the reported likelihood of the particular person, family, or household actually receiving the benefit (an important step, as participation in means-tested benefits varies widely across states). This process for detailed more thoroughly in Wheaton (2007) and TRIM3 (2012).

How do the benefit values imputed into the augmented CPS ASEC data compare to administrative records? Table 1, below, documents the share of total benefits from SNAP, TANF, SSI, and housing subsidies, as reported in administrative data, that are captured in the augmented CPS ASEC and the original CPS ASEC.

The augmented CPS ASEC data more closely mirrors administrative data on the total value of all benefits administered. Over an average of the years 2008 to 2010[5], administrative data from the Social Security Administration, for example, shows that an average of $45.9 billion was paid annually to SSI beneficiaries; the augmented CPS ASEC captures 96.3 percent of that amount, compared to 81.5 percent in the case of the uncorrected version.

For SNAP, the benefit imputations slightly overestimate the value recorded in administrative data (capturing 101.9 percent of the real total), but come much closer to the administrative data relative to the original CPS ASEC, which includes just 64 percent of total SNAP benefits.

TANF benefits also come much closer to the administrative totals in the augmented CPS ASEC -- though these are more difficult to evaluate, as administrative data only reports states' TANF appropriations toward "Basic Assistance", which, in some states, consists of more than the direct provision of cash assistance. This is likely why TANF values imputed into the augmented CPS ASEC capture about 85 percent, and not more, of the total value of "Basic Assistance" reported across the states from 2008-2010.

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[5] As detailed later in this section, three years of consecutive data are combined to produce larger state-level sample sizes and more precise state-level estimates.

Table 1: Comparison of Administrative Data on Total Benefit Levels with Augmented CPS ASEC (2008-2010 average, in $100,000s of 2009 USD)

|		Administrative Data	Augmented CPS ASEC	Original CPS ASEC
SNAP	Total Benefits	$48,890	$49,838	$31,383
	Percent Captured	100%	101.9%	64.2%
TANF	Total Benefits*	$9,546	$8,116	$6,055
	Percent Captured	100%	85.0%	63.4%
SSI	Total Benefits	$45,942	$44,254	$37,442
	Percent Captured	100%	96.3%	81.5%
Housing Subsidies	Total Benefits	$40,920	$30,595	$14,090
	Percent Captured	100%	74.8%	34.4%

Note: For "Total Benefits" within TANF, administrative data includes any spending that states report as "Basic Assistance". In some states, this category of spending includes more than cash benefits; in most states, however, it directly reflects the provision of cash assistance (CBPP, 2015). **Sources:** SNAP administrative data via USDA Food & Nutrition Assistance (2016); TANF reporting on Basic Assistance is from Center for Budget & Policy Priorities (2015); SSI data comes from the Social Security Administration (2010); Data on housing subsidies from Congressional Budget Office (2015).

Available administrative records on the distribution of these benefits across each of the 50 states suggest the benefit imputations applied here closely mirror the real totals in each state during the years of examination (not surprising, given that the benefit imputations take into account state-level eligibility criteria and variance in benefit take-up rates). In the state of New York, for example, the benefit imputations capture 95 percent of total TANF cash assistance allocated in the state, 104 percent of SNAP benefits, and 97 percent of SSI benefits. The augmented data also captures 92 percent of the real quantity of households in New York receiving the Section 8 housing subsidies (CBPP, 2017; New York State Office of Temporary and Disability Assistance, 2008; Social Security Administration, 2011).

Figure 1, below, illustrates the importance of applying these benefit corrections in analyses of low-income families and households within the U.S.. In this case, the income distribution of children in lone-parent and two-parent households is depicted using the pre-correction (CPS ASEC prior to adjustment) and post-correction (after TANF, SNAP, SSI, and housing subsidy imputations are applied to CSP ASEC) levels during an average of the years 2008-2010. Disposable household income is presented using the modified OECD equivalence scale. Though households with children are highlighted here, the implications of the benefit imputations on pensioners and working-age adults[6] are detailed in subsequent analysis (see Table 2).

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[6] Pensioners are defined here as individuals older than 65 years of age, regardless of whether they actually receive retirement income. Working-age adults are defined as individuals between the ages of 18 and 64 (inclusive). Lone-parent households include those in which at least one child but no more than one parent or guardian is present; children living with two or more married or cohabitating adults are considered to be in two-parent households.

Figure 1: The effects of correcting for underreporting of means-tested benefits on the family-type income distribution of children in lone-parent and two-parent households (2008-2010, in 2009 USD)
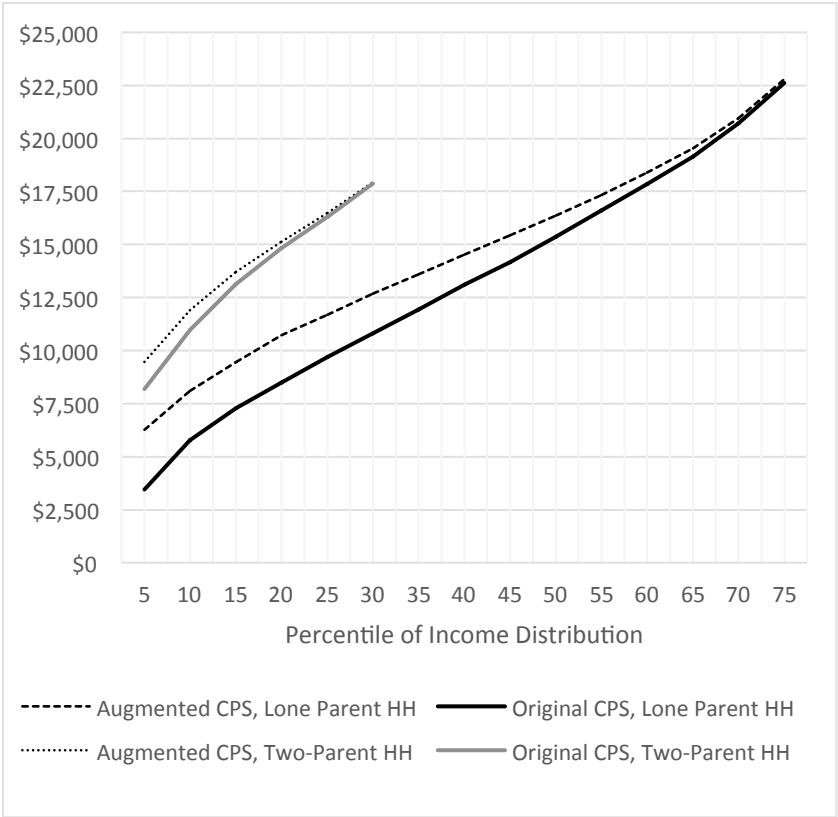
Due to the underreporting of benefits, the CPS ASEC underestimates the incomes of children in lone-parent households up until the 75th percentile, and children in two-parent households up to the 30th percentile. As would be expected, the gaps are widest at the lower end of the income distribution where households are likely to receive higher levels of income support. At the fifth percentile of children in lone-parent households, for example, corrections for underreporting deliver an estimated income level that is nearly twice the estimate in the pre-correction CPS ASEC data (a jump from $3,450 to $6,387 in 2009 USD).

Table 2, below, details the discrepancies between the original and augmented CPS ASEC income calculations for these two family types, as well as for pensioners and working-age adults. The average SNAP, TANF, SSI, and housing subsidy benefit values among each demographic are presented for both the pre- and post-augmented data. The coverage rates, defined as the proportion of the subpopulation living in a household that received any value of the benefit, are also presented.

Table 2: Estimated annual transfer benefit value & coverage rate across age groups, before and after corrections for underreporting (household income of subpopulation specified, 2008-2010 average, 2009 USD)

		Original CPS ASEC Data	Augmented CPS ASEC Data	Absolute Increase	Relative Increase
SNAP					
Children	Mean Benefit Value	$815	$1320	$505	62%
	Coverage Rate	18.9%	28.3%	9.3%	49%
Working-Age Adults	Mean Benefit Value	$308	$509	$201	65%
	Coverage Rate	9.7%	15.9%	6.1%	63%
Pensioners	Mean Benefit Value	$110	$154	$44	40%
	Coverage Rate	5.5%	8.4%	2.9%	52%
TANF					
Children	Mean Benefit Value	$182	$270	$87	48%
	Coverage Rate	4.4%	6.8%	2.4%	55%
Working-Age Adults	Mean Benefit Value	$61	$92	$32	52%
	Coverage Rate	1.7%	2.6%	0.8%	49%
Pensioners	Mean Benefit Value	$14	$28	$14	100%
	Coverage Rate	0.4%	0.8%	0.3%	80%
SSI					
Children	Mean Benefit Value	$317	$550	$234	74%
	Coverage Rate	3.8%	7.2%	3.4%	91%
Working-Age Adults	Mean Benefit Value	$369	$451	$83	22%
	Coverage Rate	4.4%	6.2%	1.8%	41%
Pensioners	Mean Benefit Value	$325	$464	$140	43%
	Coverage Rate	4.6%	7.5%	2.9%	62%
Housing Subsidies					
Children	Mean Benefit Value	$183	$427	$244	133%
	Coverage Rate	5.5%	5.3%	-0.3%	-5%
Working-Age Adults	Mean Benefit Value	$95	$183	$89	94%
	Coverage Rate	3.0%	2.7%	-0.3%	-10%
Pensioners	Mean Benefit Value	$92	$232	$140	153%
	Coverage Rate	4.2%	3.9%	-0.3%	-7%

Note: Coverage rate refers to share of the subpopulation with any amount of household income in the form of the respective benefit. Dollar values are presented in 2009 USD.

As Table 2 details, the effects of the benefit imputations vary across program and age group. The average household income of children is consistently the most affected of the age groups in terms of the absolute gains after benefit imputations; that comes as no surprise given that TANF is explicitly targeted at households with children and that SNAP benefits increase with the number of children in the household.

The average estimated annual SNAP benefit per child increases by more than 60 percent ($815 to $1,320) in the augmented CPS ASEC data relative to the original version. The estimated proportion of children living in a household that receives any SNAP benefit increases from approximately 19 percent to 28 percent, which comes much closer to matching administrative records (Keith-Jennings,

2012). With respect to SSI, the coverage rate among children nearly doubles, jumping from 3.8 percent to 7.2 percent after the benefit imputations are included.

Working-age adults also see a notable increase in SNAP benefits in the augmented CPS ASEC. The average benefit value jumps more than $200, or a 65 percent increase. SSI benefits among this age group see a more modest rise of $83, on average, and an increase in coverage of about 2 percentage points (from 4.4 to 6.2 percent).

Pensioners (again, defined as individuals over the age of 65) see the greatest gains with respect to SSI – a $140 increase in average benefit value and a 2.9 percent increase in coverage rate. Even in the augmented CPS ASEC data, less than one percent of this subpopulation lives in a household that receives TANF cash assistance. Approximately 8.4 percent were estimated to live in a household receiving food stamps during the years examined (a 3 point increase in the absolute value relative to the original CPS ASEC).

The average value of housing subsidies increased substantially among each of the three demographic groups (though still provided less support, on average, relative to SNAP and SSI). In the original CPS ASEC, housing subsidies are self-reported (per family), leading to large underreporting in the total value of the benefits (see Table 1). The coverage rate of the housing subsidies, however, slightly *decreases* for each demographic in the augmented survey data (a drop from 5.5 percent to 5.3 percent of children, for example, living in a household that receives housing assistance). These imputed values and coverage rates are nonetheless remarkably similar to estimates produced using a new variable on receipt of federal housing assistance that the U.S. Census Bureau added to the CPS ASEC in 2010. This variable, introduced as part of the SPM addendum, uses administrative data to determine a family's receipt of federal housing assistance, and correlates strongly with the TRIM3 imputations (in the 2010 file, for example, the TRIM imputations applied benefits to 99 percent of the households to which the SPM applied benefits). The relative advantage of the TRIM3 imputation, as applied here, is that these are available from 1990 onward, whereas its CPS ASEC counterpart is only available beginning in 2010.

As the evidence presented suggests, the use of the original (pre-imputation) version of the CPS ASEC is likely to underestimate the value of household income among those likely to receive assistance in the form of TANF, SNAP, SSI, of housing subsidies. The augmented CPS ASEC dataset more accurately captures means-tested transfer benefits using the TRIM3 imputations; the relevance of these corrections in estimating poverty rates is presented in Section 5.

3.3. Increasing Sample Sizes for More Precise State-Level Estimates

After establishing a comparable and comprehensive income definition and partially correcting for the underreporting of means-tested benefits, a third challenge is to generate adequate state-level sample sizes to reduce sampling variance within CPS ASEC estimates. Doing so is necessary to produce estimates with more precise standard errors and confidence intervals.

The sample of the CPS is not designed to produce state-level estimates with reasonably small confidence intervals. To obtain more refined confidence intervals for state-level measurements, the U.S. Census Bureau – the body that administers and publishes the CPS data – recommends combining consecutive years of CPS ASEC files to increase sample sizes (U.S. Census Bureau, 2015). Indeed, this practice has been adopted by researchers focusing on state-level trends in health

insurance coverage, unemployment levels, and child poverty rates (Meyer & Mittag, 2015; Rainwater & Smeeding, 2003).

Following the Census Bureau (2015) recommendations, three consecutive years of CPS ASEC data are combined in the augmented CPS dataset presented here. While this limits sampling variance to a considerable degree in estimates of state-specific poverty rates among many subpopulations (say, unemployed working-age adults in Missouri), caution should still be taken in segmenting the population too narrowly, especially in states with smaller populations.

Figure 2 illustrates the combined relevance of correcting for the underreporting of means-tested benefits, as presented in the previous section, as well as combining CPS ASEC years for more precise sample estimates. Here, the average disposable household income[7] among children in lone-parent households in New York and New Mexico – two states with relatively high proportions of lone-parent households – are presented using the augmented CPS ASEC data (left) and the single-year, uncorrected CPS ASEC data (right). Standard errors are obtained using a series of 160 replicate weights made available in the IPUMS-CPS integrated dataset; the resulting confidence intervals are presented here at the 90 percent level (Flood, King, Ruggles, & Warren, 2015).

Figure 2: Average estimated household income (in 2009 USD) of children in lone-parent households in New York and New Mexico using uncorrected, single-year CPS ASEC versus augmented, three-year-combined CPS ASEC
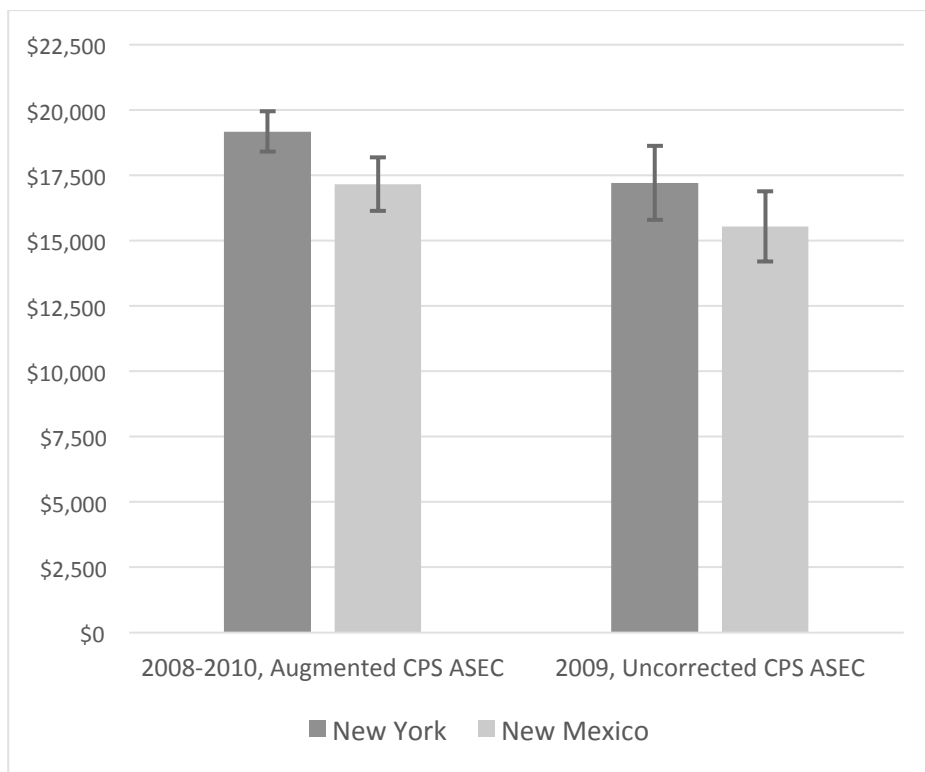
Source: Augmented CPS ASEC & Public-Use CPS ASEC
Note: Error bars represent 90 percent confidence intervals. Figure is author's own.

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[7] Household income is equivalized using the modified OECD equivalence scale. Section 4 provides more information on the choice of equivalence scale.

The original CPS ASEC file estimates that children in lone-parent households in New York received an average household income $17,214 in 2009, while similar household structures in New Mexico received an average of $15,554 (in 2009 USD). As shown, the 90-percent confidence intervals for the two states' estimates overlap; a T-test supports the notion that we cannot with ample confidence distinguish whether the population means truly differ between the two states.

The combined files in the Augmented CPS ASEC data offer larger sample sizes to produce more precise estimates, as the left half of Figure 2 shows. The point estimates for New York and New Mexico both increase due to the correcting for underreporting of transfer benefits; moreover, the confidence intervals are smaller relative to the original CPS ASEC estimates. Within the augmented CPS ASEC data, the estimations more clearly suggest that children in lone-parent families in New York had higher household incomes, on average, compared to similar families in New Mexico from 2008 to 2010 (and compared to estimates of the same households in New York in 2009 when using the original CPS ASEC).

In Figure 2 and other findings presented using the augmented CPS ASEC dataset, monetary values within each year of the combined files are converted to 2009 USD. The price index used here to account for inflation is the Personal Consumption Expenditures (PCE) deflator[8]. In the augmentations to be made public, nominal figures for each year are left in and labeled accordingly within the dataset for researchers opting to use alternative inflation adjustments.

After the three years of CPS ASEC data are combined, survey weights for each set of combined files are divided by the number of years included (three, in this case) so results sum to the average of the years examined (Smeeding & Rainwater, 2001). The benefit imputations (described previously) are applied to each year individually. The data is then "Lissified" to match the income concepts of LIS. The Stata code to apply these imputations is made available for public download (see instructions in the *Appendix*).

4. Framework for Estimating State-Level Poverty Rates

The augmented and 'Lissified' CPS ASEC dataset now allows us to compare a harmonized and comprehensive measure of income across U.S. states and the range of countries within the LIS data framework.

Using this dataset to produce comparable estimates of poverty rates, however, requires a measure of poverty that can be reasonably applied across polities of comparable economic systems while maintaining conceptual robustness. A low-income threshold based on a percentage of prevailing median household income meets these standards and is discussed in relation to the official U.S. measures.

Before diving into specifics, though, it is important to note that any discussion of how 'poverty' should be conceptualized and measured requires a series of value judgments to be made. The purpose of this section is not to take a stand on which approach to poverty measurement is 'right',

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[8] See Winship (2016) for a robust defense of PCE deflator compared to the CPI-U or other alternatives.

but instead to briefly summarize the key considerations to be made in *comparative* evaluations of poverty rates, to identify best practices in recent comparative literature, and then to apply these best practices to augmented CPS ASEC data in order to evaluate the relevance of a state-level focus on poverty trends within the U.S.

4.1. Measuring Income

This study is primarily concerned with an income-based evaluation of poverty using, as described earlier, a comprehensive measure of income ("disposable income") that includes cash transfers and refundable tax credits, among other sources of non-market income.

Technical considerations need to be made with respect to the unit of analysis and equivalence scale. Income components in the CPS ASEC data are available at the individual, family, and household levels. The U.S. OPM treats the family as the standard unit of observation, meaning that the income of the reference person and any individuals related to the reference person within the same dwelling are treated as one unit. Adoption of the family as the standard unit of observation is problematic, though, as it assumes that unrelated members of the same household, such a cohabitating couple, do not pool resources or face comparable economic need (Winship, 2016).

A more common approach in comparative research is to measure 'equivalised' household income at the individual level (Notten & De Neubourg, 2011). In this case, the incomes of all members living within the same dwelling – regardless of biological relation – are combined and divided by the equivalence factor. The resulting value is applied to each member of the household. Assessing household income is also an imperfect practice, as it assumes equal sharing of resources among all individuals living within the same dwelling (in reality, this is likely to vary by household and perhaps time or region). Nonetheless, it comes closer to accurately estimating the consumption capabilities of individuals within the households (Notten & De Neubourg, 2011).

The two most commonly used equivalence scales in comparative poverty research include the square-root scale and the modified OECD equivalence scale. Following recommendations put forth by the OECD (2016), this study assesses equivalised household income at the individual level using the modified OECD equivalence scale, which divides the combined income of a household by a formula that considers the number of adults and children in the household. Switching to the square-root scale, however, does not meaningfully alter the results presented.

4.2. Drawing the Poverty Line

Which level of equivalised income should distinguish the poor from the non-poor? At the core of this decision is whether to define the distinguishing line in terms of the cost of a specific bundle of 'necessary' consumables (oft referred to as an 'absolute' poverty line) or as a fraction of the median income within the respective state (a 'relative' or 'floating' poverty line).[9] In truth, the conceptual differences between the 'fixed' and 'relative' thresholds are blurry, as discussed below.

The U.S. OPM and much U.S.-focused research adopts the first approach, drawing an 'absolute' poverty line based on an assumption from the 1960s as to how much a typical family's budget is

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[9] Combinations of the two approaches also exist (see Ravallion & Chen, 2011).

allocated to a basic food plan (with the income cutoff adjusted each year using the Consumer Price Index). Critiques of the OPM are widely documented (see Foster, 1998; Citro & Michael, 1995; Fox et al., 2014; Brady & Destro, 2015). In short, the OPM threshold is not sensitive to changes in the average standard of living, nor does it adequately adjust for shifts in the share of income spent on food expenditures and other goods. At best, it represents an arbitrary threshold based an antiquated assumptions that are adjusted using an unideal price index. Much of U.S. poverty literature nonetheless still relies on it.

The Supplemental Poverty Measure (SPM) also adopts a 'bundle of goods' approach, but expands beyond food to look at recent trends in consumer expenditures on clothing, shelter, and utilities (Fox et al., 2014; Renwick & Fox, 2016). The SPM threshold is also adjusted regionally based on geographic differences in housing prices. While an improvement over the original U.S. measure, the SPM does not readily avail itself for cross-country comparisons. However, the aim of the SPM threshold – to capture changes in relative purchasing power and regional variation in living costs – overlaps in part with the intent of the 'floating' measure of poverty commonly used in comparative literature.

The 'floating' or 'relative' measure is based on a percentage of prevailing median incomes and is often applied in poverty studies across advanced economies (Corak, 2005; Goedemé & Rottiers, 2010; Gornick & Jäntti, 2016). Thresholds based on median incomes adjust to the relativity of living standards across place and time; moreover, they perhaps more appropriately frame the concept of poverty which, as Corak (2005) details, "cannot be defined without reference to prevailing norms of consumption among members of the relevant community" (p. 10). A rich history of sociological literature has supported this notion that, at least in advanced economies, one's deprivation must generally be understood in relation to the wellbeing of others within that society (for a thorough overview of the literature, see Brady (2009), Ch. 2). Indeed, this relative conceptualization of poverty is adopted as the preferred framing in most EU and OECD Member States.

This paper follows common practice in comparative poverty research in setting the threshold at 50 percent of median equivalised household income within the respect polity, though a 60 percent threshold is also used frequently in international literature (Corak, 2005; Jesuit, 2008; Kangas & Ritakallio, 2007).

The percent-of-median-income ('relative') [10] approach is henceforth referred to as a "low-income measure", which, in the case of the U.S., can come in two (or more) forms: (1) a national-level low-income measure, in which the low-income threshold for all states is set at a common benchmark of 50 percent of the median household income of all households within the country; or (2) a state-level low-income measure, in which each state is applied its own low-income threshold set at 50 percent of the state's respective median.

Smeeding & Rainwater (2001) advocate for the second approach, suggesting that the reference group that shapes the 'relativity' of poverty exists at the local level; individuals compare their

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[10] The distinction of this threshold as *relative* can be misleading; even the OPM, deemed an absolute threshold due to its inflation-only adjustment over time, is based on a relative concept of consumption trends at a given time. The description of Molly Orshanky, the economist credited for devising the initial U.S. poverty measure, is telling: the OPM was meant to capture "the relative wellbeing of both individuals and the society in which they live" (Orshansky, 1976).

economic and material wellbeing to that of their neighbors, community members, or others in their more-immediate presence. If so, then a more localized unit of measurement would be superior, and since even the augmented CPS ASEC data does not generally allow for precise income estimates at the county or municipal level, then the states make for the most appropriate reference point.

This claim of state-level relativity, however, can certainly be challenged. Drawing on sociological literature of reference group theory, Goedemé & Rottiers (2010) draw a distinction between privately-oriented and publicly-oriented reference groups. The first provides a conceptual framework around the notions advanced by Smeeding & Rainwater (2001) that individuals compare their livelihood relative to others in their more-immediate surrounding. Conversely, publicly-oriented reference groups, the authors argue, offer a norm as to how minimum standards of living within a particular society *ought* to be defined.

Table 3, below, illustrates the implications of each of these approaches to measuring poverty on their resulting poverty thresholds for a two-parent, two-child family in 2010.

Table 3: Poverty thresholds for a two-parent, two-child family in 2010 under different measures of poverty

		Poverty Threshold	Percent of National Median HH Income
U.S. Measures	Official Poverty Measure	$22,113	40.5%
	Supplemental Poverty Measure	$24,343	44.5%
Low-Income Measures (LIM)	National LIM	$27,330	50.0%
	Massachusetts LIM	$32,889	60.2%
	Mississippi LIM	$21,576	39.5%

Source: Thresholds for the Official and Supplemental measures are provided in Short (2012). Low-income measures are produced from the augmented CPS ASEC data introduced in this paper.
Note: The threshold for the Supplemental Poverty Measure presented here does not account for housing status or geographic variation in housing costs. In practice, thresholds vary by family unit based on local housing costs and whether the unit is renting or making mortgage payments. Low-income measures are set at 50 percent of median equivalised household income in the respective geographic unit. Dollar values are presented in 2010 USD.

During this year, the OPM threshold for the 48 contiguous states (Alaska and Hawaii are provided separate thresholds) fell in at just over $22,000, or about 40.5 percent of national median household income in that year. The baseline SPM, before taking into account a unit's housing situation or location, was set slightly higher than the OPM (about 45 percent of the national median).

By definition, the national low-income threshold falls at 50 percent of national equivalised median income, or about $27,330 in 2010. The two state-level low-income thresholds – for Massachusetts, a comparatively wealthy state, and Mississippi, the opposite – vary considerably from the national median. In an application of a state-level low-income measure of poverty, then, any two-parent, two-child household in Massachusetts with an equivalised income less than $32,889 (60.2 percent of the national median) would be deemed to living in poverty, while in Mississippi, the household would

have to earn below $21,576 (or 39.5 percent of national median) to achieve the same poverty status.[11]

As shown in the next section, the SPM measure, which lacks cross-national portability, and the state-level low-income measure, which also fluctuates by region but *is* transportable, produce estimates of state-level poverty that are not significantly different from each other at the 90-percent confidence level in 29 of the 50 states during the period of examination.

Again, it should be noted that considerations regarding the measure of poverty requires value judgments to be made. In estimating poverty rates that can be compared across cross-nationally, however, best practices within the field of comparative poverty research support the application of a national or state-level low-income measure when evaluating poverty outcomes within the U.S. The next section tests these concepts within the augmented CPS ASEC data to explore the ramifications of measuring internationally comparable estimates of state-level poverty using data that has been adjusted to account for the underreporting of means-tested benefits.

5. Revised Poverty Estimates in Comparative Perspective

Having addressed the issue of measurement error and outlined an internationally comparable conceptualization of poverty, this paper now turns to its final objective, which is to illustrate how the benefit imputations, revised measures of U.S. poverty, and the unmasking of state-level variation affect conventional understanding of American poverty outcomes.

In doing this, the section aims to briefly answer three questions: how do U.S. poverty estimates vary across different measures and conceptualizations of poverty? How do the poverty estimates change after applying the benefit corrections within the augmented CPS ASEC? And, finally, to what extent do states vary in their estimates of poverty?

5.1. Poverty Estimates Across Different Poverty Concepts

This paper has highlighted four different approaches used to measure poverty within the U.S.: the OPM, SPM, and two low-income measures. As detailed previously, each approach comes with its own income definition, equivalence scale, and/or poverty threshold. Table 4, below, shows national poverty estimates for children, working-age adults, and pensioners using each of the four measures in the year 2010 (the state-level low income measure is a slight exception, averaging over the years 2008 to 2010 to obtain adequate sample sizes). These estimates are derived from the standard, non-

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[11] The thresholds for the two states are closer than initially meets the eye when applying the regional price parities from the U.S. Bureau of Labor Statistics. Given differences of cost of living within the two states, Mississippi's poverty threshold equates to a purchasing power of $24,885 (46 percent of national median income) during this timeframe, while that of Massachusetts falls at $30,709 (56 percent of the national median). For researchers preferring a national low-income measure as opposed to the state-level versions, applying these regional price parities may make for good practice; within the state-level low-income measures, the price parities do not affect the poverty estimates, as they would simply multiply household incomes and the state's low-income threshold by the same factor.

corrected CPS ASEC for now to narrow in on the differences in poverty estimates due to the different *measures* of poverty.

Table 4: National-Level Poverty Estimates Using Different Measures Prior to Applying Benefit Corrections (2010)

U.S., National Poverty Rates Using Different Measures	U.S. Official Poverty Measure	Supplemental Poverty Measure	National-Level Low Income Measure	State-Level Low Income Measure
Children	20.7%	18.2%	20.2%	19.9%
Working-Age Adults	12.9%	15.2%	14.1%	14.0%
Pensioners	8.9%	15.9%	16.7%	16.7%

Note: Estimates for the state-level low income measure are derived from an average of three years of data (2008 to 2010) to achieve adequate sample sizes (see Section 3 for more details). **Source:** Standard (non-corrected) CPS ASEC.

Among the population of children, each of the four poverty measures produces a roughly similar estimate in 2010: an average of about 20 percent with minor variance. The SPM produces a slightly lower estimate (18.2 percent), while the other three measures fall around 20 percent. The pattern is similar among the estimates for working-age adults, but here, the OPM produces a slightly lower estimate (12.9 percent) relative to an average of the alternative measures of about 14.5 percent. The OPM also predicts a much lower rate of poverty among the 65+ age group (8.9 percent).

Applying either of the low-income measures to compare poverty estimates cross-nationally, then, is, at least among the years examined, likely to produce slightly higher estimates for the U.S. relative to what the OPM would predict. Relative to the SPM, however, the estimates are remarkably similar, albeit a point higher for children and pensioners.

As the poverty thresholds for the SPM and state-level low income measure vary geographically, it is worthwhile to see how *state-level* estimates of poverty vary between the two measures. Table 5, below, compares the estimates over the years 2010 to 2012 (the first three-year stretch in which state-level SPM estimates are available) again using the standard CPS ASEC data. Poverty estimates are derived here from the full population in each state.

Table 5 shows that the mean of the 50 state-level poverty estimates is 1.6 points higher using the state-level low income measure (15.5 percent) relative to the SPM (13.9 percent). The data also show the range and standard deviation of poverty estimates across states is slightly greater when using the SPM.

Table 5: State-Level Poverty Estimates for Total Population under Supplemental Poverty Measure and State-Level Relative Measure, Prior to Applying Benefit Corrections (2010-2012)

U.S., State Poverty Rates Using Different Measures (n=50)	Supplemental Poverty Measure	State-Level Low Income Measure	Percentage-Point Change
Mean	13.9%	15.5%	1.6%
Standard Deviation	3.12%	1.93%	-1.2%
Minimum	8.6%	10.1%	1.5%
Median	13.5%	15.8%	2.3%
Maximum	23.8%	19.3%	-4.5%

Note: Poverty thresholds are set at 50 percent of the state's respective median equivalised household income. Estimates for the Supplemental Poverty Rates

In comparing each state's poverty estimate across the two measures, however, the SPM and state-level low-income measure produce estimates that are significantly different from the other in only 21 of the 50 states.[12] In just about 60 percent of the states, then, the two measures of poverty produced estimates that were not statistically distinguishable from each other.

The states in which the state-level low income measure produces a higher poverty estimate relative to the SPM tend to be states with higher median incomes (such as Massachusetts, as demonstrated in Table 3). The percent-of-median-income approach tends to set a higher poverty threshold compared to the SPM in states with comparatively high median incomes, which helps to explain why the mean and median of states' poverty estimates is higher when using the state-level low income measure.

In sum, the different conceptualizations of poverty unsurprisingly lead to slightly different estimates of poverty rates among children, working-age adults, and pensioners. That said, the state-level low income poverty measures, which can be employed in a conceptually-sound manner within cross-national poverty research, appears to overlap closely with the SPM – not just in its intent to capture regional variation, but also in the estimates that the two measures produce. This is particularly relevant for researchers who generally apply the SPM but wish to engage in cross-national research.

5.2. Poverty Estimates After Applying Benefit Corrections

What difference do the benefit imputations make in our estimation of poverty rates? Here, the augmented CPS ASEC data introduced in Section 3 is applied to demonstrate the difference in poverty estimates after correcting for the measurement error.

Table 6 shows national poverty rates using the state-level low income measure[13] using, first, the standard CPS ASEC data and, second, the augmented CPS ASEC. Results for working-age adults and pensioners are shown again, but children are now split into two categories – those in lone-parent households (which, during the years examined, made up just over 20 percent of all children within

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[12] In each case, standard errors and confidence intervals are calculated at the 90-percent level using the set of 160 replicate weights made available in the IPUMS-CPS integrated dataset (King et al., 2010).

[13] Though the state-level low-income measure is presented here, the relative changes in poverty rates after applying the benefit imputations is similar across each of the four poverty measures discussed in this paper.

the U.S.) and those in two-parent households – to show the disproportionate effect of the benefit imputations on poverty estimates of the former.

Table 6: Change in National-Level Poverty Estimates After Applying Benefit Corrections (2008-2010)

U.S., National Poverty Rate Using State-Level Low Income Measure	Standard CPS ASEC	Augmented CPS ASEC	Absolute Change	Relative Change
Children in Lone-Parent Households	37.9%	29.7%	-8.2%	-21.7%
Children in Two-Parent Households	13.8%	12.1%	-1.8%	-12.9%
Working-Age Adults	14.0%	12.6%	-1.4%	-9.9%
Pensioners	16.7%	15.3%	-1.4%	-8.4%

Note: Poverty thresholds are set at 50 percent of the state's respective median equivalised household income, but estimates are presented at the national level. Estimates are derived from the augmented CPS ASEC presented in this paper.

As the data show, the standard CPS ASEC estimates a poverty rate of 37.9 percent among children in lone-parent households; after correcting for the underreporting of SNAP, TANF, SSI, and housing subsidies, however, the estimate drops to 29.7 percent (even as the median household income and poverty threshold increase slightly after the imputations). This is a greater than 20 percent change in the estimated poverty rate among this subpopulation, clearly a significant difference.

Among children in two-parent families, the poverty estimate falls by about 1.8 percentage points (13 percent), while for working-age adults and pensioners, the estimates drop by 1.4 points each (9.9 percent and 8.4 percent declines, respectively).

These findings suggest that poverty estimates derived from the standard CPS ASEC are likely to overestimate the incidence of poverty most significantly among children and, in particular, children in lone-parent households. Given that TANF and, to some degree SNAP, are targeted at families with children, and that single-parent families are likelier to find themselves in need of income assistance, this finding is perhaps unsurprising.

The extent of the change in poverty rates should compel a more cautious approach to analyses of U.S. poverty outcomes derived from the uncorrected CPS ASEC. At the very least, shortcomings in the standard CPS ASEC should be acknowledged in poverty estimates that are derived from it; preferably, researchers should take advantage of publicly-available benefit imputations, as applied here, to produce more accurate estimates of income and poverty levels across the U.S. Though still imperfect, the augmented CPS ASEC data provides a much more realistic version of households' disposable income situations relative to the uncorrected data.

5.3. State-Level Variation in Poverty Estimates

Finally, a key purpose of the augmentations introduced here is to be able to produce more accurate and precise estimates of poverty at the state level, as evidence (outlined in Section 2) points toward the existence of wide variation in poverty outcomes. So, to what extent do states vary in their poverty outcomes, and how might this challenge the common practice of aggregating over the regional variation?

Table 7, below, offers summary statistics of state poverty rates derived from the augmented CPS ASEC data using the state-level low income measure over the years 2008 to 2010. For each demographic group, the highest poverty estimate among the 50 states more than doubles the lowest poverty estimate, suggesting considerable variation among the states.

Among children in lone-parent households, for example, the augmented CPS ASEC estimates a poverty rate of 40.8 percent in Indiana (the highest of all states), but a rate of 11.9 percent in Hawaii (the best performing state among this group in the years examined) and 21 percent in Wisconsin (the best-performing state among the 48 contiguous United States). The median state featured a poverty rate of 29.6 percent among children in lone-parent households. Even after applying confidence intervals (see Figure 3 or the full results in the *Appendix*), these patterns of immense variation hold.

Similar patterns can be found among children in two-parent families (a span of 6.6 to 17.2 percent in terms of state poverty estimates), working-age adults (7.7 to 15.2 percent) and pensioners (9.4 to 23.9 percent). Importantly, these patterns are not unique to the poverty concept applied here; similar diversity is found when using the OPM, SPM, or national low-income measure.

Table 7: Summary of State-Level Poverty Estimates with State-Specific Poverty Thresholds, Applying Augmented CPS ASEC (2008-2010)

U.S., State Poverty Rates Using State-Level Low Income Measure (n=50)	Mean	St. Dev	Minimum	Median	Maximum
Children in Lone-Parent Households	29.7%	5.3%	11.9%	29.6%	40.8%
Children in Two-Parent Households	10.8%	2.5%	6.6%	10.8%	17.2%
Working-Age Adults	12.0%	1.7%	7.7%	12.3%	15.2%
Pensioners	15.4%	3.4%	9.4%	14.8%	23.9%

Note: Sample size consists of the 50 states and summary statistics are presented as non-weighted values of the state estimates. Poverty thresholds are set at 50 percent of the state's respective median equivalised household income. Estimates are derived from the augmented CPS ASEC presented in this paper.

To provide a better frame of reference for the extent of this state-level variation, Figure 3, below, plots point estimates of state poverty rates for children in lone-parent households relative to similar estimates in a selection of OECD and EU Member States. LIS is used here to produce poverty rates for children in lone-parent households in the 15 EU and OECD countries during 'Wave VIII' of LIS data collection, which centers around 2010.

Again, an advantage of the income and poverty concepts presented here is that they can be easily applied in a cross-national context; in this case, the income definition for each of the American states matches the income definition used for each of the EU/OECD Member States in LIS, while the percentage-of-median-income poverty approach, as adopted in the state-level low-income measure, is seamlessly applied across the polities.

A review of evidence suggests that most OECD Member States, and Member States of the EU, in particular, do not experience the same underreporting of means-tested benefits in national datasets. A review of EU-SILC Quality Reports, for example, provides no mentions of underreporting or severe measurement error (Eurostat, 2014). In many countries, this appears to be partly due to closer cooperation between administrative and survey data operations (Jäntti, Veli-Matti, & Marlier, 2013), but it may also be due less reliance in general on means-tested transfers or less stigma in reporting

such transfers in survey data collection. Thus, we can be reasonably sure that applying the augmented CPS ASEC datasets to produce measures of poverty comparable to those in other nations will not "overcorrect" the American estimates but, instead, provide a more accurate portrait of them.

In Figure 3, the states are ranked in order of the point estimates of poverty rates for children in lone-parent households. Not all American states are listed; only those that rank just above or just below the EU/OECD Member States are presented with their relative ranking compared to other American states listed in parentheses. For example, the label "Wisconsin (2)" indicates that Wisconsin featured the second lowest point estimate among the 50 American states.

Figure 3: Estimates of poverty rates among children in lone-parent households, 2008-2010
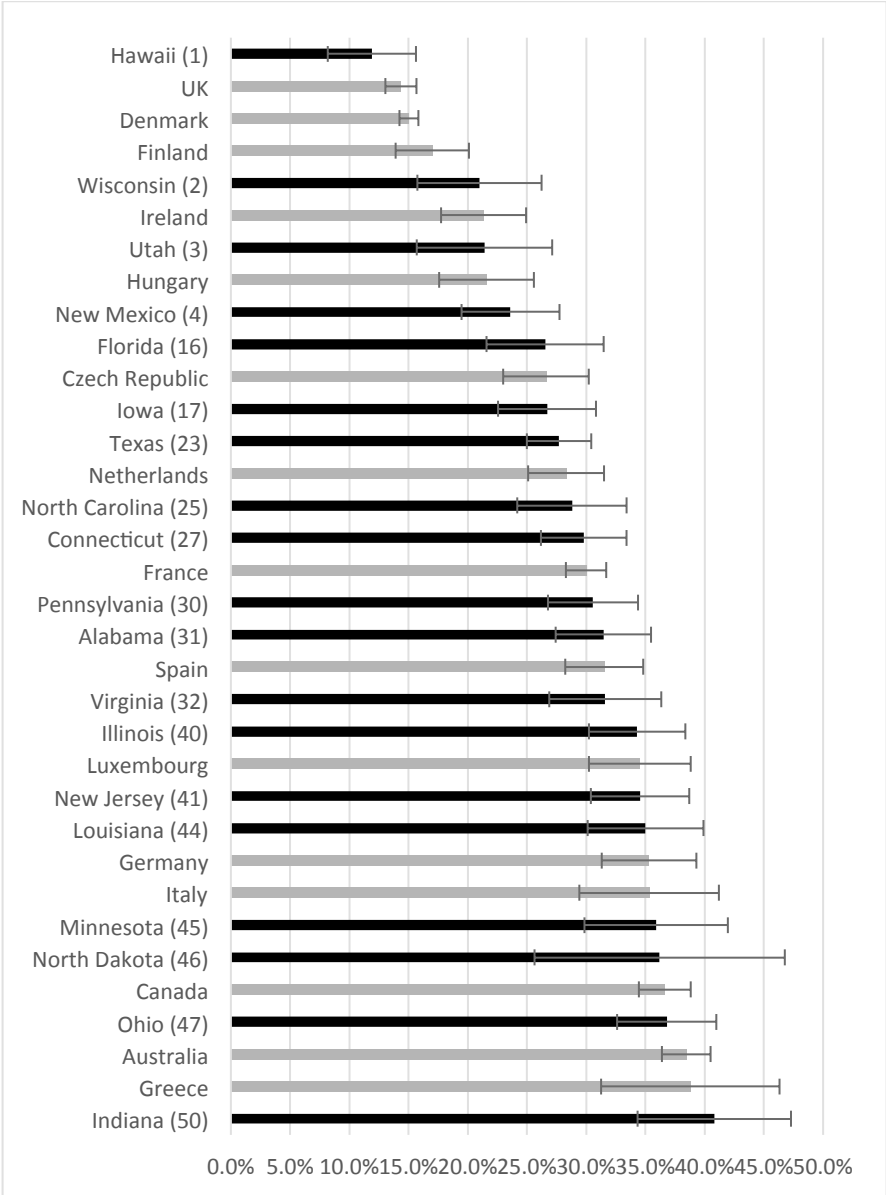
Note: Poverty thresholds are set at 50 percent of equivalised household median income in the respective state. Confidence intervals (90%) for U.S. estimates are produced using set of 160 replicate weights; for OECD/EU estimates, LIS weights are applied. Figure is author's own.
Source: Augmented CPS ASEC (U.S. states) over the years 2008-2010 and LIS, the Cross-National Data Center in Luxembourg (OECD states) for the year 2010.

As the figure shows, the span of poverty estimates for children in lone-parent households across the 50 United States is wider than the range found among the EU Member States around the year 2010.

Denmark, Finland, the United Kingdom featured the lowest estimated poverty rates among EU Member States for children in lone-parent households in the year of examination; this matches expectations and aligns with data presented in prior studies (Ferrarini, 2006; Gornick & Jäntti, 2016; Maldonado & Nieuwenhuis, 2015). The rank order of the United States, however, contradicts previous analyses that relied on an aggregation of state estimates and the uncorrected CPS ASEC data.

Hawaii actually appears to perform better than all U.S., EU, or OECD Member States with a poverty estimate of 11.9 percent. Among the 48 contiguous states, 22 appear to perform better than the Netherlands (led by Wisconsin which, with a poverty rate of 21 percent among children in lone-parent households, sits just after Finland), the next Western European state to make the list. When evaluating point estimates, 27 Americans states rank ahead of France (30 percent), and 40 ahead of Luxembourg (34.5 percent). The median U.S. state, meanwhile, performs worse than the Czech Republic, but better than Italy, Luxembourg, Spain, Australia, and Canada. On the tail end of the list, Indiana performs the worst among all states, falling right behind the point estimate of Greece in 2010.

While the precise rank order of many of the states and countries presented should be interpreted cautiously (confidence intervals among many of the mid-performing states and countries overlap), it is nonetheless clear that the range of poverty outcomes across the United States spans across comparable outcomes found in EU Member States. This holds even when using a federal low-income measure or when evaluating all children, as opposed to simply children in lone-parent households (though the rank order changes and the range of outcomes decreases slightly in either case).

To be clear, this should not be interpreted as a defense of the American welfare state; the social floor across all states is meager relative to EU and OECD counterparts, and no other country has institutionalized the provision of food stamps in the way that the U.S. has (Parolin, 2016). What the evidence does suggest, though, is that the practice of aggregating American poverty rates into a single indicator seems to indeed mask sizable variation across the 50 states, and may provide an incomplete or misleading view of the state of poverty across the U.S. While this applies largely to cross-national comparative research, the findings have equally important implications for intra-U.S. poverty research: given increasing heterogeneity in state-level social and labor market policies, as well as the wide range of poverty outcomes that exist across the 50 states, future research should leverage such differences and adopt a comparative approach to help explain the causes and consequences of this immense cross-state diversity.

The augmentations to the CPS ASEC presented here, which allow for more accurate and precise estimates of poverty at the state level, should help in that pursuit.

6. Discussion & Conclusion

This paper set out to address three common shortcomings regarding the estimation of U.S. poverty rates and, more broadly, the integration of the United States into comparative social policy research.

From a data and measurement perspective, the underreporting of means-tested transfers within American survey data, and the CPS ASEC in particular, has likely led to consistent overestimations of poverty rates within the U.S. As detailed, income or 'near-cash' support from TANF, SNAP, and SSI, as well as the provision of housing subsidies, tend to be substantially underestimated in the survey data. To address this, the Urban Institute's TRIM3 benefit imputations were applied to the CPS ASEC, bringing the estimated level of transfers much closer to the values listed within administrative data.

Using a definition of income that (a) takes into account the full range of taxes and transfers (such as SNAP, refundable tax credits, housing subsidies, and other programs as outlined in the *Appendix*) and (b) matches the concept of "disposable income" used within LIS, the Cross-National Data Center in Luxembourg, this study found that the application of the TRIM3 benefit imputations substantially increased the estimated household income of those toward the bottom of the income distribution. The fifth percentile of the household income distribution of children in lone-parent families, for example, increased substantially (a jump from $3,540 to $6,387 in 2009 USD) after the benefit corrections were applied.

Though children in low-income households appeared to see the greatest gains in estimated disposable income in this augmented CPS ASEC dataset, working-age adults and individuals over the age of 65 also saw notable increases in SNAP and SSI receipt, in particular.

Moving from estimates of income to estimates of poverty, this paper outlined best practices in comparative poverty literature and suggested the use of either a national or state-level low-income measure – in which poverty estimates are set at a percentage of the prevailing equivalised median household income – for estimating American poverty rates in a manner that can be compared across time and country. The state-level low-income measure, in particular, overlaps closely with the U.S. Supplemental Poverty Measure, both in its intent to capture regional variation in living standards and in the estimates it produces. In 29 of 50 states over the years 2010 to 2012, the differences between the SPM and state-level low-income poverty estimates were not significantly different from zero. The low income measure should not be understood as a replacement for the SPM, but as a measure of poverty that can more seamlessly be embedded into cross-national poverty research and, in the process, produce poverty estimates that appear, within most states, to be comparable to the estimates of the SPM.

Regardless of the measure applied, poverty estimates decline considerably when deriving them from the augmented CPS ASEC dataset as opposed to the standard (pre-imputation) version. Among children in lone-parent households, for example, national poverty estimates during the years 2008 to 2010 drop from 38 percent to 29.7 percent after applying the benefit imputations (these poverty estimates apply the state-level low income measure, but the relative effect of the benefit imputations is similar across all measures discussed). Among children in two-parent households, working-age adults, and pensioners, the reductions each hover around 10 percent. These findings suggest that, regardless of poverty measure used, estimates derived from the standard CPS ASEC have likely overestimated the actual incidence of poverty across the U.S.

After the underreporting of means-tested transfers and the measurement of poverty, the third shortcoming identified was the common practice within intra-U.S. and internationally comparative research of masking immense state-level heterogeneity in social outcomes across the United States. The augmentations to the CPS ASEC presented here enable more precise and accurate state-level

estimates; when evaluated, the findings suggest the aggregation of the 50 states' poverty estimates into a single national indicator does, indeed, blur significant interstate variation.

When states' estimates of poverty outcomes among children in lone-parent families are plotted (using a common income definition and poverty measure) against similar estimates for a selection of OECD and EU Member States, the findings (as shown in Figure 3) reveal that the range of point estimates among the American states mimics the range of the estimates found in the EU Member States. Similarly, the highest of the state-level poverty estimates within the U.S. for both working-age adults and pensioners doubles the value of the best-performing state.

These findings have several ramifications for future research on U.S. income and poverty dynamics and, in particular, the integration of the U.S. into comparative research.

To start, researchers should acknowledge and address the issue of underreporting of means-tested transfers in the CPS ASEC when it used to produce estimates of the incidence or severity of poverty in the U.S. It is likely that prior estimates derived from the CPS ASEC have overstated the incidence of poverty across the U.S. Moving forward, augmentations to the survey data, such as those presented here, can be used to produce more accurate estimates in future research, though it should be recognized that such imputations are still imperfect relative to administrative data.

For U.S.-focused and international comparativists alike, the augmentations to the CPS ASEC also allow for more precise *state-level* poverty estimates with a measure of income that can be compared across countries using LIS, the Cross-National Data Center in Luxembourg.

Evidence of state-level divergence in social and labor market policies, as well as continued economic diversity across the states, seems to necessitate this more dissected view of the country's policy and poverty landscape. Indeed, the findings presented highlight the need for an expanded research agenda on the causes and consequences of state-level policy decisions and the immense cross-state diversity in American poverty outcomes. Addressing issues related to inadequate state-level sample sizes and measurement error within the survey data, the augmentations to the CPS ASEC should allow researchers to more effectively pursue this research agenda.

The findings presented here also equip poverty researchers with an expanded set of guidance and tools to more fruitfully approach the practice of integrating the U.S. into cross-national poverty research. With more accurate data, an internationally comparable and conceptually-sound measure of income and poverty, and a demonstration of state-level diversity in global comparative context, this paper takes a step forward in overcoming what Brady & Destro (2014), as cited previously, reference as the "main limitation" of American social policy literature.

Moving forward, researchers can utilize and build on these data augmentations to more accurately estimate American poverty rates, investigate the cross-state diversity of poverty outcomes across the 50 states, and ensure a more worthwhile integration of the United States into comparative social policy research.

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Appendix

Appendix A: Downloading and applying the augmentations to the CPS ASEC to future research

A key purpose of this paper is to encourage the practice of producing more accurate, precise, and internationally comparable estimates of poverty at the state level; the augmentations presented provide a means to achieving that. In order to support future research and further progress in this effort, I have made the Stata programs available online for fellow researchers to evaluate and apply to their own work.

The documentations and programs include (a) the process for applying the TRIM3 benefit imputations to the CPS ASEC, (b) the process of converting the CPS ASEC variables into the disposable income definition, as applied within the LIS Cross-National Data Center framework and detailed in Appendix B, and (c) standard programs for calculating poverty rates using the Census Bureau's replicate weights.

The augmentations to the CPS ASEC cover five sets of combined files, which conveniently align with the 'waves' of LIS data. Caution is taken to ensure, as best as possible, that the combined years do not overlap with large policy or economic shifts that might significantly alter outcomes in one of the three years. The five sets of years include 1990-1992, 1993-1995, 1998-2000, 2003-2005, 2008-2010.

To find and download these programs, visit http://www.zachparolin.com/data/ or send an email to zachary.parolin@uantwerpen.be.

Appendix B: Converting U.S. income data to LIS "disposable income" measure

As detailed in the paper, LIS, the Cross-National Data Center in Luxembourg, harmonizes data from more than 40 countries to create comparable measures of income. The augmentations to the CPS ASEC presented here follow the LIS framework to provide a measure of disposable income than can be used for comparing American states to any of the countries within the LIS data infrastructure. Please note any temporary benefit programs (implemented and disbanded within a short time-period) are not included in this list or in the augmented dataset applied within this study.

The following variables are included in the measure of disposable income:

Income from market wages
Income from non-farm business activities
Income from farm wages
Income from Social Security (pensions)
Income from other retirement funds
Income from interest
Unemployment Insurance benefits
Workers' compensation benefits
Veteran's benefits
Survivor's benefits
Disability benefits (excluding assistance from Supplemental Security Income)

Income from dividends

Income from rent

Income for education assistance

Income from child support

Income from alimony

Income from friends or relatives not living in same household

Other reported sources of income

Value of energy subsidy (heating assistance)

Cash assistance from TANF *(imputed)*

Food and nutrition assistance from SNAP *(imputed)*

Supplemental Security Income benefits *(imputed)*

Housing assistance *(*Section 8 Housing Choice Voucher Program and Project-Based Rental Assistance*; imputed)*

Federal tax liabilities, net of (non-)refundable credits

State tax liabilities, net of (non-)refundable credits

Payroll taxes (FICA)

Appendix C: Poverty Rates by State Using State-Level Low-Income Measure and Augmented CPS ASEC (2008-2010)

Poverty rates are relative to state-level poverty thresholds, set at 50 percent of a state's median equivalised household income. Confidence intervals are produced using set of 160 replicate weights. The augmented CPS ASEC with imputations for TANF, SNAP, SSI, and housing subsidies is applied.

State	Children in Lone-Parent Households	90 percent C.I. (±)	Children in Two-Parent Households	90 percent C.I. (±)	Working-Age Adults (18-64 y/o)	90 percent C.I. (±)	Pensioners (65+)	90 percent C.I. (±)
Alabama	31.1%	4.0%	8.07%	1.6%	13.12%	1.87%	14.88%	2.35%
Alaska	24.3%	6.0%	11.35%	2.8%	11.27%	1.70%	19.16%	3.82%
Arizona	37.6%	6.6%	17.18%	4.0%	15.19%	2.43%	14.44%	2.91%
Arkansas	27.1%	5.0%	7.40%	3.0%	10.76%	2.05%	13.84%	3.09%
California	24.9%	2.3%	15.33%	1.0%	13.18%	0.60%	13.17%	1.09%
Colorado	37.0%	4.7%	15.20%	2.6%	14.24%	1.60%	19.67%	2.47%
Connecticut	29.8%	3.6%	11.53%	2.1%	12.33%	1.22%	14.72%	2.20%
Delaware	25.9%	4.8%	10.43%	2.2%	11.62%	1.15%	17.98%	3.23%
Florida	26.5%	4.9%	19.06%	5.2%	14.13%	1.43%	22.80%	3.07%
Georgia	25.7%	3.5%	12.49%	2.0%	14.06%	1.19%	17.81%	2.52%
Hawaii	11.9%	3.7%	6.66%	1.7%	7.85%	1.04%	9.88%	1.61%
Idaho	23.7%	6.2%	6.71%	2.3%	7.69%	1.86%	11.19%	2.92%
Illinois	34.3%	4.1%	13.61%	1.7%	12.46%	0.93%	13.69%	1.82%
Indiana	40.8%	6.5%	11.10%	2.3%	11.52%	1.52%	11.88%	2.68%
Iowa	26.7%	4.1%	9.14%	2.7%	10.18%	0.93%	14.87%	2.27%
Kansas	26.9%	7.2%	10.39%	2.1%	11.10%	1.77%	12.57%	3.82%
Kentucky	32.0%	4.7%	8.89%	2.9%	13.51%	1.98%	14.49%	3.84%
Louisiana	35.0%	4.9%	9.43%	3.2%	14.56%	1.70%	20.24%	2.88%
Maine	25.0%	5.4%	10.20%	2.5%	10.46%	1.29%	14.83%	2.67%
Maryland	29.4%	4.2%	12.95%	1.9%	13.36%	0.94%	19.33%	2.34%
Massachusetts	33.5%	5.8%	10.72%	2.4%	12.23%	1.38%	17.75%	2.41%
Michigan	37.0%	5.3%	10.05%	1.7%	12.80%	1.14%	11.68%	2.16%
Minnesota	35.9%	6.1%	12.35%	3.4%	10.52%	1.34%	16.38%	2.19%
Mississippi	27.6%	8.3%	6.59%	1.2%	13.00%	1.59%	15.22%	2.80%
Missouri	28.9%	5.0%	13.82%	3.5%	13.03%	1.41%	14.52%	2.71%
Montana	34.1%	7.6%	8.53%	1.9%	10.88%	1.81%	12.08%	2.46%
Nebraska	33.7%	6.0%	7.43%	1.7%	9.70%	1.06%	13.80%	2.28%
Nevada	25.8%	4.5%	13.87%	3.2%	11.50%	1.56%	15.33%	2.77%
New Hampshire	32.7%	6.3%	9.82%	1.7%	11.69%	1.21%	23.90%	2.95%
New Jersey	34.6%	4.1%	14.58%	2.6%	13.61%	1.41%	23.12%	2.94%
New Mexico	23.6%	6.8%	12.95%	3.1%	14.64%	2.46%	14.71%	2.54%
New York	27.2%	2.3%	10.35%	1.6%	11.94%	0.68%	15.37%	1.80%
North Carolina	28.8%	4.6%	9.50%	1.8%	11.34%	1.12%	13.75%	2.43%

North Dakota	36.2%	10.6%	10.91%	4.2%	11.57%	2.16%	23.40%	2.96%
Ohio	36.8%	4.2%	8.49%	1.4%	12.94%	1.02%	15.44%	1.81%
Oklahoma	25.7%	4.0%	10.85%	2.3%	11.11%	1.33%	13.16%	2.21%
Oregon	30.1%	6.1%	9.98%	2.3%	11.40%	1.35%	9.63%	1.94%
Pennsylvania	30.5%	3.8%	9.14%	1.1%	11.83%	0.99%	16.37%	1.80%
Rhode Island	34.3%	4.6%	13.29%	2.5%	12.51%	1.25%	16.14%	2.83%
South Carolina	27.6%	4.7%	8.17%	2.2%	12.71%	1.13%	14.80%	1.74%
South Dakota	35.0%	6.1%	11.20%	3.3%	12.55%	2.44%	12.51%	2.50%
Tennessee	32.6%	5.2%	8.25%	1.9%	12.38%	1.59%	13.75%	3.06%
Texas	27.7%	2.7%	14.24%	1.3%	13.34%	0.82%	16.18%	1.78%
Utah	21.4%	5.7%	8.60%	2.2%	7.81%	1.18%	9.42%	2.32%
Vermont	24.9%	5.8%	7.34%	2.0%	9.15%	1.01%	20.07%	2.95%
Virginia	31.6%	4.7%	12.63%	2.0%	12.64%	1.61%	21.69%	3.18%
Washington	30.1%	5.7%	14.07%	2.0%	12.86%	1.37%	16.36%	2.46%
West Virginia	35.0%	6.9%	12.43%	2.6%	14.65%	1.40%	11.90%	2.15%
Wisconsin	21.0%	5.2%	10.27%	2.3%	9.96%	1.28%	13.63%	2.63%
Wyoming	26.2%	6.3%	9.57%	2.0%	10.85%	1.34%	21.66%	2.50%
U.S. (National)	29.7%	0.77%	12.1%	0.32%	12.6%	0.20%	15.3%	0.40%
U.S. (Mean of State Estimates)	29.7%	5.2%	10.9%	2.3%	12.0%	1.4%	15.7%	2.5%

Additional Estimates of National Poverty Rates (2008-2010):

(state-level low-income measure, augmented CPS)

All Children: 16.5% (±0.33%)

Total Population: 13.9% (±0.17%)