Poverty in the United States

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Abstract

This paper provides new estimates of poverty in the United States, showing how the bottom of the income distribution changes after correcting for misreporting of survey incomes and accurately incorporating taxes, expenses, and in-kind transfers. As part of the Comprehensive Income Dataset (CID) Project, we link a wide range of administrative tax and program microdata to the Current Population Survey Annual Social and Economic Supplement for 2016. At a broad level, using better data shifts up the income distribution at every percentile in the bottom half. Starting from a baseline of survey pre-tax money income, the share of individuals with incomes below official thresholds falls by 21% after broadening the income concept and by an additional 41% after using the CID. Alternatively, poverty thresholds would have to increase by more than a third to keep poverty rates unchanged after using better data and changing the income concept. Relative poverty also falls by 61% after all adjustments. For most analyses, the corrections for measurement error are more important than the conceptual changes to income. Our measurement improvements lead to a demographic shift, with single individuals becoming a larger share or the poor and children a smaller share. Part of the explanation for the large role played by better data is that the static poverty reduction of government programs is much larger using the CID, nearly doubling for SNAP, housing assistance, and Social Security Disability Insurance.

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1. Introduction

For decades, policymakers and researchers have grappled with how to measure poverty (Orshansky 1965, Ruggles 1990, NRC 1995, ITWG 2021, NASEM 2023). In the United States, the Census Bureau's Official Poverty Measure (OPM) classifies an individual as being in poverty if their family's pre-tax money income falls below a fixed threshold. The OPM is widely cited as a key barometer of deprivation, and versions of it are used to determine eligibility for numerous government programs, allocate government funds, and guide policies. Yet, the OPM suffers from many shortcomings. Perhaps most prominently, its resource measure ignores tax credits and in-kind transfers, whose share of the overall safety net has increased dramatically in recent decades.[1] In 2011, the Census Bureau began reporting the Supplemental Poverty Measure (SPM), which addresses many disadvantages of the OPM.[2] However, the SPM and OPM both suffer from a key flaw: they are based on survey reports of income, which are often misreported and omit a large and rising share of income sources (see, e.g., Meyer, Mok, and Sullivan 2015, Bee and Mitchell 2017, Meyer and Mittag 2019, Meyer et al. 2021). As a result, these existing poverty measures may mischaracterize who is poor and misstate the poverty reduction of various programs.

In this paper, we use linked survey and administrative microdata that are part of the Comprehensive Income Dataset (CID) Project to calculate how the bottom of the income distribution changes after 1) correcting for measurement error in pre-tax money income and 2) incorporating tax liabilities, tax credits, and in-kind transfers in an accurate way. We start by taking a broad view and focusing on the entire bottom half of the income distribution, before exploring applications to prototypical poverty analyses. To the best of our knowledge, no other study has simultaneously linked the range of administrative income sources that we do – covering earnings, asset income, retirement income, and adjusted gross income from Internal Revenue Service (IRS) tax records, as well as key safety net programs such as Social Security (OASDI), Supplemental Security Income (SSI), the Supplemental Nutrition Assistance Program (SNAP), public and subsidized housing, and Temporary and Needy Assistance to Families (TANF) – to surveys to re-

[1] The OPM also relies on a narrow definition of resource-sharing units, treating, for example, unmarried cohabitors as separate units. The equivalence scale implicit in the OPM thresholds, which characterizes how thresholds change for families with different sizes and compositions, has also been criticized for its odd properties.
[2] At the same time, the SPM introduces some methodological choices that may be undesirable. One such aspect is the geographic adjustment of poverty thresholds for differences in cost-of-living (specifically rent), which Meyer, Wu, and Curran (2022) show identifies a less deprived population in poverty.

examine the measurement of income and poverty.[3] We link these administrative data to the Current Population Survey (CPS) Annual Social and Economic Supplement – the source of official poverty and inequality statistics in the U.S. – for the 2016 reference year.

Research comparing survey and administrative income values in the U.S. goes back more than fifty years, and efforts have proliferated in recent years using linked survey and administrative data to measure incomes more accurately (for a summary of this literature see Meyer and Mittag 2021). Administrative microdata are regarded as the gold standard for many income sources, but they are often incomplete as a result of gaps in the data and unlinked records. This understatement tends to be less pronounced for certain government benefits (administered by agencies whose data are accurate and nearly complete) while more evident for an income category like earnings (which is complicated to measure and incompletely reported to tax authorities). A key innovation of this paper is thus a new measurement error model for administrative and survey data. This model, while simple, implies a new and transparent way of combining earnings data from different sources, leading us to reconcile discrepancies between multiple administrative records and incorporate survey values when they reflect earnings plausibly missed in tax records. To validate our approach, we compare aggregate values of our combined earnings to national accounting totals reported in the Bureau of Economic Analysis' National Income and Product Accounts (NIPA).

Given that the goal of poverty measurement is to assess deprivation, it is also appropriate to account for all resources available for consumption. We therefore go beyond solely analyzing pre-tax money income and account for tax liabilities and credits, subtract certain expenses (child support paid and work expenses), and include in-kind transfers in income. A wide range of studies have argued for counting in-kind transfers as income (see, e.g., Ellwood and Summers 1985, NRC 1995, Blank 2008). In this paper, our broadest income concept incorporates in-kind transfers that support food and housing consumption, including SNAP, housing assistance, the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), free school lunch, and energy assistance. We follow the methodology of the Supplemental Poverty Measure (SPM) and

[3] Another project based out of the Census Bureau – the National Experimental Wellbeing Statistics (NEWS) Project – is also undertaking the valuable task of linking a substantial array of administrative records to Census surveys to measure income and poverty statistics. The NEWS Project aims to address multiple sources of biases (from unit non-response, item non-response, and measurement error among respondents), while our paper focuses specifically on misreporting (which embeds biases from both item non-response and measurement error among respondents). The initial version of the NEWS estimates also focuses exclusively on corrections to pre-tax money income (Bee et al. 2023), while our paper applies corrections to a broader set of income concepts including taxes and in-kind transfers. Later in this paper, we compare and contrast our methods and results with those of NEWS in greater detail.

value these in-kind transfers at cost. SNAP, the largest of these in-kind transfers, features benefits that can be plausibly treated as cash, as its benefit amounts usually fall below the pre-receipt food expenditures for recipients (Ben-Shalom, Moffitt, and Scholz 2012, Hoynes, McGranahan, and Schanzenbach 2015). Housing assistance, the second largest of these in-kind transfers, is today mostly in the form of housing vouchers, which are valued at close to the subsidy amount given that gross rents are comparable to market rents (Olsen 2019).

To motivate our results, we start by noting the striking degree to which survey-reported incomes are underreported in the aggregate: for example, only 53%, 55%, and 65% of SNAP, retirement income, and EITC dollars are reported or imputed in the CPS (Figure 1). In contrast, we capture 90-100% of all dollars after correcting for misreporting using administrative data, with the CID estimates continuing to slightly understate national accounting totals. The high-level implication for the income distribution is that using better data leads incomes to increase, relative to survey-only estimates, at *every* percentile of the bottom half. The fractional increases are largest at the very bottom, with pre-tax money incomes increasing by 21%, 15%, and 9% at the 10th, 25th, and 50th percentiles, respectively. Incomes accounting for taxes, expenses, and in-kind transfers also increase by 22%, 17%, and 14% at the aforementioned percentiles after using the CID.

We turn next to applications for three prototypical poverty analyses, which reflect unidimensional "snapshots" of the income distribution. First, we analyze the shares of individuals with incomes below official thresholds – akin to rates of absolute poverty. Using survey data alone, we find that 11.4% of individuals have pre-tax money incomes below poverty thresholds and 9.0% have incomes (accounting for taxes, expenses, and in-kind transfers) below such thresholds. Using the CID reduces these rates to 8.5% and 5.3%, respectively. Better data account for 60% of the overall decline in poverty (from 11.4% to 5.3%) when changes to the income concept are brought in first. Alternatively, when making step-by-step adjustments in which we sequentially incorporate better data and change the income concept, better data account for 95% of the overall decline in poverty. As a result, the usage of the CID consistently explains more of the decline in poverty than the broadening of the income concept. This result holds across fractions and multiples of the poverty line.

Second, we analyze how much poverty thresholds would have to change to keep absolute poverty rates constant. Starting again from a survey pre-tax money income baseline, thresholds would have to increase by 13% after changing the income concept – and by 36% after the combination of changing the income concept and using better data – to keep absolute poverty rates unchanged at 11.4%. Using the CID accounts for 64% of the increase when changing the income concept first, while it accounts for 100% of the increase in poverty thresholds using sequential adjustments. Third, we examine the rate of relative poverty, defined as the share of individuals with incomes below a given fraction of median income. Our default fraction is approximately 30% of median income, chosen such that the baseline absolute and relative poverty rates using survey pre-tax money income are equivalent. Relative poverty falls from 11.4% to 6.3% after broadening the income concept, and it additionally declines to 4.5% after using the CID. Here, better data play a smaller but still substantial role in explaining the overall decline in relative poverty.

In addition to the three prototypical poverty analyses, we examine how the corrections and adjustments vary across demographic subgroups and change our understanding of *who* is in poverty. Broadening the income concept leads to the largest reductions in poverty rates for children, those with less than a high school diploma, and Black individuals. These are groups who tend to be targeted by tax credits and in-kind transfers. Using the CID further leads to large reductions in poverty for the elderly, multiple childless individuals, and those living in rural areas. These are groups who tend to underreport incomes to a greater degree (e.g., elderly individuals heavily underreport retirement incomes). Consequently, those remaining in poverty after changing the income concept and using better data are more likely to be white, childless, and educated.

Finally, as a partial explanation for the large role played by better data, we find that the static poverty reduction effects of government programs are consistently larger using the CID compared the survey alone. In the absence of any taxes or transfers, poverty increases by 205% using the CID, which is 40% larger than the survey-only estimate. The differences are particularly dramatic for certain programs, as the effects using the CID are each 80-90% larger for Social Security Disability Insurance (DI), housing assistance, and SNAP relative to the survey alone. The gaps are also more pronounced for different programs at different fractions and multiples of the poverty line. Using the CID, the deep poverty reduction effects are more than 60% larger for DI and SSI and the near poverty reduction effects are more than twice as large for housing assistance, SNAP, and TANF.

The remainder of the paper is structured as follows. Section 2 describes the survey and administrative data used and how they are linked. Section 3 details the methods used to calculate resource measures, focusing on how we resolve discrepancies between multiple sources of earnings, correct other sources of pre-tax money income, incorporate tax liabilities and credits, and account for expenses and in-kind transfers. Section 4 starts by presenting results on the bottom of the income distribution, and Section 5 describes our main results on poverty. Section 6 examines how the adjustments change our understanding of the demographics of the poor, and Section 7 analyzes the poverty reduction effects of government programs. Section 8 concludes.

2. Data

In this section, we describe the various survey and administrative data sources that we link in this paper. We focus on reference year 2016, as it is a recent year for which the available administrative data are relatively complete for all income sources.

2.1. Survey Data

Our survey data come from the 2017 Current Population Survey Annual Social and Economic Supplement (CPS ASEC, hereafter referred to as CPS). The Census Bureau relies upon the CPS to produce its annual Official Poverty Measure, Supplemental Poverty Measure, and historical median income series. The CPS contains a wide variety of questions on income sources and amounts, and it includes an extensive set of demographic information on respondents that is unavailable in most administrative sources. The 2017 survey interviewed nearly 70,000 households (covering 186,000 individuals) between February and April of 2017 about their annual incomes in the previous calendar year (2016).

2.2. Administrative Data

Table 1 describes the various sources of administrative data that we have for each income component. We first describe the data from Internal Revenue Service (IRS) tax records. Earnings records come from several sources. Wage and salary amounts are available from IRS Form W-2, the Detailed Earnings Record (DER) database of the SSA (which itself is partly derived from IRS W-2 Forms), and IRS Form 1040. While there is substantial overlap in information across these three sources, there are also important differences that we discuss in greater detail in Section 3. Self-employment earnings are available from the DER, which pulls amounts from Schedule SE of IRS Form 1040. In addition to covering earnings for tax filers, the 1040s contain information on multiple sources of asset income – including taxable and tax-exempt interest and taxable dividends – and adjusted gross income (AGI). Although our 1040 extracts do not contain actual amounts for taxes paid and tax credits received, they cover enough line items (e.g., AGI, filing status, etc.) that we can calculate tax liabilities and credits relatively accurately (see Meyer et al. 2022 for detailed methods). Data on retirement distributions come from IRS Form 1099-R, which cover gross payments from employer-sponsored plans and Individual Retirement Account (IRA) withdrawals.

Next, we describe the administrative program records that come from various federal and state agencies. These programs are all paid out at the monthly level. Social Security benefits come from the SSA's Payment History Update System (PHUS) file, and we use the SSA's Master Beneficiary Record (MBR) to distinguish between payments from Old-Age and Survivors Insurance (OASI) and from Disability Insurance (DI). Our preferred administrative measures of OASI and DI are gross amounts that include medical insurance premiums withheld from the net disbursement. Supplemental Security Income (SSI) benefits come from the SSA's Supplemental Security Record (SSR) file, which includes federal and federally-administered state payments but excludes state-administered payments. OASI, DI, and SSI are all paid out at the individual level.

Housing assistance records come from the Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification System (TRACS) files, which cover almost all public and subsidized housing assistance programs under the jurisdiction of the Department of Housing and Urban Development (HUD). We calculate a household's benefit amount as the difference between the gross rent and actual tenant payment.[4] Supplemental Nutrition Assistance Program (SNAP) records come from state agencies and are available for twenty-three states in 2010. Finally, TANF administrative records come from either the Department of Health and Human Services (HHS) or from individual state agencies and are available for thirty-six states. For some of the state agencies (though not HHS), the TANF records cover other state-administered cash welfare programs like General Assistance. Housing assistance and SNAP benefits are paid out at the household level, and TANF benefits are paid out at the family level.

[4] For public housing units, which have missing gross rent amounts and make up less than a quarter of all households in the administrative data, we impute the market rent based on the average rent by 5-digit zip code, household size, and year (and, if rent is still missing, by 3-digit zip code/household size/year, 5-digit zip code/year, and 3-digit zip code/year in that order). We consider a household as receiving payments in a given month if it is within twelve months of the most recent certification date and is prior to any termination date.

2.3. Linking Data Sources

We link the administrative data to surveys using individual identifiers called Protected Identification Keys (PIKs). PIKs are created by the U.S. Census Bureau's Person Identification Validation System (PVS), which is based on a reference file containing Social Security Numbers (SSNs) linked to names, addresses, and dates of birth (Wagner and Layne 2014). Over 99% of most administrative records are linked to PIKs, and approximately 90% of individuals in the CPS are associated with a PIK. Our sample of analysis in the CPS consists of individuals whose families have at least one member with a PIK and no member that is wholly imputed.[5] This leads to a sample size of 145,000 individuals, comprising 78% of the original sample.

To account for the bias arising from non-random missing PIKs and whole imputations, we divide individual survey weights by the predicted probability that at least one member of the family (SPM unit) has a PIK and no member is wholly imputed, conditional on observables in the survey (see Wooldridge 2007). This approach keeps the samples in both surveys as complete as possible, but we will understate the administrative incomes of individuals who do not have a PIK but are part of families with at least one member who does. This understatement should be small for income sources like SNAP and housing assistance, as we link all benefit dollars from an assistance unit to a survey family as long as there is at least one common individual between each unit.[6] However, the understatement will be more pronounced for income sources – including earnings, asset income, retirement income, OASI, DI, and SSI – where the administrative data are at the individual level. As a result, for these sources, we continue to use survey values (which will still be understated if these values are on net underreported) for un-PIKed individuals in our sample.

There are a number of reasons to think that our reweighted PIKed and non-whole imputed sample does not distort the income distribution. Our inverse probability weights condition on a wide array of covariates that include survey-reported income and program receipt. We are only able to control for survey values of these income sources, as administrative values are not available for both linked and unlinked individuals. However, survey values are likely to be highly correlated with administrative values. Prior work has also shown that unit non-response does not seem to be

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[5] We define an observation to be wholly imputed if they provided some responses to the March supplement but not enough for an interview or did not provide enough income data as part of the supplement interview (i.e., values of "2" or "3" for the FL_665 variable). Approximately 16% of individuals in the 2017 CPS ASEC were wholly imputed.

[6] If an administrative case links to multiple families, then we distribute administrative dollars in proportion to the number of individuals linked to each family.

biased in income, although it is associated with other factors like marital status and the number of children (Bee, Gathright, and Meyer 2015, Rothbaum and Bee 2021). Finally, we are able to validate our reweighting methodology by comparing the share of individuals with survey incomes below various fractions of the poverty line (encompassing the entire bottom half of the distribution) between the full sample with original weights and the reweighted subsample. We find that deep, regular, near, and twice poverty rates (reflecting 50%, 100%, 150%, and 200% of the poverty line) change by only 1.9%, 1.2%, 1.3%, and 0.8% after using the reweighted subsample. These small differences pale in comparison to the magnitudes of changes we obtain after using administrative data to correct incomes (which often change poverty rates by 50% or more).

3. Methods

This section discusses the methods used to calculate incomes using the survey and CID. We start by discussing our broad income concepts of interest, as well as the sharing units over which incomes are calculated and the equivalence scale used to adjust incomes across families of different sizes and compositions. We then discuss how we use the CID to correct pre-tax money income and accurately incorporate taxes, expenses, and in-kind transfers into the income concept. We pay special attention to the treatment of earnings, introducing and validating a new approach that combines values from both survey and administrative sources.

3.1. Income Concepts, Sharing Unit, and Equivalence Scale

Throughout the paper, we focus on three main income concepts that we estimate using survey data alone or the CID. The first income concept is pre-tax money income, which is the resource measure used for the OPM. For most individuals, earnings comprise the bulk of pre-tax money income, although examples of other components are asset income, retirement distributions, and cash transfers like Social Security, SSI, and unemployment compensation. The second income concept is money income net of taxes and certain expenses. The final, and most complete, income concept is money income net of taxes and expenses plus the value of non-medical in-kind transfers, including rental housing assistance, SNAP, WIC, school lunch, and energy assistance.

We rely on the SPM family unit as our resource-sharing unit, which includes related individuals, cohabitating unmarried couples, unrelated children under the age of 15, and foster children under the age of 22. We equivalize incomes using the SPM three-parameter equivalence scale, which standardizes incomes based on the number of adults and children and allows for a different adjustment for single parents (Creamer et al. 2022).[7] This equivalence scale offers a number of improvements over the scale implicit in the OPM thresholds, including greater transparency and exhibiting diminishing marginal costs with each additional child or adult.

3.2. Correcting Pre-Tax Money Income and Broadening the Income Concept

Pre-Tax Money Income

We start with survey-reported pre-tax money income and correct only the components for which we have analogs in administrative records. For the majority of such components, we simply replace survey values with values from administrative records. We replace survey reports of asset income (namely interest and dividends) with their administrative counterparts from the 1040s.[8] For retirement income, we replace combined survey reports of retirement, survivor, and disability income (excluding Social Security and veterans' benefits) with gross amounts from employer-sponsored pensions and IRA distributions from 1099-Rs.[9] We replace survey reports of OASI and DI, decomposable from total OASDI using the reasons reported for receipt, with gross amounts of OASI and DI from the administrative data. We also replace the entire survey value of SSI with the amount of federally-administered SSI from administrative records.

There are several components of pre-tax money income that are not as straightforward to correct. The first is earnings, for which there are multiple administrative sources that are each incomplete and miss informal earnings that may be reported on surveys. As the next subsection discusses in greater detail, we combine all of these administrative sources and continue to use survey values when they reflect amounts that are plausibly missed in the tax records. Second, we use AGI on 1040s to provide a lower bound for the taxable portion of pre-tax money income. Specifically, if AGI exceeds the taxable portion of CID pre-tax money income (which excludes non-taxable transfers like SSI, TANF, and veterans' benefits as well as any earnings not appearing on tax forms), then we include the difference in our CID income measure. This approach offers a

[7] The three-parameter equivalence scale takes the following form, given the number of adults A and number of children C: $A^{0.5}$ for one and two adults, $[A + 0.8 + 0.5(C - 1)]^{0.7}$ for single parents, and $[A + 0.5C]^{0.7}$ for all other families.

[8] For joint returns where a spouse is absent in the survey, we allocate half of asset income to each of the primary and secondary filers. We do not correct survey reports of rents and royalties, as the surveys ask about net amounts while our 1040 extracts contain only gross amounts.

[9] The CPS splits what we designate as "retirement income" into pensions or retirement income, survivor and window's pensions, estates, trusts, or annuities, and disability income.

way to implicitly correct for the under-reporting of income sources like Unemployment Insurance, alimony, and capital gains that are a part of AGI but for which we do not have individual administrative sources. Nevertheless, this is a conservative correction because AGI is net of various deductions that should not be subtracted from pre-tax money income.[10]

Finally, we rely administrative data from the HHS or state agencies to correct survey reports of TANF. For a small number of states where we have administrative records from multiple sources, we take the larger value as our preferred administrative value. However, the survey asks about TANF in conjunction with other state and local cash welfare benefits, which cover a broader set of programs than what is available in the administrative HHS records (and perhaps even the state records). We therefore continue to bring in values from survey respondents who do not appear in the administrative records, assuming that they reflect values for programs missed in the administrative data. Because we have TANF data for 36 states and it is a relatively small program, we correct TANF amounts only for a small subset of analyses and always after other adjustments.

Incorporating Taxes and Expenses

Next, we discuss how we simulate federal and state income taxes as well as payroll taxes on both wages (FICA) and self-employment (SECA). The tax credits that we focus on are the Earned Income Tax Credit (EITC), for which we simulate both the federal and state amounts, as well as the non-refundable and refundable portions of the Child Tax Credit (CTC). For the survey-only estimates, we rely on CPS tax liabilities and credits calculated by the Census Bureau using their internal tax model (for more details, see O'Hara 2004, Lin 2022).

For the CID estimates, we use the National Bureau of Economic Research's TAXSIM calculator to simulate taxes using inputs from a combination of IRS tax records and other sources (Feenberg and Coutts 1993). We rely on AGI and tax unit structure (e.g., filing status, number of dependents) from the 1040s and estimate the number of qualifying dependents for a given tax credit by linking birth dates from the SSA's Numerical Identification System (Numident). We calculate payroll taxes on wages from W-2s (since Social Security taxes are capped at the individual level and payroll taxes are collected even for non-filers) and self-employment earnings from the DER. We also calculate taxes for families and individuals who do not appear in the 1040s

[10] Ideally, we would use total money income from 1040s (the portion of AGI before deductions), but the 1040 extracts do not contain a clean version of total money income.

(in the event that they are unlinked, filed late, or had taxes withheld), relying on their survey family structure and on incomes from other IRS information returns or the survey. Meyer et al. (2022) provides additional methodological details and shows that estimates of taxes using the CID are much closer to IRS-published totals than those calculated using survey data alone.

We also bring in survey reports of certain expenses, namely child support paid and work expenses.[11] We do not have analogs in the administrative data for either of these expenses. To obtain a full measure of money income after taxes and expenses, we add the EITC and CTC and subtract tax liabilities (net of all other credits) and expenses from pre-tax money income.

Incorporating In-Kind Transfers

Finally, we incorporate the monetary value of in-kind transfers that support food and housing consumption. We first discuss how we calculate amounts based on survey reports, relying on imputations using the SPM methodology (Fox 2017). For SNAP, the CPS asks about amounts at the household level, which are prorated to families within each household. Housing assistance amounts are the difference between imputed market rent and imputed tenant payment (Johnson, Renwick, and Short 2010), which are capped at the housing portion of the SPM poverty thresholds. Again, housing assistance amounts are prorated to families within each household. For families reporting WIC receipt, the assumption is that all children under age 5 receive the benefit and the mother also receives the benefit if her child is under age 2. WIC amounts are imputed using USDA program information. For the National School Lunch Program, benefits are calculated by multiplying the number of children in a family receiving free lunch by USDA's reimbursement rate and the number of school days in a year. Finally, households report benefit amounts received for the Low-Income Home Energy Assistance Program (LIHEAP) over the past year.

We subsequently replace survey values of housing assistance and SNAP with amounts from the administrative data. An advantage of the administrative records is that they contain accurate information on benefit spells, whereas survey imputations often assume continuous receipt over all twelve months of the reference year. For housing assistance, given that the

[11] While the Supplemental Poverty Measure additionally subtracts child care expenses and medical out-of-pocket expenses, we do not do so given concerns over whether or not they help identify the most disadvantaged individuals. In particular, prior work has found that those identified as "poor" after out-of-pocket medical expenses are subtracted from income have higher consumption, more education, and more rooms in their home (Meyer and Sullivan 2012) and appear to be of higher socioeconomic status (Creamer 2022).

administrative amounts cover only HUD-administered programs, we continue to bring in amounts from survey recipients who do not appear in the administrative data. This may overstate housing assistance if there are false positives in the survey, but housing assistance may yet be understated given false negatives associated with non-HUD programs. For SNAP, we bring in administrative data for 23 states. To calculate incomes after accounting for the administrative SNAP values, we multiply income levels after all other adjustments (calculated over all 50 states) by the fractional change in incomes due to incorporating the administrative SNAP data (calculated over 23 states). This proportional adjustment assumes that the 23 states are representative of the U.S. only in the *marginal* impact of the administrative SNAP data rather than in the *level* of income.

Gaps in Non-Earnings Administrative Sources

Although we incorporate administrative data for a number of income sources, we find that administrative records almost invariably understate, rather than overstate, incomes. Housing assistance records from HUD, for example, miss payments received by at least two million households from programs administered by the Department of Agriculture (USDA), states, and localities (Olsen 2018). Federal SSI records also miss state-administered funds, and our SSI data files for federally-administered benefits have been found to understate the number of such recipients by 2-6% per year (Wyse et al. 2024b). In addition, our exclusive reliance on tax return amounts for certain income sources (such as asset income and AGI) also risks understating these sources. Prior work has found that 14% of UI recipients do not file 1040s, and an additional 11% do not report UI amounts even conditional on filing (Meyer et al. 2023). In addition, 4% of OASDI recipients do not report receipt on 1040s (Wyse et al. 2024a). Moreover, the administrative TANF records from HHS miss General Assistance payments, and state TANF microdata fall short of aggregates in some states and years. Thus, we are likely to understate incomes in many of the instances where we simply replace survey values with their administrative counterparts.

3.3. Correcting Earnings

The single largest component of income is earnings and it is among the most consequential sources to correct. We start by describing the general principles behind our approach to correcting for its mismeasurement. We then discuss the qualitative and quantitative evidence on the discrepancies between multiple earnings sources and how they apply to our principles. Finally, we use the available evidence to justify a new procedure for addressing measurement error in both survey and administrative sources of earnings, and we validate our approach by comparing our totals to publicly available aggregates from NIPA.

Principles for Combining Multiple Sources of Earnings Data

Our key modeling assumption is that survey reports of earnings are both under- and overreported, while administrative earnings records are only underreported. While not strictly true, the evidence on the general incompleteness of administrative data suggests that this assumption a good approximation. As previously discussed, there is much evidence of administrative data being understated and little evidence of overstatement. All administrative sources are also conceptually incomplete to some degree, along with having missing values and un-PIKed and thus unlinkable records. These assumptions have several direct implications. First, when combining administrative sources, one should rely on the largest value since other sources can only be lower due to incompleteness and underreporting. Second, one should only rely on survey-reported earnings when they exceed administrative data-based earnings, as the administrative data are either accurate or underreported. Of course, this approach does not argue for always relying on the survey values when they exceed administrative values, but only in selective cases. Specifically, our approach uses survey amounts to "fill in" holes when we most suspect the administrative values to be incomplete (e.g., in the case of informal earnings that are not reported to tax authorities).

However, taking the maximum of multiple sources comes with the risk of overstatement if the discrepancies reflect earnings misclassification borne out of confusion. Indeed, the literature provides some evidence of confusion between different sources of earnings (specifically wage/salary and self-employment amounts).[12] Our approach takes the maximum of administrative

[12] For example, Abraham et al. (2013) find that 18% of wage earners in the CPS do not appear in UI wage records (as part of the Longitudinal Employer-Household Dynamics dataset), while 6% of workers in the UI wage records do not appear as CPS workers. They find evidence that the CPS workers not in UI records are statistically significantly more likely to have survey characteristics consistent with being an independent contractor. Abraham et al. (2021) find even more striking differences for self-employment: 52% of CPS self-employed earners do not appear as self-employed in the DER file, while 67% of DER self-employed earners do not appear as self-employed in the CPS. Of the latter share, more than a third report earning wages in the CPS – consistent with earnings misclassification. Finally, Collins et al. (2019) find that 1040 filers who have self-employment income from online labor platforms (based on third-party information returns) are more likely than the average tax filer to report the presence of "other income" on 1040s (12% versus average of 5%) but no more likely to report 1040 wages exceeding W-2 wages (13% versus average of 15%). This result suggests that self-employment amounts may be misclassified as other miscellaneous income on tax returns.

sources of wage/salary earnings and then adds a single source of self-employment income from the DER (derived from 1040 Schedule SE). We largely avoid the double-counting of earnings *between administrative sources* because confusion can only occur on 1040s, given that wage amounts on the DER and W-2 are employer-reported wages and salaries. The only case where our approach double-counts earnings is when individuals report W-2 wages as self-employment on a 1040, a scenario for which we know of no evidence. Our approach also avoids the double-counting of misclassified earnings *between survey and administrative sources*, because we only bring in survey amounts when total survey earnings exceed total administrative earnings.

One setting where there is a suggestion of administrative data overreporting is the self-employment income of EITC recipients reported on Form 1040. Saez (2010) finds bunching of claimed amounts at the first convex kink point of the EITC schedule. This clumping is likely a mix of overreporting and underreporting. While the EITC subsidy tax rate would incentivize over-reporting, these incentives are not understood by claimants (Romich and Weisner 2000, Chetty and Saez 2013). Likely more salient marginal incentives to underreport come from public and subsidized housing, Medicaid, ACA subsidies, and other programs. The empirical evidence from tax audits indicates that self-employment income is most likely to be under-reported by those with the lowest reported income (Auten and Langetieg 2021), and our comparisons to national accounts discussed below indicate pronounced under-reporting of self-employment income even after our corrections.

Gaps in Administrative Sources

We now provide details on the extent to which our administrative sources of earnings are incomplete. We start by discussing conceptual gaps among our three administrative wage sources and our single administrative source of self-employment. IRS W-2 data cover formal sector wages and salaries from the universe of W-2s filed by employers, which are received by employees regardless of whether or not they file 1040s. Wages on the DER are derived from W-2s, but the DER contains records only for individuals with valid SSNs and thus misses millions of W-2s filed using ITINs.[13] Both the W-2s and DER miss additional categories of wages that appear on 1040s,

[13] While the IRS instructs employers to file W-2s only for employees with SSNs, some employers inevitably file W-2s for employees without SSNs but with Individual Taxpayer Identification Numbers (ITINs). In its instructions to

such as unreported tips and scholarships. Moreover, self-employment earnings from the DER reflect only the Medicare-taxable portion (92.35%) of net self-employment earnings on Schedule SE of the 1040s, which has already been reduced by any health insurance deduction.

In practice, there are additional gaps associated with these administrative sources. First, while PIK rates are nearly 100% in tax records because of the presence of SSNs and ITINs, there are many instances where an individual has a PIK in one source but not another. Second, some administrative sources may not be up to date; wages in the DER and W-2, for example, may conflict if one source has been updated more recently. Third, variables constituting specific components of earnings are missed in certain sources. Allocated tips, for example, are missing in the IRS W-2 data but included in the DER. Both the IRS W-2s and DER also miss the pre-tax portion of wages that are used to pay health insurance premiums. Finally, and perhaps most importantly, gaps can arise from non-filing and missing records. For example, 1040 wages may be understated if employees do not file a 1040 or, conditional on filing, omit wages from at least one W-2. Some employers may also fail to file W-2s for their employees or do so late.[14] In addition, not all self-employment earnings are accompanied by an IRS information return (like Forms 1099-MISC or 1099-K), and not all amounts on these returns are listed on a 1040 (Collins et al. 2019). More generally, many off-the-books or non-standard earnings remain unreported to tax authorities, with Basker et al. (2024) estimating that tax records miss $11 billion per year in tip earnings.

Quantitative Evidence on Differences Between Sources of Administrative Wage Data

Having discussed conceptual differences between administrative sources of earnings data, we now discuss the empirical magnitudes of these differences and the characteristics of those with conflicting amounts (see Table 2 for a summary). We focus on taxable wages to make apples-to-apples comparisons across the sources. We start by comparing wages between W-2s and the DER, with Appendix Table A1 providing more details. First, 0.26% for all individuals aged 15 and over

employers, the IRS states "Do not accept an IRS individual taxpayer number (ITIN) in place of an SSN for employee identification or for Form W-2 reporting" (p. 7 of https://www.irs.gov/pub/irs-prior/iw2w3--2016.pdf). However, the IRS does not require that employers verify the SSN of an employee before submitting a W-2: "An employer must make an initial solicitation for the employee's SSN at the time the employee begins work," but "[t]he employer may rely in good faith on the number provided by the employee and use it when filling out the employee's Form W-2" (p. 13 of https://www.irs.gov/pub/irs-pdf/p1586.pdf).

[14] For example, Marifian et al. (2002) discuss cases where an employer misclassified employees as shareholders in an S-corporation (leading to no W-2s being filed). Moreover, NELP (2020) documents many instances in which employers misclassify employees as independent contractors (as opposed to filing W-2s) as a way to avoid paying employment taxes.

(and 0.37% for the subset designated as poor under the OPM) have W-2 wages that exceed DER wages. Among all individuals with higher W-2 wages, the share consisting of ITIN holders is 61%, which is likely understated since we can only identify ITINs who appear on 1040s and will miss non-filers who receive W-2s based on their ITINs. Among non-ITINs with higher W-2 wages, 38% have wages missing in the DER altogether and 62% have more employers in the W-2s than in the DER. In other words, the DER likely misses a job for the majority of these individuals.

Next, we find that 0.70% of all individuals and 0.49% of individuals living in poor families have DER wages that exceed W-2 wages. As expected, there are no ITINs among these employees, as the DER only contains records filed using SSNs. Among all individuals with higher DER wages, 47% do not have any wages in the W-2 data, and 86% have an employer missing in the W-2 data. For individuals with higher DER wages, we also observe that DER wages – and not W-2 wages – are more likely to align with the amounts recorded on 1040s. These differences may arise from the datasets being updated to reflect corrections or late filers at different times or to differing degrees.

We now move to comparing taxable wages between W-2s and 1040s, with Appendix Table A2 providing more details. First, 4.4% of all tax units and 7.0% of tax units in poor families have 1040 wages that exceed the combined W-2 wages of the filers in a tax unit.[15] Of the 4.4% of tax returns, 9% are filed by ITINs (versus only 1% of all tax units). Among the non-ITIN returns with higher 1040 wages, 47% have characteristics consistent with conceptual differences between 1040 and W-2 wages (versus 33% of all tax units). Among the most prominent characteristics: 17% are a full- or part-time student, 14% work in a commonly tipped industry, 11% live in a household with child care expenses, and 7% likely misclassify self-employment earnings as wages.[16]

On the flip side, 5.3% of all tax units (and 10.8% of tax units in poor families) have combined W-2 wages that exceed 1040 wages (conditional on filing a 1040). The vast majority (71%) of these tax units have the exact difference between W-2 wages and 1040 wages equal to the wages on one or two W-2s, with 65% having the difference equal to wages on a single W-2. This provides striking evidence that most of these filers omitted wages from one of their W-2s on their tax returns. While our administrative tax data contain IRS corrections for simple math errors,

[15] Collins et al. (2019) find that 14.8% of tax units have 1040 wages that exceed W-2 wages in 2016, but their estimate may include small rounding differences.
[16] We say an individual likely misclassifies self-employment earnings as wages if they receive a 1099-MISC, do not file a 1040 Schedule C (for self-employment business income), and report wages on a 1040. A caveat is that one could receive a 1099-MISC for reasons other than non-employee compensation.

they do not reflect corrections for more substantive errors (e.g., not including all W-2 income on one's tax return) that the IRS might follow up on as part of its enforcement process.

Combining Earnings Data

These conceptual and quantitative comparisons suggest that whenever wage amounts differ between administrative sources, the source with the higher value tends to be more reliable. We therefore start by taking the higher of taxable wage amounts across these sources (in most cases).[17] To avoid double counting with non-earnings income sources, we do not bring in 1040 wages for non-elderly individuals receiving a 1099-R (who may report disability pensions reported as wages on a 1040) or for individuals reporting scholarship income in the survey. We then include non-taxable wages by taking the higher of deferred compensation amounts to retirement plans in the DER and W-2s.[18] While older studies have tended to treat administrative sources of earnings as measures of "truth" (Bound and Krueger 1991, Bound et al. 1994, Bollinger 1998), more recent work assumes that the administrative data may contain errors or be incomplete (Abowd and Stinson 2013, Bee et al. 2023). We therefore continue to use survey earnings that exceed combined administrative earnings if they reflect earnings that are plausibly missed in the tax records.

As a prerequisite, we consider bringing in survey earnings only if we have some supporting evidence that the survey reports are high quality. Specifically, only if the amounts are not imputed and many employment characteristics – including hours worked, weeks worked, industry of job, job occupation, and size of employer – are not imputed. Using only non-imputed earnings from non-imputed jobs is crucial, given errors in imputation (e.g., Hokayem, Bollinger, and Ziliak 2015, Bollinger et al. 2019). We also require at least one of the following conditions to hold:

- Our files are missing all administrative earnings sources (DER, W-2s, and 1040s),[19]
- The number of survey-reported employers exceeds the number of employers in the administrative data,[20]

[17] We combine wages at the tax unit level, meaning we take the union of 1040 wages and DER/W-2 wages combined across the primary and secondary filers on the 1040. In the few cases where one of the primary or secondary filers from a joint return is absent in the survey, we bring in half of the 1040 wage amount. We include allocated tips as part of DER wages prior to combining, since allocated tips are technically part of taxable wages recorded on the 1040.
[18] Deferred compensation is the sum of elective deferrals to 401(k), 403(b), 408(k), 457(b), and 501(c) plans.
[19] We augment this condition by continuing to rely on survey earnings even when they are imputed, so long as the respondent reports working for pay and has all other employment characteristics not imputed.
[20] The number of employers in the administrative data is the number of unique employer identification numbers in the W-2 or DER. Because the number of employers is capped at three in the CPS but uncapped in the W-2 or DER, we understate the frequency with which this case applies in the survey. We count self-employment as a single employer.

- The respondent reports being self-employed in the survey, or
- The respondent reports working for a small employer (<10 employees) in the survey.

The first two cases reflect situations where the administrative data appear to be missing a job. The latter two cases reflect employment that is often done outside of the formal sector (Abraham et al. 2013, 2021). We combine *total* survey and administrative earnings, rather than wage and self-employment amounts separately, to ensure that we do not double count earnings that are misclassified as wages in one source and self-employment in another source.

While 33.7% of all individuals report survey earnings that exceed administrative earnings, we rely on survey amounts for only 22% (7.33%/33.71%) of such individuals (Table 3). Of those for whom we bring in survey earnings, 27% (1.97%/7.33%) have earnings missed entirely in the tax records and 42% have at least one job missed in the tax records. Because the former is a subset of the latter, the majority of those missing a job in the administrative data have earnings missed at the extensive margin. Moreover, 46% of the individuals for whom we rely on survey earnings report being self-employed, and 79% report working for a small employer. Focusing on individuals designated as poor under the OPM, we bring in survey earnings for 37% (3.96%/10.66%) of such individuals. Nearly two-thirds of this group have a job that is missed in the administrative data, and nearly three-quarters report working for a small employer.

Since the NEWS Project (Bee et al. 2023) provides perhaps the closest analog to our paper, it is worth comparing and contrasting our methods to theirs. Like the CID, Bee et al. (2023) recognize that jobs may be missed in administrative data and also use survey earnings when administrative amounts are zero ("extensive margin disagreement"). But unlike the CID, when there is "intensive margin disagreement" between survey and administrative values, Bee et al. (2023) choose the "best" value from a given source using an earnings measurement model. However, if nearly all of these sources is structurally understated (as we show), then whichever amount is chosen by the model may continue to be understated. Moreover, the NEWS method uses only 1040 values for self-employment, which are heavily understated, rather than combining sources as the CID does. The implication is that our method likely captures more earnings than the NEWS method, and we assess the validity of our approach by comparing to national accounting totals.[21]

[21] Additionally, the NEWS method likely understates other components of money income more than the CID method. For example, NEWS takes as truth most income components reported on a 1040, even though filers have been found

Validating the Earnings Measure

Using the CID, we estimate $8.88 trillion in total earnings in 2016, constituting 97.1% of the NIPA benchmark of $9.15 trillion (Table 4). The NIPA aggregates use data from random audits to adjust for the under-reporting of earnings to tax authorities (Ruser et al. 2004). While the total amount of CID earnings still falls short of the NIPA estimate by 3%, it is considerably closer than the survey-only and administrative-only totals – which fall 10% and 8% below NIPA totals, respectively. Examining the components of earnings, we estimate $8.21 trillion in total wage/salary earnings using the CID, which is 2% higher than the NIPA benchmark of $8.02 trillion. This overstatement may be partly due to independent contractor income being misclassified as wages in the survey. On the other hand, we estimate $668 billion in self-employment earnings using the CID, which falls 41% short of the NIPA benchmark of $1.13 trillion. As a result, combining survey and administrative earnings can fill in only a small fraction of the self-employment earnings that are missed in the tax records.

In the end, we estimate that 5% of combined earnings come exclusively from the survey. For context, the IRS estimates that the tax gap (the fraction of all taxes owed that are not collected on time) was approximately 15% and amounted to roughly $496 billion in missed taxes between tax years 2014-2016 (Internal Revenue Service 2022). Using a technique called detection-controlled estimation, the IRS calculates the tax gap based on estimates from audits and excludes income derived from illegal activities (Feinstein 1999). While the tax gap is driven by non-compliance on a number of margins (Slemrod 2019), more than a quarter of the estimated gap ($130 billion) is explained by the under-reporting of business income to the IRS. Several studies have also found that missed earnings (specifically self-employment income) tend to be larger at the *bottom* of the *reported* income distribution (Christian 1994, Auten and Langetieg 2021).

While CID earnings are closer to NIPA totals than survey- or administrative-only estimates, we are likely to still *understate* true earnings. A number of studies have concluded that surveys understate informal earnings, especially those from self-employment (Hurst, Li, and Pugsley 2014, Abraham and Amaya 2019). Since IRS tax records miss the vast majority of

to underreport income sources such as UI and Social Security on their tax returns (Meyer et al. 2023). Furthermore, NEWS entirely misses several income sources that do not appear in their administrative data, including capital gains, child support received, transfers from family and friends, and miscellaneous income.

informal earnings, our combination of survey and administrative earnings will fail to capture all informal earnings. As we have also discussed, our only source of administrative self-employment amounts (from the DER) is limited in scope and further misses self-employment earnings for those with ITINs. We miss amounts from Form 1099-MISC, which covers earnings received by independent contractors regardless of whether or not they file a 1040.

It is worth mentioning that many individuals who are unlikely to report earnings do seem to appear in Census surveys, as weighted CPS totals of linked ITINs compare favorably to administrative aggregates. Assuming ITIN holders respond to surveys at similar rates as other unauthorized workers, this suggests that a large share of unauthorized workers also appear in Census surveys. Abowd, McKinney, and Zhao (2018) indicate that 5.8% of Unemployment Insurance wage records in 2010 came from potentially unauthorized immigrant candidates, and we are only able to link 1040 wages to the subset who have ITINs. For many of these individuals, a number of whom are un-PIKed but are part of PIKed families, we cannot link any administrative records and must therefore rely on potentially underreported survey earnings.

4. Results: Income Distributions

In our first set of results, we take a broad view and show how the entire bottom half of the income distribution changes after broadening the income concept and using the CID to correct for measurement error. For ease of interpretation, we equivalize incomes to be representative of a family with two adults and two children. Figure 2a starts by showing the bottom 50 percentiles of pre-tax money income using survey-only data (hollow circles) and the CID (solid circles), with Appendix Table A3 showing the exact values of the percentiles. Notably, CID pre-tax money incomes are higher than the survey analogs at every percentile of the bottom half. The differences are particularly pronounced at the lowest percentiles. CID incomes exceed survey incomes by more than 100% in the bottom three percentiles, and by 45% at the 5th percentile. Subsequently, CID incomes are 21% higher at the 10th percentile, 15% higher at the 25th percentile, and 9% higher at the 50th percentile, with the absolute differences ranging from $4,700 to more than $7,500.[22]

[22] Bee et al. (2023) find that correcting for misreporting leads to slightly smaller increases in household pre-tax money income of 17.1%, 10.3%, and 6.8% at the 10th, 25th, and 50th percentiles, respectively.

Figure 1b next overlays the distributions of our most complete income concept – which accounts for taxes, expenses, and in-kind transfers – using survey-only data and the CID.[23] CID incomes are again higher than the survey analogs at every percentile, with the survey-CID differences being similar to those using pre-tax money income. CID incomes are higher by more than 100% in the 1st and 2nd percentiles, 36% at the 5th percentile, and 14-22% between the 10th and 50th percentiles. Moreover, the distributions for pre-tax money income and income after taxes, expenses, and in-kind transfers intersect between the 18th and 19th percentiles using survey data alone and the 20th and 21st percentiles using the CID. In other words, we would conclude using survey data that 18% of individuals receive more in tax credits and in-kind transfers than they owe in tax liabilities and expenses. This share increases to 20% using the CID, with much of the difference explained by the under-reporting of SNAP and housing assistance in the CPS.

Finally, it is useful to directly compare the role of broadening the income concept against the role of using better data via the CID. When we change the income concept using only the survey data, incomes increase by more than 100% for the bottom two percentiles and by 15% or more for the bottom ten percentiles (Appendix Figure A2b). These are the individuals who are targeted most by means-tested in-kind transfers and tax credits. Yet, when starting from a baseline of survey-reported pre-tax money income, employing better data via the CID always explains a larger fraction of the increase in incomes than broadening the income concept using survey data. Specifically, at every percentile, more than 59% of the increase in incomes due to all adjustments can be attributed to better data. Using the combination of income concept changes and better data, incomes increase by more than 100% for the bottom four percentiles and by more than 15% for the bottom twenty percentiles. In the end, the combination of all adjustments leads to increased incomes, relative to a survey pre-tax cash baseline, for the bottom 35% of all individuals. Notably, between the 19th and 36th percentiles of income, the increases in income due to using the CID are large enough to outweigh the decreases in income due to income concept changes.

5. Results: Applications to Prototypical Poverty Analyses

Having discussed income distributions at a broad level, we now show three separate applications to prototypical poverty analyses. As we discuss below, all of these applications can

[23] Appendix Figure A1 shows the distributions for the intermediate income concept (income after taxes and expenses).

be thought of as unidimensional “snapshots” of the broader income distributions. Our first and primary application focuses on the share of the population with incomes below absolute thresholds (i.e., those in absolute poverty). Our second application, which is the mirror image of the first application, analyzes the degree to which thresholds need to be rescaled to maintain absolute poverty rates at baseline levels. Our third and final application examines the share of the population with incomes below some fraction of median income (i.e., those in relative poverty).

5.1 Application 1: Share with Incomes Below Absolute Thresholds

In our first application, we analyze how the share of the population with incomes below absolute thresholds changes after broadening the income concept and using the CID to correct for measurement error. Let the income distributions in Figure 2 serve as inverse cumulative distribution functions (CDFs). Then, for any income threshold on the y-axis, the share of individuals with incomes below that threshold (i.e., absolute poverty rate) is the corresponding value on the x-axis where the threshold intersects the CDF (Appendix Figure A3). For two different income measures, the difference in absolute poverty rates is the horizontal distance between the two CDFs at a threshold. This framework shows how an analysis of absolute poverty rates is akin to taking a snapshot of the inverse CDFs along a single dimension and at a single threshold.

Absolute Thresholds

The poverty threshold that we use is derived from the OPM threshold for a family with 2 adults and 2 children, which was $24,339 in 2016. Rather than keeping the threshold unchanged and comparing to equivalized incomes that are representative of a 2-adult, 2-child family, we apply the SPM 3-parameter equivalence scale to the poverty threshold and compare it to un-equivalized incomes. While this differs from the method used to calculate the income distributions in Figure 2, it is consistent with traditional methods for calculating absolute measures of poverty. We also consider multiples of these thresholds that correspond to being in deep poverty (50% of threshold), near poverty (150% of threshold), and twice poverty (200% of threshold). Unlike the SPM, we do not adjust incomes for regional differences in cost-of-living, given that geographic adjustments have been shown to identify a less deprived population in poverty (Meyer, Wu, and Curran 2022).

Shares of Individuals Below Absolute Thresholds by Income Concept

Table 5 (Panel A, Column 1) displays the shares of individuals with family incomes below absolute poverty thresholds under various income concepts, using either survey-only data or the CID. As a starting point, 11.42% of individuals have survey-reported pre-tax money income below official thresholds. This rate falls to 8.49% – a 26% decrease from the survey baseline – after using the CID to correct for measurement error in pre-tax money income.[24] Under an income concept of money income after taxes and expenses, the poverty rate relying only on survey information is 11.44%, with an analog of 8.22% using the CID. Note that incorporating taxes and expenses leads to an increase in poverty when relying on survey data alone but a decrease in poverty when using the CID. This is partly due to tax credits like the EITC and CTC being under-imputed in the CPS. Moving finally to an income concept that incorporates taxes, expenses, and non-medical in-kind transfers, we find that the poverty rate is 8.99% using only survey data and 5.29% using the CID. In other words, from a survey pre-tax money income baseline, poverty falls by 21% after the conceptual changes to survey income and by an additional 41% after bringing in the CID.

Shares of Individuals Below Absolute Thresholds After Step-by-Step Adjustments

Presenting the results from a slightly different angle, Figure 3 is a waterfall chart showing shows how rates of absolute poverty change after sequentially introducing each correction and adjustment. Visualizing the results this way is useful for identifying which adjustments have the largest impacts. Unlike the prior results, we start from a well-known benchmark in the Official Poverty Measure (OPM), which allows us to clarify the role of changes we make to the resource unit, equivalence scale, and sample of analysis. The bars in Figure 3 are also shaded to identify different types of adjustments, with the sample, sharing unit, and equivalence scale changes in maroon, the measurement corrections in blue, and the conceptual changes to survey income in orange. Appendix Table A4 shows the levels corresponding to each step for different multiples of the poverty line, while Appendix Table A5 breaks down the steps by family type.

With the full CPS sample, we start with a rate of 12.7% for the OPM in 2016. The rate drops by 1.28 percentage points after expanding the resource-sharing unit to include cohabiting

[24] In contrast, Bee et al. (2023) find a 1.1 percentage point reduction in poverty (from 11.8% to 10.7%) using pre-tax money income. A large reason for the difference, as we discuss in Section 3, is that our methods capture more earnings (e.g., from self-employment) and also more incomes generally. Bee et al. (2023) also incorporate adjustments for unit non-response and imputation, which leads to a slight increase in poverty and offsets the decline from correcting for survey misreporting. In addition, Bee et al. (2023) rely on reference year 2018, while we use reference year 2016.

partners and young unrelated children, suggesting that a non-trivial fraction of these individuals would be considered poor on their own but not poor when grouped with other household members. Using the SPM 3-parameter equivalence scale marginally decreases the poverty rate by 0.13 percentage points. Removing individuals who are whole-imputed or in un-PIKed families (and adjusting survey weights) leads the poverty rate to tick back up by 0.13 points. The small effect of these latter changes helps to validate the inverse probability weighting model used to reweight PIKed and non-whole-imputed individuals to be representative of the full population. Note that the poverty rate after this step is 11.42%, which is the starting rate for the analyses in Table 5.

We then discuss the step-by-step corrections to pre-tax money income. Replacing survey earnings with only administrative earnings from the DER leads poverty to increase by 1.42 percentage points, directionally consistent with the findings in Hokayem, Bollinger, and Ziliak (2015). Additionally bringing in W-2 earnings reduces poverty by 0.25 percentage points, due primarily to the inclusion of ITINs in W-2s who are not in the DER. Bringing in 1040s alongside the DER and W-2s additionally decreases poverty by 0.68 percentage points. As a result, nearly two-thirds of the initial increase in poverty from using the DER is eliminated by incorporating W-2s and 1040s together. Combining administrative and survey earnings further reduces the absolute poverty rate by 1.75 points, making it the single largest correction to pre-tax money income.

Although the earnings corrections play a large role, more than 50% of the decline in poverty using pre-tax money income still comes from integrating administrative data for other sources. Replacing survey values with administrative values for asset income (interest and dividends) and also retirement income leads to reductions of 0.08 and 0.60 percentage points, respectively. Similar to Bee and Mitchell (2017), we find that poverty rates fall dramatically (by more than 2 percentage points) for elderly families after bringing in administrative values for retirement distributions (Appendix Table A5). Further bringing in administrative values for OASI, DI, and SSI together decreases poverty by 0.54 percentage points, suggesting that survey respondents in the CPS under-report – rather than simply misclassify – their SSA benefits. Finally, bringing in AGI from the 1040s as a lower bound for pre-tax money income leads the poverty rate to fall by 0.45 points, likely due to the under-reporting of income sources such as Unemployment Insurance and alimony in the CPS. This gets us to the CID rate of 8.49% using pre-tax money income. It is worth noting that for every source of pre-tax money income where the administrative data are most complete, simply replacing survey values with administrative values leads to a decline in poverty – yielding striking evidence that individuals at the bottom under-report their incomes in survey data.

After correcting measurement error in pre-tax money income, we incorporate tax liabilities, tax credits, and expenses into our income concept. Subtracting survey-reported taxes (before credits) from corrected pre-tax money income increases the poverty rate by 2.68 percentage points, but replacing survey taxes with values simulated using administrative tax records brings the poverty rate back down by 1.87 points. For those who appear in the tax records, we rely solely on their tax incomes when calculating tax liabilities. Given that individuals at the bottom tend to report fewer earnings on W-2s and 1040s than in the survey, it makes sense that their tax liabilities simulated from the administrative records are also lower than the survey-only estimates.[25] Bringing in survey values of the EITC and CTC reduces the overall poverty rate even more, with the administrative data amplifying the poverty reduction effects of each tax credit. After accounting for all tax liabilities and credits, the poverty rate using the CID is 7.15%. This rate increases to 8.23% after subtracting child support payments and work expenses from the resource measure.

Lastly, we account for non-medical in-kind and find that including their survey values collectively decreases the share of individuals with incomes below official thresholds by 2.3 percentage points. Housing assistance and SNAP account for 85% of this decrease. After correcting survey reports of housing assistance and SNAP using the administrative data, we find that poverty further declines by 0.33 and 0.31 percentage points, respectively. This results in a rate of 5.29%, which is also the CID poverty rate using the full income concept in Table 5. As a final adjustment, we correct for measurement error in TANF, but we implement this last and so rely only on the 18 states that have both administrative SNAP and TANF data.[26] The overall poverty rate drops by an additional 0.06 percentage points after correcting for misreporting of TANF.

Summed across all steps, the corrections to measurement error amount to a decline in poverty of 5.9 percentage points while the conceptual changes to survey income lead to a decline of 0.29 points. Thus, after accounting for sample, sharing unit, and equivalence scale changes, the

[25] This raises an important distinction between the earnings on which individuals are taxed and the actual earnings received. For those who file tax returns or receive a W-2, we treat their taxable earnings as the values observed by the IRS. However, individuals can also receive informal earnings which can be partially filled in using survey records and are unreported to the IRS. We assume that individuals do not accrue any tax liabilities on these earnings.
[26] Specifically, to calculate poverty rates after accounting for combined TANF values, we multiply the poverty rate after accounting for all other adjustments by the fractional change in poverty due to incorporating the combined TANF data (calculated over 18 states). This is similar to the method used to account for administrative SNAP values.

corrections using better data can explain 95% of the overall decline. These results contrast with those of Table 5, in which the conceptual changes to income are implemented first. Under that framework, the measurement corrections account for only 60% of the overall decline in poverty. By construction, adjustments incorporated earlier tend to have larger impacts than adjustments included later. This is because two adjustments may remove the same individual from poverty, but the adjustment implemented earlier will receive the credit for removing that individual from poverty. As a result, first broadening the income concept magnifies the role of conceptual changes (Table 5), while the step-by-step adjustments magnifies the role of better data (Figure 3). Yet, better data still explain a majority of the overall decline when given the least weight, suggesting that correcting for measurement error plays a larger role than changing the income concept.

Shares of Individuals Below Multiples of the Poverty Line

Table 5 (Panels B-D, Column 1) displays more generally the shares of individuals with incomes below various multiples of official poverty thresholds using survey-only data or the CID. In percentage terms, our collective adjustments yield larger impacts at lower thresholds. In the CPS, deep poverty falls by 70% (4.66% to 1.42%) after all adjustments, poverty falls by 54% (11.42% to 5.29%), near poverty falls by 29% (20.13% to 14.2%), and twice poverty falls by 8% (28.72% to 26.49%). At every multiple and for every income concept, the share of individuals with incomes below a given threshold using survey-only data is always greater than the share using the CID. Furthermore, the inclusion of taxes, expenses, and in-kind transfers always reduces deep and regular poverty, as those at the bottom of the income distribution receive more in tax credits and in-kind transfers than they owe in tax liabilities and expenses. However, broadening the income concept actually increases near and twice poverty, since those with higher incomes owe more in tax liabilities and expenses than they receive in tax credits and in-kind transfers.

Once again, we find striking evidence across multiples of the poverty threshold that using better data via the CID plays a larger role in explaining the decline in poverty than the conceptual changes to income. Figure 6a shows that when the conceptual changes to income are implemented first, using the CID accounts for 58% and 60% of the decrease in deep and regular poverty, respectively. They explain more than 100% of the decrease in near and twice poverty, since broadening the income concept leads to increases in these rates. When examining step-by-step adjustments, using the CID accounts for 95% of the decline in regular poverty and more than 100%

of the decline in deep, near, and twice poverty (Figure 6b). These results further validate the empirical pattern that whichever changes are implemented first tend to receive greater weight.

5.2 Application 2: Thresholds Needed to Keep Poverty Rate Constant

In our second application, we analyze how much poverty thresholds would have to change to keep poverty rates fixed after corrections and adjustments. As motivation, consider again the income distributions in Figure 2. For any quantile (i.e., "poverty rate") on the *x*-axis, the relevant poverty threshold is the analogous value on the *y*-axis where the quantile intersects the CDF (Appendix Figure A4). For two different income measures, the difference in thresholds corresponding to a poverty rate is the vertical distance between the two CDFs at that poverty rate. Consequently, one can think of this exercise as the mirror image of Application 1.

Table 5 (Panel A, Column 2) displays the multipliers applied to official thresholds that are needed to keep poverty rates fixed at 11.42%.[27] This multiplier is trivially 1 for survey-reported pre-tax money income, as 11.42% is the baseline poverty rate corresponding to this resource measure. After using the CID to correct for misreporting in pre-tax money income, thresholds would have to increase by 20% to maintain the poverty rate at its baseline level. Relative to the survey pre-tax money income baseline, broadening the income concept leads thresholds to increase by 13% and using the CID leads thresholds to rise by an additional 23 percentage points. Panels B-D (Column 2) also show that deep, near, and twice poverty thresholds increase by 90%, 16%, and 5% after all adjustments to keep rates fixed at their baseline levels.

As Figure 4 shows, the single most impactful adjustments for *increasing* the poverty thresholds are the combination of survey and administrative earnings and the replacement of survey tax liabilities before credits with estimates using tax records. In contrast, the single most important adjustments for *decreasing* the poverty thresholds are the inclusion of survey taxes before credits (a conceptual change to income) and the direct replacement of survey earnings with DER earnings. Summing across all corrections for measurement error using the CID, thresholds would have to increase by 38% to keep poverty rates at their baseline levels. In contrast, summing across all conceptual changes to income, poverty thresholds must actually *decrease* by 2% to keep poverty rates at their baseline levels. In other words, when applying the step-by-step adjustments,

[27] Appendix Table A6 shows the multipliers corresponding to each step for different multiples of the poverty line, while Appendix Table A7 breaks down the steps by family type.

the usage of better data can explain more than 100% of the increase in poverty thresholds needed to hold poverty rates fixed (compared to nearly two-thirds of the overall increase in thresholds when broadening the income concept first). Figures 6c and 6d continue to show that, better data always explain more of the increase in thresholds than the conceptual changes to income, regardless of the poverty line analyzed or the ordering of adjustments.

5.3 Application 3: Share in Relative Poverty

In the third and final application, we analyze the share of the population with income below some fraction of median income (i.e., "relative poverty") after expanding the income concept and using the CID to correct for measurement error. Whereas absolute poverty assesses the share of individuals with incomes below some *fixed* threshold, relative poverty assesses the share of individuals below some *relative* threshold. In other words, relative poverty captures deprivation relative to other people's standing in the economy. To build intuition, consider the distribution of income as a share of the median, where the value corresponding to the 50^{th} percentile is equal to one by construction (Appendix Figure A5). For any relative income threshold (i.e., baseline fraction of median income) on the y-axis, the share of individuals with incomes below that threshold (i.e., relative poverty rate) is the corresponding value on the x-axis where the threshold intersects the CDF. For two different income measures, the difference in relative poverty rates is the horizontal distance between the two CDFs at that relative threshold.

Researchers and organizations like the OECD typically use half of median income as the threshold for measuring relative poverty. However, we use 0.298 (rather than half) as our preferred fraction of median income, since this corresponds to the dollar value of the threshold that yields a baseline poverty rate of 11.42% using survey-reported pre-tax money income. Doing so provides a common starting point for our analyses of both absolute and relative poverty. Nevertheless, we also calculate relative poverty using fractions of 0.149, 0.448, and 0.597, which correspond to the dollar values of the threshold that yield the deep, near, and twice absolute poverty rates calculated using survey pre-tax money income. This enables us to assess a wide spectrum of relative poverty thresholds spanning many of the conventional definitions used in the literature.

Table 5 (Panel A, Column 3) shows the rates of relative poverty under various income concepts, using survey-only data or the CID. Starting from a baseline of 11.42%, the relative poverty rate decreases to 8.35% after accounting for survey taxes and expenses and to 6.31% after further incorporating survey in-kind transfers. These patterns result from the progressive nature of the tax system and the targeting of in-kind transfers to those at the bottom of the income distribution. For every major income concept, the usage of better data further reduces the relative poverty rate relative to the survey estimate. Using the CID, relative poverty is 9.71% under pre-tax money income (15% below the survey analog), 7.06% after incorporating taxes and expenses (15% below the survey analog), and 4.49% after additionally accounting for in-kind transfers (29% below the survey analog). These results can be explained by under-reporting of income sources being most pronounced among those with the lowest incomes. Panels B-D (Column 3) of Table 5 also show that deep relative poverty declines by 72% after all adjustments from a survey pre-tax baseline, near relative poverty declines by 39%, and twice relative poverty declines by 18%. Even at the higher thresholds (150% and 200%) that straddle half of median income, using the CID consistently leads to a reduction in relative poverty compared to the survey estimate.

Figure 5 shows the impacts of step-by-step adjustments to the relative poverty rate.[28] Nearly every adjustment (whether a conceptual change to income or a correction for measurement error) leads to either a decline or a negligible increase in relative poverty. The only exceptions are the replacement of survey earnings with DER earnings and the subtraction of work expenses. The two most important corrections for measurement error are the combination of survey and administrative earnings and the replacement of survey taxes before credits with administrative values. The most impactful conceptual changes to income are the incorporation of the EITC, SNAP, and housing assistance. It is worth noting that incorporating survey taxes before credits leads to a reduction in relative poverty, whereas the opposite is true for absolute poverty. This is because incomes always fall in absolute terms, but the progressivity of the tax system implies that incomes fall to a lesser degree among those at the bottom distribution (who owe fewer taxes).

Taken together, the usage of better data explains 48% of the overall decline in relative poverty when the adjustments are incorporated sequentially and 26% of the overall decline when the income concept changes are brought in first. For most thresholds and orderings of adjustments, the conceptual changes to income have a larger impact on reducing relative poverty than the usage of the CID (Figures 6e and 6f). This contrasts with the patterns for absolute poverty, where better data outweighed the conceptual changes to income in explaining the decline in poverty. A key

[28] Appendix Table A8 shows the levels corresponding to each step for different multiples of relative poverty, while Appendix Table A9 breaks down the steps by family type.

reason for this discrepancy is that the conceptual change to incorporate tax liabilities before credits contributes to a sizable increase in absolute poverty while reducing relative poverty.

6. Results: Patterns by Demographic Subgroups

Having analyzed changes in poverty for the population as a whole, we now disaggregate these patterns across demographic subgroups. We start by showing for more than two dozen subgroups how absolute poverty rates change after first broadening the income concept and subsequently bringing in the CID. Honing in on different family types, we compare the importance of changes to the income concept versus better data, as well as changes in absolute poverty thresholds and relative poverty. We finally discuss how our adjustments alter the composition of the poor, focusing not just on *how many* individuals are in poverty but *who* remains in in poverty.

Changes in Poverty by Demographic Subgroups

Figure 7 shows the fractional declines in absolute poverty for 27 subgroups defined by 8 demographic categories: family type, age, race/ethnicity, immigrant status, geographic region of residence, urban/rural status, education level of the family head, and student status of the family head. Each category contains two to five mutually and exclusive subgroups. For each subgroup, we start from a baseline poverty rate calculated using survey-reported pre-tax money income, which we report in parentheses as part of the *y*-axis labels. We first incorporate changes to the income concept (bringing in taxes, expenses, and in-kind transfers) using survey data alone before using better data via the CID to correct for measurement error. This method will give more weight to the income concept changes, but later in this section we also show results by family type using step-by-step adjustments (which give more weight to changes using better data). Appendix Tables A10-A13 show the absolute poverty rates for each of the subgroups under various income concepts, as well as rates corresponding to deep, near, and twice poverty.

Breaking out results first across family type, units headed by an elderly individual (age 65+) see the largest reduction in poverty of 69%. Nearly four-fifths of this decrease is attributable to corrections for measurement error using the CID. Among non-elderly-headed families, poverty rates decline by 61-62% for single parent and multiple parent families, for whom the conceptual changes explain more of the overall decline. This is partly because a number of tax credits and in-kind transfers (e.g., the EITC, CTC, WIC, and school lunch) are explicitly targeted to families with children. In contrast, for non-elderly families containing either multiple childless individuals or single individuals, poverty falls by 41% and 20%, respectively. For both of these groups, the changes to the income concept actually lead to an *increase* in poverty – as the tax credits and in-kind transfers they receive are too minimal to offset the tax liabilities and expenses they owe.

The changes by age closely mirror the changes by family type. Child poverty declines by 63%, with the conceptual changes to income contributing to three-fifths of this decline. The usage of the CID matters more for older individuals; those aged 18-64 see a 44% decline and those aged 65+ see a 67% decline in poverty.[29] For both of these groups, the usage of the CID explains approximately three-quarters of the overall reduction. We also break out results by race/ethnicity, classifying individuals as either Hispanic or falling into one of four non-Hispanic race categories. For Hispanic and black non-Hispanic individuals, poverty falls by 57% and 64%, respectively, with measurement error corrections using the CID contributing to slightly more than 50% of the decline. For white, Asian, and other race individuals, poverty declines by a smaller fraction (41-47%) after all adjustments, although better data via the CID account for approximately two-thirds to three-quarters of the overall reduction. Examining next immigrant status, we find that poverty falls by 55% for non-immigrants and 46% for immigrants. Better data explain the majority of the reduction for both groups, although the changes to the income concept are comparatively more impactful for non-immigrants (who may be more connected to the safety net).

Next, we find relatively homogeneous declines in poverty across geographic regions. Poverty declines by 60% for those residing in the Northeast and by 51-54% for those residing in the Midwest, South, and West regions. While the conceptual changes to income explain most of the reduction in poverty for the Northeast, the opposite is true (i.e., better data are more impactful) for the other regions. Poverty also declines by 54% in urban areas and 50% in rural areas. While these declines are similar overall, they mask differences in the distribution of adjustments: better data account for 57% of the overall decline in urban poverty and 78% of the decline for rural areas. We further observe a gradient in the fractional decline by the education level of the family head. Families headed by someone with less than a high school diploma see a 60% decline in poverty, whereas those headed by someone with a college degree see a 48% decline. The conceptual

[29] The decline in poverty among elderly individuals is slightly different than the decline in poverty among elderly-headed families. This is because elderly-headed families may include non-elderly individuals, and elderly individuals may appear in non-elderly-headed families.

changes play a larger role for those with a less-educated family head, who are potentially more reliant on tax credits and in-kind transfers. Finally, families headed by a current student see a much smaller fractional reduction in poverty (22%) than non-student-headed families (56%).

In sum, evaluated against a baseline of survey pre-tax money income, the fractional declines in poverty are largest for the elderly, children, black non-Hispanic individuals, those with less than a high school diploma, and those living in the Northeast. For all of these subgroups, poverty falls by more than 60% after all adjustments. In contrast, the fractional declines in poverty are smallest (20-22%) for single individuals and individuals in non-student-headed families. For the majority of subgroups, the role of better data outweighs the role of income concept changes despite the latter being incorporated first. However, the impacts of expanding the income concept tend to be relatively larger for subgroups with higher initial rates of poverty. These groups have lower levels of market income (e.g., earnings) and are thus more likely to be eligible for the tax credits and in-kind transfers that constitute a large portion of the conceptual changes to income.

Income Concept Changes versus Better Data (by Family Type)

In this subsection, we compare the role of better data versus income concept changes in explaining the reduction in poverty for five family types: elderly, single parent, multiple parent, single individual, and multiple individual families. We show results incorporating the income concept changes first and also aggregated from step-by-step adjustments. Moreover, we examine changes in absolute poverty, poverty thresholds, and relative poverty.

Focusing first on absolute poverty, we find that the step-by-step adjustments again give more weight to better data in explaining the reduction in poverty (Appendix Figures A6a and A6b). For elderly-headed families, better data account for 88% of the overall decline after sequential adjustments– compared against 80% when the CID is incorporated last. For single and multiple parents, better data contribute to 47% and 90% of the total declines in absolute poverty, respectively – up from 33% and 48% when the income concept changes are brought in first. Finally, for single and multiple childless individuals, better data continue to account for more than 100% of the decline in absolute poverty, as broadening the income concept would lead to an even larger *increase* in poverty rates following step-by-step adjustments.

As was the case for absolute poverty, we find that the increases in thresholds needed to hold poverty rates fixed are highest for elderly-headed, single parent, and multiple parent families

(Appendix Figures A6c and A6d).[30] Specifically, thresholds would have to increase by 47% for elderly families, 52% for single parents, and 35% for multiple parents to fix poverty rates at their baseline levels. In contrast, thresholds would have to increase by only 17% and 25% for single individuals and multiple childless individuals, respectively. Even after bringing in the conceptual changes to income first, we find that better data account for more than 100% of the increase in thresholds for single and multiple individuals, 85% for the elderly, 54% for multiple parents, and 35% for single parents. With the sequential adjustments, better data account for more than 100% of the increase for *every* family type except single parents.

Finally, we find that relative poverty rates decline most for multiple parents (71%) and multiple childless individuals (58%), while also decreasing by 41% for elderly families, 39% for single individuals, and 26% for single parents (Appendix Figures A6e and A6f).[31] The conceptual changes to income play a much larger role in explaining the overall declines in relative poverty for most family types, mirroring the results for the entire population. When the income concept changes are incorporated first, they explain 63-85% of the overall decline in relative poverty for all family types except multiple individuals (for whom they explain 50%). Even after the step-by-step adjustments (laid out in more detail in Appendix Table A15), better data account for the majority of the decline in relative poverty for elderly, single parent, and multiple parent families.

Taken together, for all family types except single parents, we find that better data explain the majority of the decline in absolute poverty rates and the increase in absolute thresholds needed to maintain rates at a fixed baseline. These patterns persist even after the conceptual changes to income are brought in first and given more weight. Strikingly, when adjustments are incorporated sequentially, better data explain more than 100% of the increase in poverty thresholds needed to fix absolute rates for every family type except single parents. Relative poverty declines the most for multiple parents. Furthermore, the income concept changes tend to explain more of the reduction in relative poverty for most family types (except multiple individuals).

[30] Appendix Table A14 shows the change in poverty thresholds attributable to each individual step.

[31] We use a different fraction of median income for each family type so that the starting relative poverty rate is identical to the absolute poverty rate under survey pre-tax money income for each subgroup. For elderly families, multiple parents, and single individuals, the fractions are very similar and range from 0.32 to 0.34. In contrast, the relevant fraction of median income is 0.77 for single parents and 0.20 for multiple childless individuals (Appendix Table A15). These differences are largely due to the baseline poverty rate being particularly high for single parents (39.76%) and lower for multiple individuals (5.00%). the smaller reduction for single parents could be attributable to the higher fraction of median income applied for this subgroup.

Characteristics of Those Remaining in Poverty

Motivated by the aforementioned results, we now discuss how these adjustments change our understanding of *who* is in poverty. Doing so is important for understanding the types of individuals who are most disconnected from government transfers and who continue to have low incomes after correcting for measurement error. Specifically, Table 6 shows how the conceptual changes to income and the use of the CID reshape the demographic characteristics of individuals in absolute poverty. Column 1 shows the shares of individuals with various attributes among the 11.42% of the population classified as poor under our baseline measure of survey-reported pre-tax money incomes. Column 2 uses the CID to correct for measurement error in pre-tax money income only. While most characteristics remain largely unchanged, the key exception is a lower share of elderly individuals among the poor in Column 2 – which is consistent with prior work showing that elderly individuals are especially likely to underreport retirement income.

Column 3 broadens the income concept using survey values of taxes, expenses, and in-kind transfers, showing that the remaining poor have a smaller share of single and multiple parents (and thus children), Black individuals, and those with less than a high school diploma relative to baseline. In contrast, they have a larger share of single and multiple childless individuals, white individuals, immigrants, rural residents, and student-headed families. In other words, the groups that report relying more on tax credits and in-kind transfers are the ones represented to a lesser degree among the poor in Column 3.

Column 4 displays the characteristics of those remaining in poverty after additionally bringing in the CID and keeping the expanded income concept. Relative to the results in Column 3, the use of better data identifies a poor population that is less elderly and Black but more likely to be a single individual or in a student-headed family. The lower share of Black individuals is consistent with prior work showing that Black individuals are more prone to underreporting SNAP (Meyer, Mittag, and Goerge Forthcoming) in surveys. Relative to the baseline results in Column 1, the combination of all adjustments leads to the identification of a poor population that is more likely to be part of a family unit consisting of a single individual (from 16% to 27%) or multiple childless individuals (from 11% to 14%), be white non-Hispanic (from 40% to 45%), be an immigrant (from 18% to 21%), live in a rural area (from 17% to 19%), have a bachelor's degree (from 12% to 14%), or be in a student-headed family (from 7% to 12%).

Because the adjustments lead fewer individuals to be classified as poor (5.29% in Column 4 versus 11.42% in Column 1), one concern is that those in Column 4 are simply a more targeted and deprived segment of the poor. Thus, we also examine the characteristics of those in poverty after adjusting thresholds so that 11.42% are classified as "poor" under CID income after taxes, expenses, and in-kind transfers (Column 5). This enables a comparison of the groups in Columns 1 and 5 on an even footing. Even when holding constant the share of individuals in poverty, the existing differences between Columns 1 and 4 largely persist but are more muted. Specifically, after broadening the income concept and using the CID, the 11.42% of the population with the lowest incomes are less elderly, less likely to be single parents, more likely to be a family unit with a single individual or multiple childless individuals, more likely to be white, more likely to be an immigrant, more likely to live in rural areas, and less likely to have less than a high school diploma.

7. Results: Poverty Reduction of Government Programs

The substantial decreases in poverty from our adjustments can be attributed in large measure to the important role played by government transfer programs. In particular, the conceptual changes to income encompass a number of important government programs like the EITC, SNAP, and housing assistance, while the usage of the CID corrects measurement error that is particularly pronounced in survey reports of program participation. In this section, we take a closer look at the anti-poverty effects of government programs and show effects calculated using either survey values alone or the CID. We focus on the static poverty reduction effects of programs and thus assume no behavioral responses to program receipt.

To calculate the poverty reduction of a government program, we consider how the poverty rate would change if that program were eliminated, holding all other income sources constant. We do so in two ways. First, using survey data alone, we start from an income base after taxes, expenses, and in-kind transfers and calculate the change in the poverty rate if the value of a given program were subtracted from the income base. This is similar to the methodology used by the SPM to calculate poverty reduction effects of various programs (Fox 2017). We compare these estimates to those where we subtract the administrative (or combined) value of a program from a CID income base that accounts for taxes, expenses, and in-kind transfers (allowing us to accurately measure both the income base as well as the values of government programs). Our estimates are calculated over the 23 states with administrative SNAP data in 2016, as this enables us to include administrative SNAP values in the CID income base. In contrast, the estimates for TANF are calculated over the 18 states with administrative SNAP and TANF data in 2016.

Poverty Reduction of Individual Programs

Table 7 (Panel A, Column 1) shows the percentage change in the poverty rate associated with the removal of a given government program. Since we can only examine the programs for which we have administrative data, we exclude major programs like Unemployment Insurance and child support from this analysis. Focusing on the CID effects around 100% of the poverty line (Column 1), we find that OASI yields by far the largest poverty reduction, with 92% more individuals (nearly all of whom are elderly) falling into poverty were it removed *ceteris paribus*. The next most important programs are DI and SNAP, with 32% and 29% more individuals, respectively, remaining in poverty if they were eliminated *ceteris paribus*. The anti-poverty effects of the EITC, housing assistance, and SSI are slightly below that of DI and SNAP but still range between 18-23%. Conversely, the CTC and TANF have relatively small anti-poverty effects (approximately 4-5%) when other programs are taken into account.

Using the CID almost always leads to larger poverty reduction estimates relative to what the survey data alone would imply (Appendix Figure A7). For example, the poverty reduction effects of SNAP and housing assistance are 90% and 91% higher, respectively, when using CID values relative to survey values. The under-reporting of program receipt also extends to a number of cash transfers, with the poverty reduction of DI and TANF being 83% and 57% higher, respectively, using the CID. The administrative values also lead to a 17% larger poverty reduction of the EITC, relative to survey reports simulated from the CPS tax calculator.[32]

We also estimate effects at other multiples of the poverty line. Focusing on deep poverty, we find that OASI, DI, and SSI are more important in fractional terms while SNAP, housing assistance, and the EITC are less important. In contrast, focusing on near poverty, the EITC, SNAP, and housing assistance are the most important programs outside of OASDI. These patterns

[32] This contrasts with Jones and Ziliak (2022), who find similar antipoverty effects of the EITC using CPS and linked administrative values (on a survey pre-tax income base). Yet, we find that the CPS *understates* the poverty reduction of the EITC after using a post-tax/transfer income base that also relies on the CID to correct for measurement error.

hold to some extent for twice poverty, but are not as dramatic. Yet, even as the poverty reduction effects of programs tend to be smaller at higher thresholds, the proportional understatement of program effects in the survey tends to be larger at higher thresholds. Specifically, the near poverty reduction effects are more than twice as large for SNAP, housing assistance, and TANF and 70-80% larger for the EITC, DI, and SSI using the CID relative to survey data alone.

Poverty Reduction of Combined Programs

To obtain better summary measures of program effects, Panel B of Table 7 displays the poverty reduction effects of select combinations of programs. Looking at the combined effects of programs also has the advantage of accounting for misclassification across individual programs. We examine several combinations of programs. The combination of SSA programs encompasses OASI, DI, and SSI. The combined cash programs include the aforementioned SSA programs as well as Public Assistance, Unemployment Insurance, child support, veterans' benefits, and workers' compensation. The effects calculated using the CID continue to use survey values of veterans' benefits, Unemployment Insurance, child support, and workers' compensation because we lack sufficient administrative data for these programs.[33] Taxes include both tax liabilities and tax credits (like the EITC and CTC). Finally, the combined in-kind transfers include SNAP, housing assistance, WIC, energy assistance, and school lunch. Once again, the effects calculated using the CID continue to use survey values of WIC, energy assistance, and school lunch because administrative data are unavailable for these income sources.

Using the CID, poverty would increase by 205% if all taxes and transfers were eliminated. This effect is 40% higher than the impact calculated using survey values alone. Pre-tax cash programs explain the majority of this overall anti-poverty effect, with the poverty rate increasing by 159% if all pre-tax cash programs were removed. The effect calculated using the CID is 30% higher than the effect estimated using survey values, with most of this difference due to SSA programs being underreported (rather than misclassified). In contrast, removing all taxes and in-kind transfers would lead to a 65% increase in poverty. However, the gap between survey and administrative effects is much larger for taxes and in-kind transfers, as the collective poverty reduction of taxes and in-kind transfers using the CID is more than double what we would obtain

[33] We also continue to use survey (rather than CID) values for TANF, enabling us to calculate poverty reduction effects over a broader group of 23 (rather than 18) states.

using only survey values. Around half the poverty line, the elimination of all taxes and transfers would increase deep poverty by 524% using the CID, a 60% increase over the survey-only estimate. Around one-and-a-half times the poverty line, the elimination of all taxes and transfers would increase near poverty by 85% using the CID, a 24% increase over the survey estimate. A key implication of these results is that government transfers reach many more individuals than would be predicted by survey data alone, providing further evidence that rates of program take-up are likely to be sharply understated when estimated using the CPS.

8. Conclusions

This paper calculates new measures of poverty that utilize more complete resource measures (accounting for taxes, expenses, and in-kind transfers) and bringing in administrative data to correct for measurement error in survey reports. This paper introduces a number of methodological innovations, including a novel way of combining earnings data to account for values that are plausibly missed in multiple survey and administrative sources. Using the linked data (CID), we find an upward shift in the bottom half of the income distribution for every income concept analyzed. Starting from a survey pre-tax money income baseline, the collective adjustments lead to a decline in the rate of absolute poverty by 54%, an increase in poverty thresholds by 36% to keep poverty rates unchanged, and a reduction in the rate of relative poverty by 61%. For most analyses, the corrections for measurement error are more important than the conceptual changes to income. The adjustments lead to more single individuals, white non-Hispanic individuals, and rural residents in poverty. We also find that the poverty reduction effects of government programs are larger using the CID for nearly all transfers examined.

While using the CID leads us to identify considerably higher incomes across the entire bottom half of the distribution, we likely still understate incomes for a myriad of reasons. As discussed earlier, CID earnings – especially from self-employment – are still underestimated compared to NIPA totals. We are still missing a variety of administrative self-employment data (including amounts from 1099-MISC, 1099-K, and Schedule SE for ITIN filers), DER self-employment amounts are net of health insurance costs, and self-employment earnings are heavily under-reported in the CPS. We also use AGI as a lower bound for taxable money income, but AGI is net of deductions totaling $153 billion for 39 million tax units in 2016. We miss administrative dollars for un-PIKed individuals in PIKed families, for whom we continue to use survey incomes that are likely to be under-reported. Finally, we miss administrative dollars for a number of non-taxable cash transfers (such as child support and state-administered SSI) as well as in-kind transfers (such as WIC, school lunch, and energy assistance). Each of these missed programs are underreported in aggregate in the CPS, and we estimate $68 billion of missed administrative dollars corresponding to them (Figure 8).

In future work, we plan to bring in administrative records corresponding to a wider array of income sources such as WIC and energy assistance. We also plan to further expand the income measure to account for all resources available for consumption. This includes imputing service flows for home ownership, vehicles, and liquid assets and incorporating the cash-equivalent values of private health insurance and medical in-kind transfers (namely Medicare and Medicaid) into our income measure. The results in this paper also motivate a wide range of additional analyses, including evaluating particular adjustments based on changes in material deprivation, assessing inequality more broadly by comparing to the top half of the income distribution, and looking at more years before and after 2016 to construct an accurate series of poverty over time.

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Tables and Figures

Table 1. Administrative Data Sources

Income Source	Administrative Source	Income Unit	Income Frequency	States Covered
Earnings	DER (SSA), Forms W-2 & 1040 (IRS)	Individual & Tax Unit	Annual	All
Asset Income	Form 1040 (IRS)	Tax Unit	Annual	All
Retirement Income	Form 1099-R (IRS)	Individual	Annual	All
AGI & Other Cash	Form 1040 (IRS)	Tax Unit	Annual	All
Social Security	PHUS & MBR (SSA)	Individual	Monthly	All
SSI	SSR (SSA)	Individual	Monthly	All
Taxes (simulated)	Form 1040 (IRS)	Tax Unit	Annual	All
SNAP	State Agencies	Household	Monthly	23 States
Housing Assistance	PIC & TRACS (HUD)	Household	Monthly	All
TANF	HHS & State Agencies	Family	Monthly	36 States

Note: For each income component with available administrative data, this table contains information on the source of the data, the unit at which the administrative dollar amounts are reported, the frequency at which the administrative dollars are reported, and the states covered in the administrative data. There are 18 states with administrative data for both SNAP and TANF.

Table 2. Empirical Evidence on Conflicting Wage Amounts from Tax Records

Unit	Comparison	Magnitudes	Characteristics
Individuals	W-2 > DER	0.26% of all persons 15+ 0.37% of poor persons 15+	Over 60% are ITINs known to us (when filing 1040); Among remainder, 62% have more W-2 employers
Individuals	DER > W-2	0.70% of all persons 15+ 0.49% of poor persons 15+	86% have more DER employers and 79% of those linking to 1040s have DER wages (not W-2 wages) matching Box 7 of 1040
Tax Units	1040 > W-2	4.44% of all tax units 7.04% of poor tax units	47% have characteristics consistent with conceptual differences between 1040/W-2 wages or misclassification of SE earnings as wages (vs. 33% of all tax units)
Tax Units	W-2 > 1040	5.32% of all tax units 10.75% of poor tax units	71% have difference between W-2s and 1040s equal to wages on one or two W-2s (suggesting that filers did not include all of their W-2s on tax returns)

Source: 2017 CPS ASEC linked to SSA DER and IRS Forms 1040 and W-2
Notes: This table broadly describes the share and characteristics of individuals aged 15+ with discrepancies between W-2 and DER wages (within \$5) and of tax units with discrepancies between 1040 and W-2 wages (within \$5). Sample consists of individuals in the linked CPS sample, dropping non-PIKed and whole imputed individuals in the CPS and adjusting survey weights using inverse probability weighting. DER and W-2 wages correspond to Box 1 (wages, tips, other compensation) of the W-2 summed across all W-2 forms received by an individual for that tax year, and 1040 wages correspond to taxable wages and salaries on Box 7. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table 3. The Use of Survey Earnings in Our Combined Earnings Measure

Characteristic	All Persons Aged 15+ (1)	OPM Poor Persons Aged 15+ (2)
Share with Survey Earnings > Admin Earnings	33.71%	10.66%
Share for Whom We Use Higher Survey Earnings:		
Missing Admin Earnings [1]	1.97%	2.07%
More Survey Employers than Admin Employers [2]	3.08%	2.54%
Report Being Self-Employed in Survey	3.38%	1.16%
Report Working for Small Employer in Survey [3]	5.79%	2.94%
Any of the Above Reasons	7.33%	3.96%
Sample Size	112,000	12,500
Population (Weighted)	258,800,000	29,420,000

[1] Defined as having no wage/salary or self-employment earnings in the DER, W-2 or 1040
[2] Capped at 3 employers, which is the maximum reported in CPS; count self-employment as a single employer
[3] Defined as working for company with less than ten employees

Source: 2017 CPS ASEC linked to SSA DER and IRS Forms 1040 and W-2
Notes: Sample in Column (1) consists of individuals aged 15+ in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Sample in Column (2) consists of all PIKed and non-whole imputed individuals aged 15+ who are poor under the Official Poverty Measure (OPM). Shares are all conditional on having survey earnings not imputed (except for "missing admin earnings" category) and having a host of other employment characteristics (hours/weeks worked, industry, occupation, and number of employers) not imputed. Approved for release by the Census Bureau’s Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table 4. Aggregate Earnings from Survey-Only, Admin-Only, CID, & NIPA Sources

Earnings Category	Survey-Only (1)	Admin-Only (2)	CID (3)	NIPA (Public) (4)
		A. Total Dollars (millions)		
Wage/Salary Earnings	7,852,000	7,846,000	8,214,000	8,018,032
DER		7,648,000		
Form W-2		7,577,000		
Form 1040		7,153,000		
Self-Employment Earnings	419,400	600,800	667,700	1,131,149
Total Earnings	8,272,000	8,447,000	8,882,000	9,149,181
		B. As Percentage of NIPA Aggregates		
Wage/Salary Earnings	97.9%	97.9%	102.4%	
DER		95.4%		
Form W-2		94.5%		
Form 1040		89.2%		
Self-Employment Earnings	37.1%	53.1%	59.0%	
Total Earnings	90.4%	92.3%	97.1%	

Source: 2017 CPS ASEC linked to SSA DER and IRS Forms 1040 and W-2
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Panel A shows total dollars in millions, and Panel B shows survey-only, admin-only, and CID dollars as a fraction of NIPA aggregates. Survey-only earnings in Column (1) are aggregated from the CPS microdata. Admin-only earnings in Column (2) come from DER, W-2, and 1040 sources. For wages, admin-only dollars take the maximum of DER, W-2, and 1040 (where the DER and W-2 amounts are the taxable amounts on Box 1) and adds allocated tips from the DER and deferred compensation from the DER/W-2. For total earnings, admin-only dollars take the sum of combined admin wages and DER self-employment amounts. CID earnings in Column (3) rely on admin-only dollars as a baseline and take survey earnings when they exceed admin-only earnings when they are not imputed, many employment characteristics (hours worked, weeks worked, industry, occupation, and the number of employers) are not imputed, and one of the following conditions holds: 1) administrative earnings are missing, 2) the number of survey employers exceeds the number of admin employers, 3) respondent reports being self-employed in survey, or 4) respondent reports working for a small employer in survey. Finally, NIPA earnings in Column (4) come from Table 2.1 of the publicly available National Income and Product Accounts and serve as benchmarks for the weighted totals in the first three columns. Following Rothbaum (2015), we adjust the NIPA numbers downward since the NIPA totals are calculated over some individuals not included in the survey frame. Specifically, we incorporate sample frame adjustments for decedents, the institutionalized, those in the military, and those living overseas. For NIPA wages, we subtract from the baseline value (wages and salary) food furnished to employees, employees' lodging, and standard clothing issued to military personnel while adding the wages of foreign professional and migratory workers. For NIPA self-employment (non-farm) income, we subtract from the baseline value (non-farm proprietors' income with inventory valuation and capital consumption adjustments) the inventory valuation adjustment, the capital consumption adjustment, proprietorship and partnership income paid to fiduciaries, defaulter's gain/bad debt expense, margins on owner-built housing, income from tax-exempt cooperatives, and disaster adjustments. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table 5. Applications to Prototypical Poverty Analyses (by Major Income Concepts)

Resource Measure	Share with Income Below Absolute Thresholds (%)	Multiple of Thresholds to Hold Poverty Rate Fixed	Share with Income Below Relative Thresholds (%)
	(1)	(2)	(3)
		A. Regular Poverty	
Survey-Only			
Pre-Tax Money Income	11.42	1.00	11.42
Post-Tax/Expenses	11.44	1.00	8.35
Post-Tax/Expenses + In-Kind Transfers	8.99	1.13	6.31
CID			
Pre-Tax Money Income	8.49	1.20	9.71
Post-Tax/Expenses	8.22	1.19	7.06
Post-Tax/Expenses + In-Kind Transfers	5.29	1.36	4.49
		B. Deep Poverty (50% of Poverty Line)	
Survey-Only			
Pre-Tax Money Income	4.66	1.00	4.66
Post-Tax/Expenses	4.70	0.99	3.97
Post-Tax/Expenses + In-Kind Transfers	3.29	1.36	2.78
CID			
Pre-Tax Money Income	2.31	1.50	2.67
Post-Tax/Expenses	2.45	1.52	2.22
Post-Tax/Expenses + In-Kind Transfers	1.42	1.90	1.31
		C. Near Poverty (150% of Poverty Line)	
Survey-Only			
Pre-Tax Money Income	20.13	1.00	20.13
Post-Tax/Expenses	22.61	0.93	16.02
Post-Tax/Expenses + In-Kind Transfers	20.82	0.98	13.63
CID			
Pre-Tax Money Income	16.20	1.16	18.58
Post-Tax/Expenses	17.54	1.08	15.25
Post-Tax/Expenses + In-Kind Transfers	14.20	1.16	12.27
		D. Twice Poverty (200% of Poverty Line)	
Survey-Only			
Pre-Tax Money Income	28.72	1.00	28.72
Post-Tax/Expenses	34.51	0.87	25.86
Post-Tax/Expenses + In-Kind Transfers	33.83	0.89	24.68
CID			
Pre-Tax Money Income	24.31	1.13	27.43
Post-Tax/Expenses	28.33	0.89	25.14
Post-Tax/Expenses + In-Kind Transfers	26.49	1.05	23.50
Sample Size		145,000	
Population (weighted mil.)		320.3	

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Column (1) shows the share of individuals with incomes below absolute thresholds. Column (2) shows multiples of thresholds needed to hold absolute poverty rates fixed at 11.42%. Column (3) shows the share of individuals with incomes below relative thresholds corresponding to 29.8% of median income, yielding an absolute poverty rate of 11.42%. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table 6. Characteristics of Individuals Remaining in Poverty

Population Subgroups	Pre-Tax Cash		Post-Tax/Expenses/In-Kind Transfers		
	Survey	CID	Survey	CID	CID (fixed)
	(1)	(2)	(5)	(6)	(7)
Elderly	0.16	0.12	0.17	0.11	0.13
Single Parents	0.20	0.23	0.15	0.17	0.16
Multiple Parents	0.38	0.38	0.33	0.31	0.38
Single Individual	0.16	0.19	0.21	0.27	0.20
Multiple Individuals	0.11	0.09	0.15	0.14	0.13
Hispanic	0.30	0.29	0.28	0.28	0.30
White (non-Hisp.)	0.40	0.40	0.44	0.45	0.46
Black (non-Hisp.)	0.23	0.23	0.20	0.17	0.17
Asian (non-Hisp.)	0.06	0.06	0.06	0.07	0.07
Immigrant	0.18	0.18	0.20	0.21	0.20
Northeast	0.14	0.16	0.11	0.12	0.12
Midwest	0.18	0.18	0.17	0.18	0.18
South	0.44	0.43	0.47	0.46	0.45
West	0.24	0.23	0.25	0.24	0.24
Age<18	0.33	0.35	0.26	0.26	0.30
Age 18-64	0.54	0.54	0.60	0.64	0.59
Age 65+	0.13	0.10	0.14	0.09	0.11
Rural	0.17	0.17	0.20	0.19	0.20
Less than High School	0.28	0.28	0.25	0.24	0.26
High School Graduate	0.36	0.36	0.36	0.35	0.36
Some College	0.25	0.25	0.25	0.27	0.26
BA or More	0.12	0.10	0.14	0.14	0.12
Student	0.07	0.08	0.09	0.12	0.08
Percent of Population	11.42	8.49	8.99	5.29	11.42

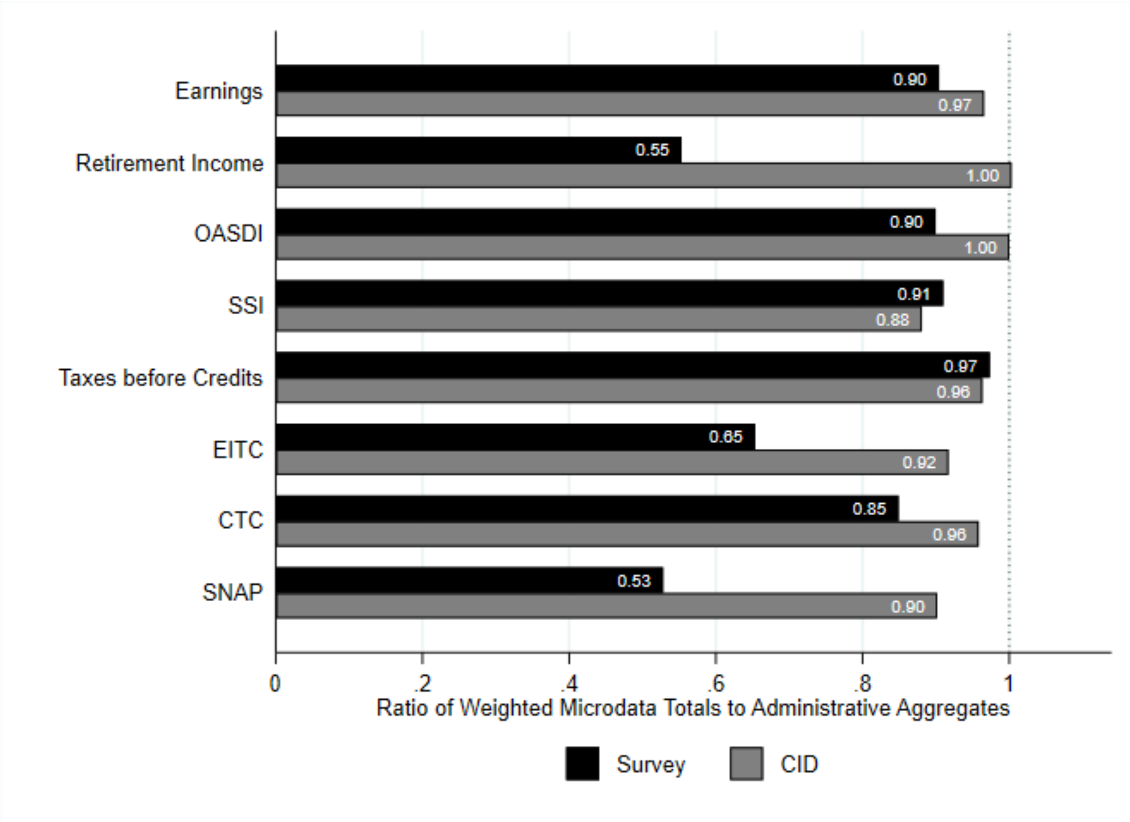
Source: 2017 CPS ASEC linked to various administrative records
Notes: This table shows the characteristics of individuals remaining in absolute poverty for a given income concept. Each row corresponds to the share of poor individuals with a given characteristic. Columns 1 and 2 show the characteristics of those in poverty using survey-reported and CID pre-tax money income, respectively. Columns 3 and 4 show the characteristics of those in poverty using survey-reported and CID income after incorporating taxes, expenses, and non-medical in-kind transfers, respectively. Column 5 shows the characteristics of those in poverty using the same income concept in Column 6 but scaling thresholds such that 11.42% of individuals remain in poverty (which is the baseline share using the survey income concept in Column 1). The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table 7. Percent Increase in Poverty in the Absence of Government Programs

Program	Data Source	Poverty (1)	Deep Poverty (2)	Near Poverty (3)	Twice Poverty (4)
		A. Individual Programs			
OASI	Survey	79.73	160.30	33.68	18.29
	CID	91.86	195.10	42.66	23.83
DI	Survey	17.36	37.39	7.19	3.22
	CID	31.79	63.12	13.16	6.27
SSI	Survey	12.55	21.36	4.12	1.63
	CID	18.13	34.34	7.04	2.28
EITC	Survey	17.86	7.53	9.14	1.95
	CID	20.93	7.58	15.56	4.64
CTC	Survey	5.28	1.00	6.44	3.21
	CID	5.58	--	8.10	3.62
SNAP	Survey	14.98	15.50	5.79	1.26
	CID	28.53	24.11	12.93	3.64
Housing Assistance	Survey	12.03	15.43	4.01	0.64
	CID	22.92	14.47	12.51	4.06
TANF	Survey	2.86	2.70	0.71	0.24
	CID	4.49	2.43	2.03	0.68
		B. Combinations of Programs			
All Taxes & Transfers	Survey	146.50	327.40	84.95	66.43
	CID	205.00	523.70	105.00	66.88
All Cash Programs	Survey	122.40	264.40	49.21	25.55
	CID	158.90	371.60	69.57	35.43
All SSA Programs	Survey	111.00	239.50	43.94	22.49
	CID	144.30	335.50	62.12	31.81
All In-Kind Transfers	Survey	30.96	45.40	10.76	2.31
	CID	64.93	59.50	26.88	8.15
All Taxes & In-Kind Transfers	Survey	26.99	43.23	29.91	36.19
	CID	50.85	65.04	31.64	25.24
All Taxes	Survey	2.85	0.96	15.93	33.53
	CID	-1.19	9.43	3.52	15.07
Baseline Poverty Rate (%)	Survey	8.16	2.99	19.51	32.44
	CID	4.71	1.34	13.17	25.10
Sample Size			61,000		
Population (weighted mil.)			132.7		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Survey (CID) effects are calculated as the percentage change in the poverty rate using survey (CID) reports of program receipt and survey-reported (CID) baseline income. Effects are calculated using the 23 states for which we have admin SNAP data (except TANF, for which effects are calculated using 18 states with both admin SNAP and TANF data). The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

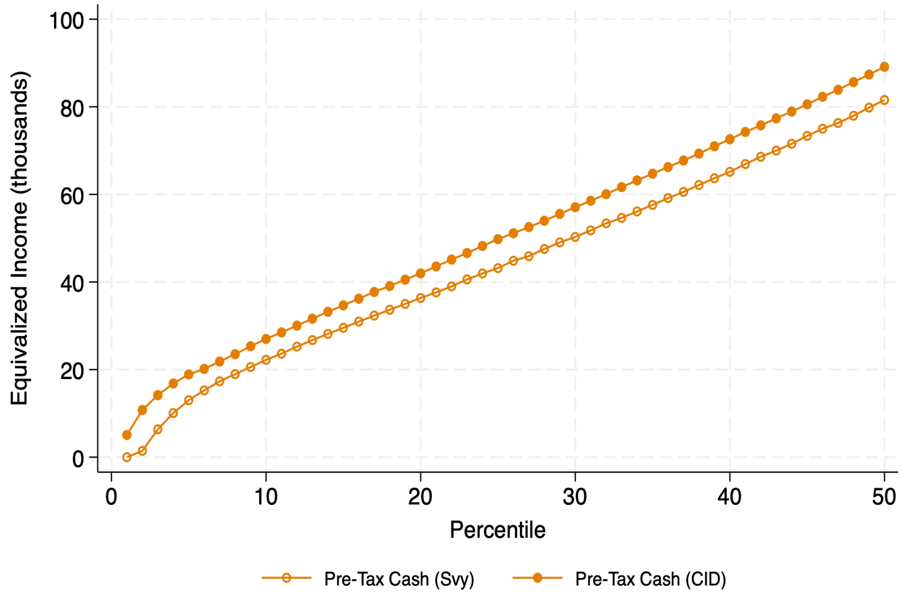
Figure 1. Aggregate Dollar Reporting Rates from Microdata for Selected Income Sources



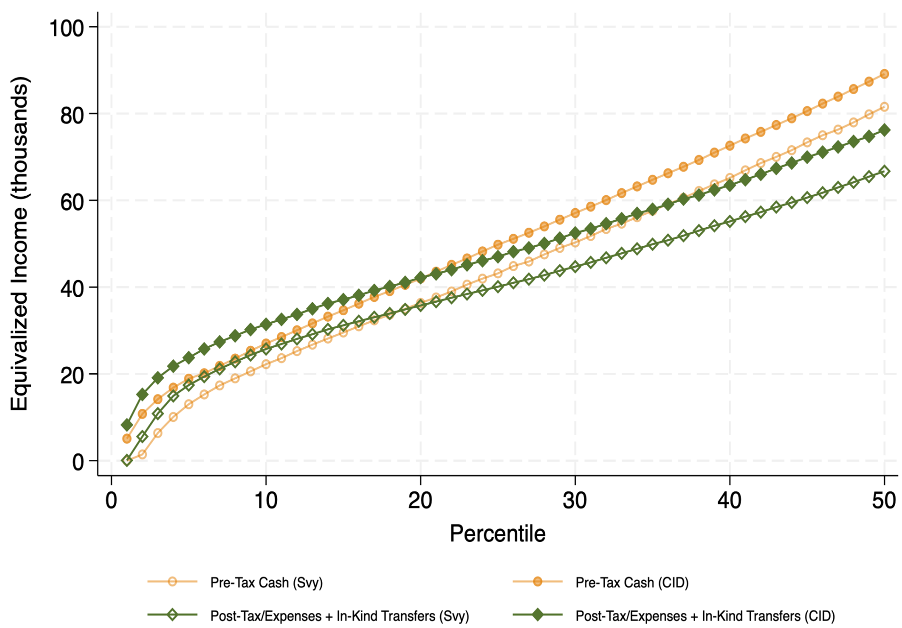
Source: Corinth, Meyer, and Wu (2023)

Notes: Ratios correspond to aggregate dollars for major income sources using information from the survey data alone or from the CID as a share of aggregate amounts from publicly available administrative records. Aggregates from the microdata (numerator) are dollars (summed over SPM units) reported in the CPS ASEC for a given reference year. Administrative aggregates (denominator) are dollars according to administrative sources such as NIPA and program records. Where applicable, we remove income received by the institutionalized, those living overseas, military personnel, and decedents from the administrative aggregates.

Figure 2. Bottom Fifty Percentiles of the Income Distribution



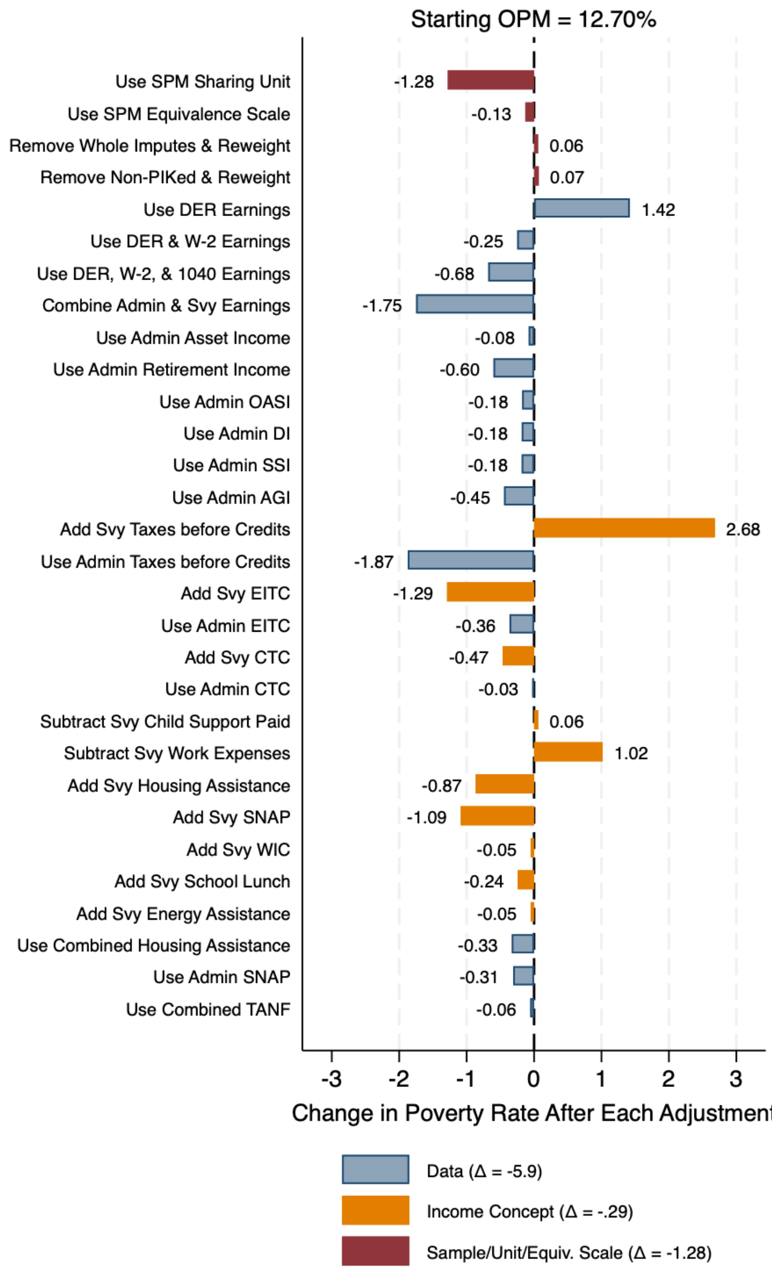
(a) Pre-Tax Money Income



(b) Income After Taxes, Expenses, and In-Kind Transfers

Source: 2017 CPS ASEC linked to various administrative records
Notes: Percentiles are calculated over individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Incomes are equivalized using the SPM equivalence scale to be representative of a family with 2 adults and 2 children. Percentiles for the income concept in Panel B (CID post-tax/expenses plus in-kind transfers, including admin SNAP) are calculated using proportional adjustments for admin SNAP based on the 23 states for which we have SNAP data in 2016. All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

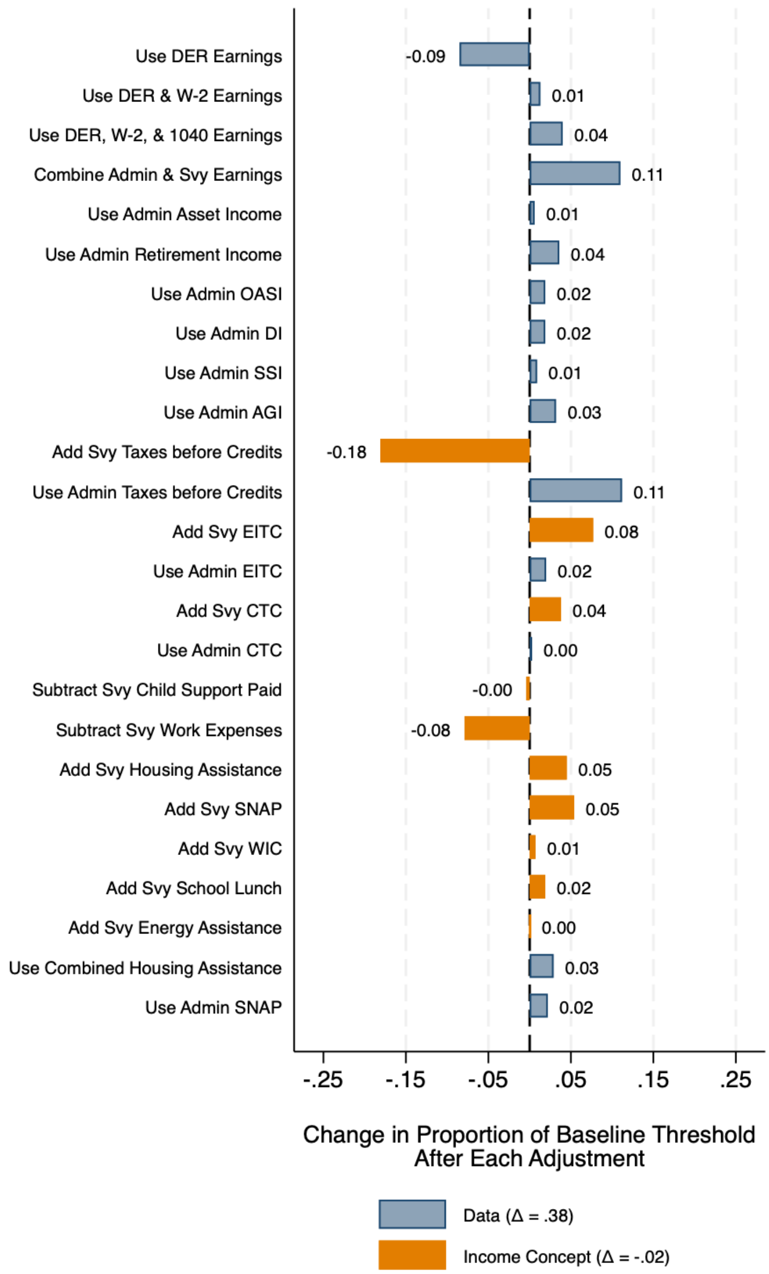
Figure 3. Changes to Absolute Poverty Rates After Step-by-Step Adjustments



Source: 2017 CPS ASEC linked to various administrative records

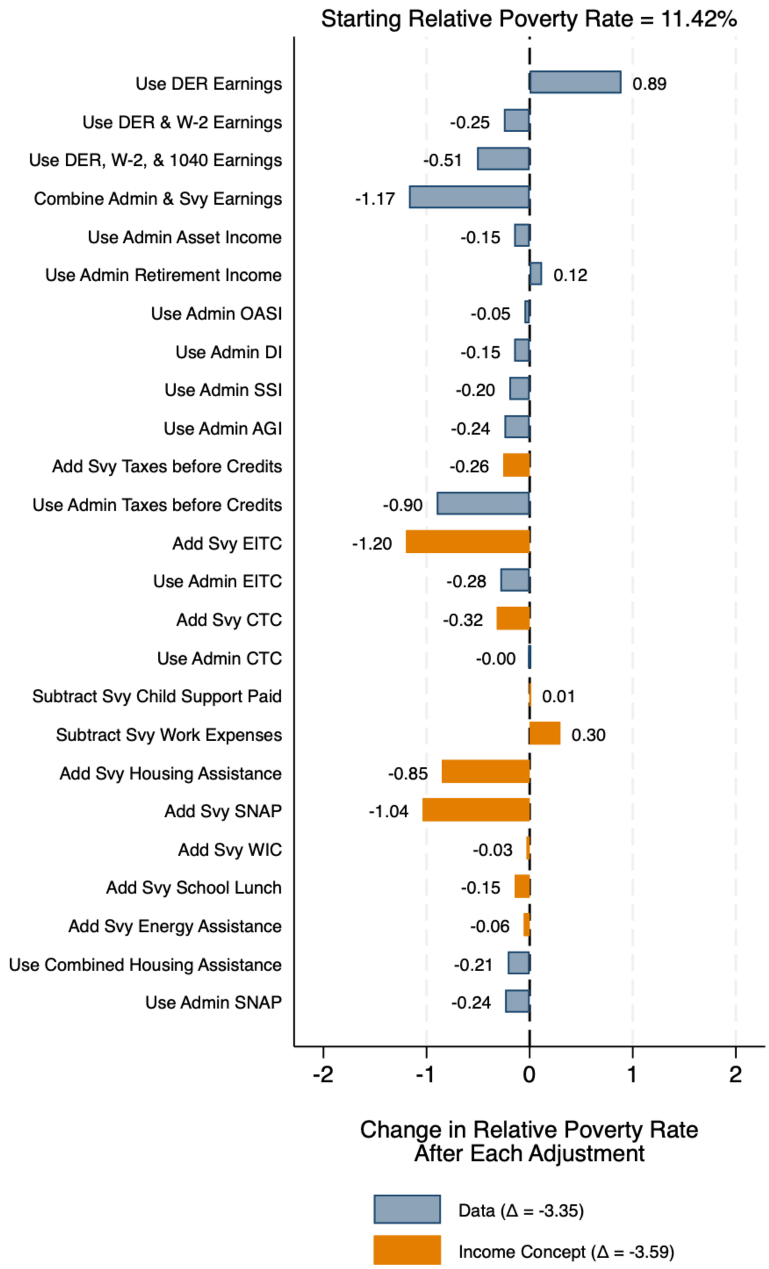
Notes: This waterfall chart shows the percentage point change in the share of individuals with incomes below absolute thresholds after each adjustment, starting from the Official Poverty Measure (OPM). The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. All estimates are calculated over the entire U.S., except for the adjustments using administrative SNAP data (calculated using proportional adjustments for 23 states with SNAP data) and administrative TANF data (calculated using proportional adjustments for 18 states with SNAP and TANF data). Approved for release by the Census Bureau’s Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure 4. Changes to Threshold Multipliers After Step-by-Step Adjustments



Source: 2017 CPS ASEC linked to various administrative records
Notes: This waterfall chart shows the change in the multiplier applied to official thresholds to keep absolute poverty rates fixed at 11.42% after each adjustment, starting from a baseline of survey pre-tax money income. The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. All estimates are calculated over the entire U.S., except for the adjustments using administrative SNAP data (calculated using proportional adjustments for 23 states with SNAP data). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

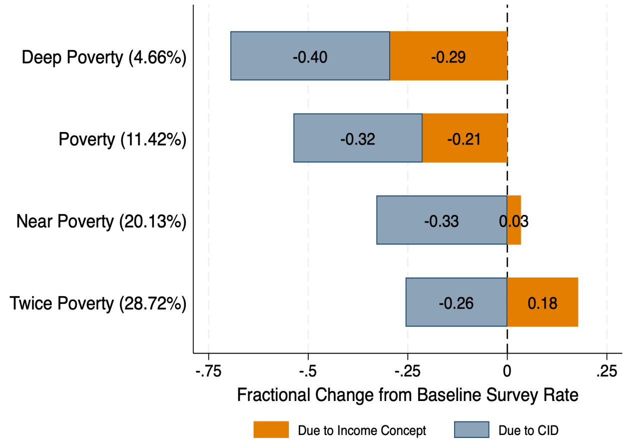
Figure 5. Changes to Relative Poverty After Step-by-Step Adjustments



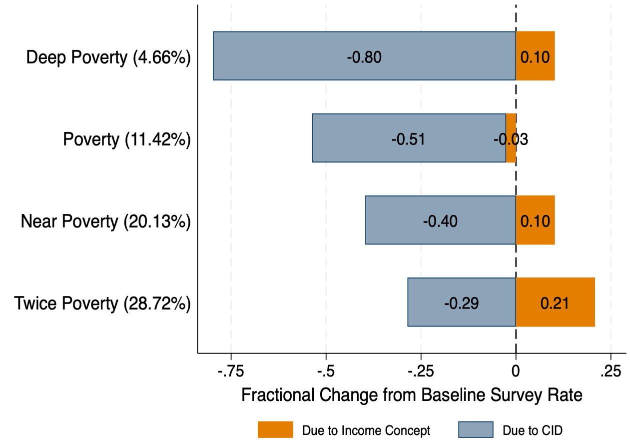
Source: 2017 CPS ASEC linked to various administrative records

Notes: This waterfall chart shows the percentage point change in the share of individuals in relative poverty after each adjustment, starting from a baseline of survey pre-tax money income. Relative poverty is defined as the share of individuals with incomes below some fraction of median income – we use a fraction of 0.298, which corresponds to the absolute poverty rate using survey pre-tax money income. The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. All estimates are calculated over the entire U.S., except for the adjustments using administrative SNAP data (calculated using proportional adjustments for 23 states with SNAP data). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

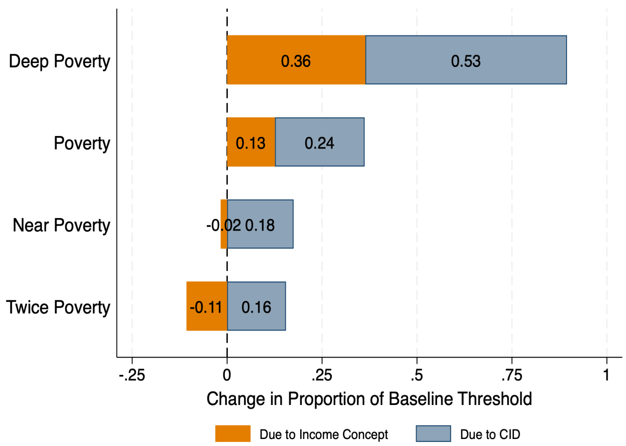
Figure 6. Role of Better Data vs. Income Concept Changes for Prototypical Poverty Analyses



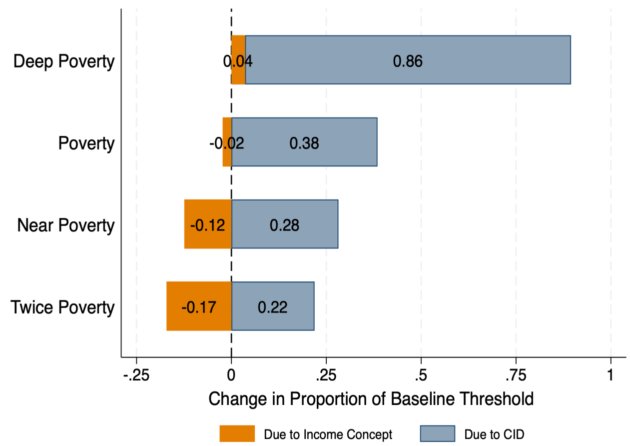
(a) Absolute Poverty: Change Income Concept First



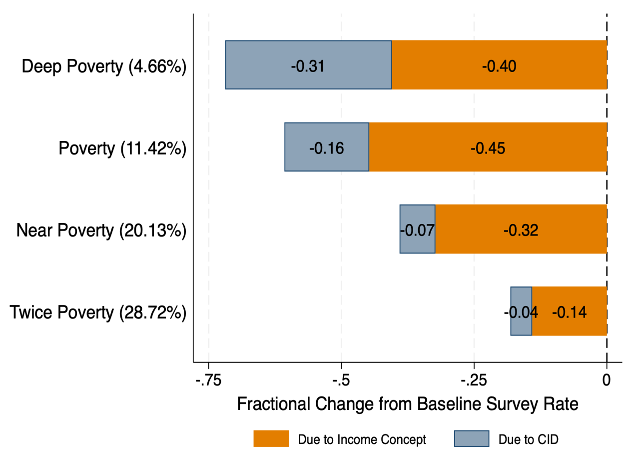
(b) Absolute Poverty: Step-by-Step Adjustments



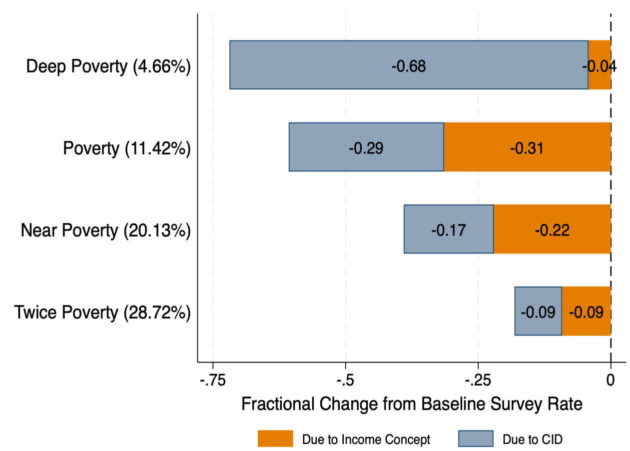
(c) Poverty Thresholds: Change Income Concept First



(d) Poverty Thresholds: Step-by-Step Adjustments



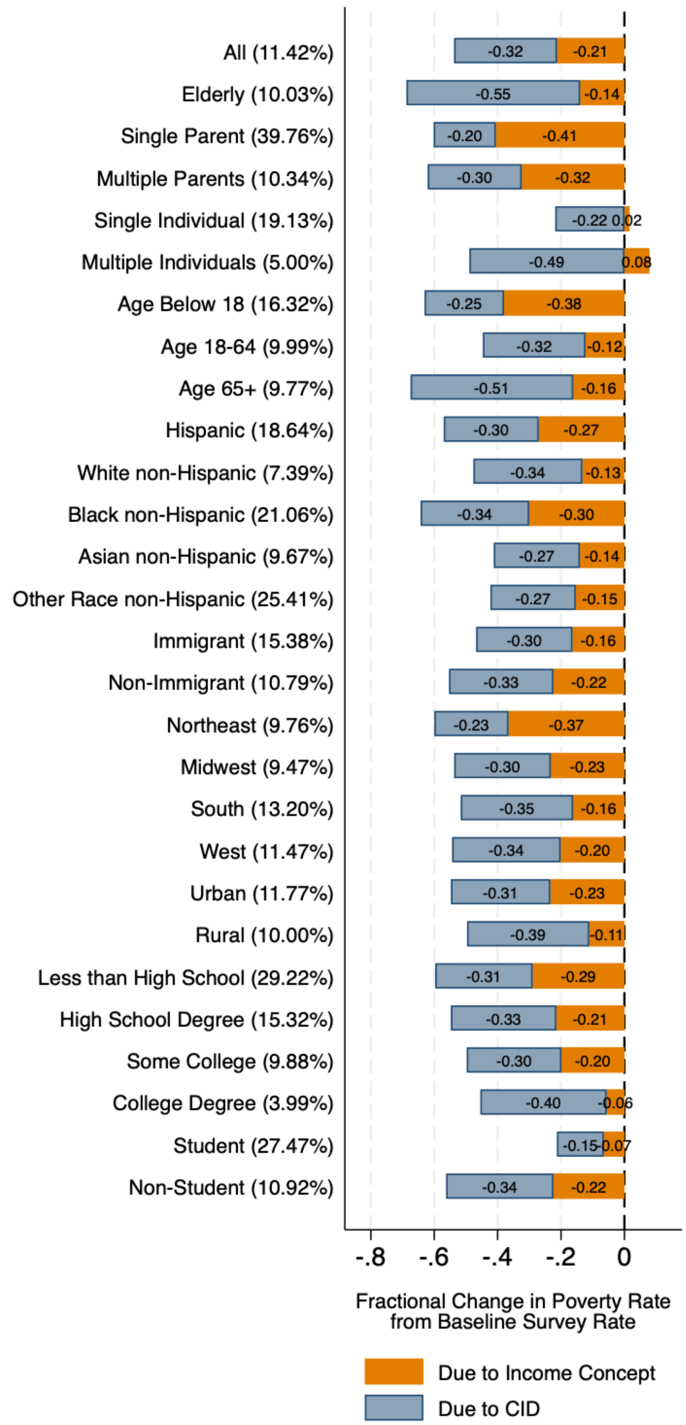
(e) Relative Poverty: Change Income Concept First



(f) Relative Poverty: Step-by-Step Adjustments

Source: 2017 CPS ASEC linked to various administrative records
Notes: This figure shows the fractional decline in absolute poverty rates (Panels A and B), fractional increase in poverty thresholds needed to hold poverty rates fixed at 11.42% (Panels C and D), and fractional decline in relative poverty rates (Panels E and F) at different multiples of the poverty line after bringing in conceptual changes to income first and after step-by-step adjustments. The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

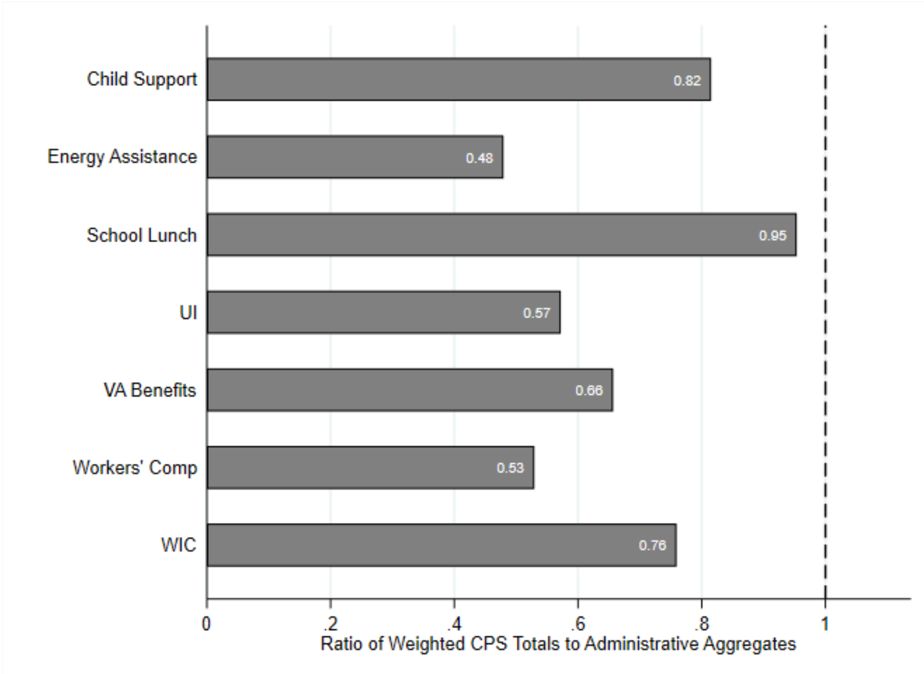
Figure 7. Fractional Decline in Absolute Poverty Rate by Demographic Subgroups



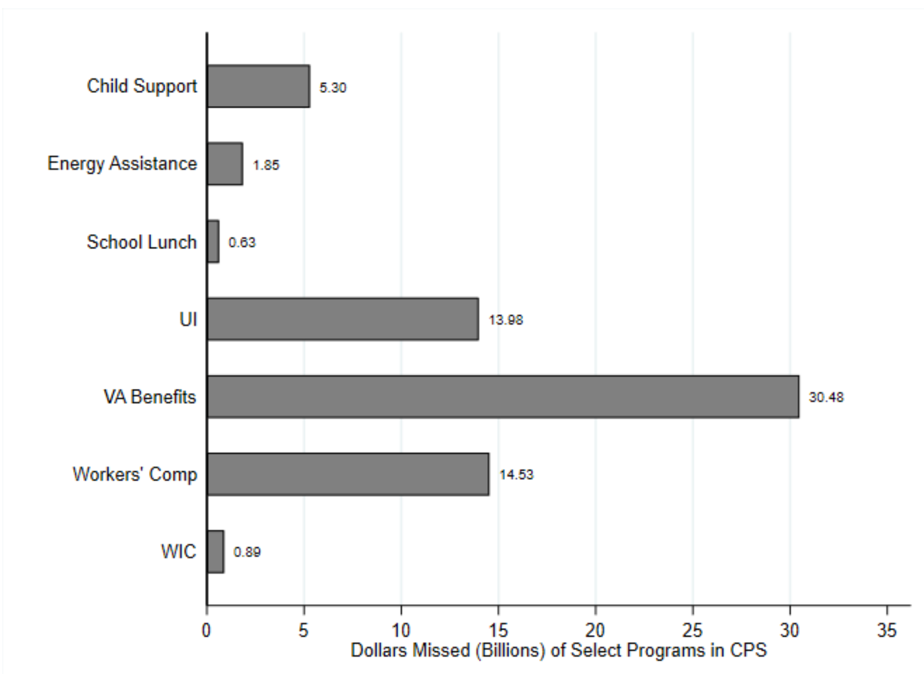
Source: 2017 CPS ASEC linked to various administrative records

Notes: This figure shows the fractional decline in absolute poverty rates for demographic subgroups after first bringing in conceptual changes to income and then using the CID to correct for misreporting. Sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Baseline poverty rates using survey pre-tax money income are in parentheses. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure 8. Dollars Missed from Income Sources without Administrative Microdata



(a) Reporting Rate for Aggregate Dollars



(b) Total Dollars Unreported (Billions) in CPS

Source: 2017 CPS ASEC linked to various administrative records
Notes: Panel A shows the reporting rates for aggregate dollars in the CPS among selected income sources for which we do not have administrative microdata. The numerator reflects survey dollars summed over SPM units and the denominator reflects dollars according to administrative sources such as NIPA and program records. Panel B shows the magnitude of the total administrative dollars that are unreported in the CPS.

Appendix Tables and Figures

Table A1. Characteristics of Individuals with Discrepant W-2 and DER Wages

Characteristic	All Persons 15+		OPM Poor Persons 15+	
	Share of Individuals (1)	Share of Dollar Diff. (2)	Share of Individuals (3)	Share of Dollar Diff. (4)
	A. W-2 Wages > DER Wages			
ITIN 1040 Filer	61.27%	50.26%	62.87%	80.18%
Among Non-ITINs:				
Zero DER Wages	38.16%	16.26%	--	--
# W-2 Employers > # DER Employers	61.63%	24.07%	94.05%	99.91%
Among Non-ITINs Filing Non-Joint 1040:				
W-2 Wages = 1040 Wages	--		--	
DER Wages = 1040 Wages	56.14%		--	
Share of Individuals Aged 15+	0.26%		0.37%	
Sample Size	350		60	
Population (Weighted)	679,000		118,500	
	B. W-2 Wages < DER Wages			
ITIN 1040 Filer	0.00%	0.00%	0.00%	0.00%
Among Non-ITINs:				
Zero W-2 Wages	46.64%	75.49%	38.23%	57.27%
# W-2 Employers < # DER Employers	86.45%	95.78%	84.22%	95.73%
Among Non-ITINs Filing Non-Joint 1040:				
W-2 Wages = 1040 Wages	6.93%		--	
DER Wages = 1040 Wages	78.51%		63.93%	
Share of Individuals Aged 15+	0.70%		0.49%	
Sample Size	850		80	
Population (Weighted)	1,828,000		156,700	

* Estimates marked "--"are suppressed due to disclosure risk from small cell sizes

Source: 2017 CPS ASEC linked to SSA DER and IRS Form W-2
Notes: Sample in Columns (1) and (2) consists of individuals aged 15+ in the linked CPS sample, dropping non-PIKed and whole imputed individuals and adjusting survey weights using inverse probability weighting. Sample in Columns (3) and (4) consists of all PIKed and non-whole imputed individuals aged 15+ who are poor under the Official Poverty Measure (OPM). DER and W-2 wages correspond to Box 1 (wages, tips, other compensation) of the W-2 summed across all W-2 forms received by an individual for that tax year. Amounts in one source are designated as equal to those in another source if they are within $5 of each other. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A2. Characteristics of Tax Units with Discrepant 1040 and W-2 Wages

Characteristic	All Tax Units Share of Discrepant Tax Units (1)	All Tax Units Share of Discrepant Dollar Diff. (2)	Share of All Tax Units (3)	OPM Poor Tax Units Share of Discrepant Tax Units (4)	OPM Poor Tax Units Share of Discrepant Dollar Diff. (5)	Share of All Poor Tax Units (6)
			A. 1040 Wages > W-2 Wages			
ITIN 1040 Filer	9.22%	13.58%	1.00%	13.39%	32.45%	2.07%
Among Non-ITINs:						
Presence of 1099-R, ≤ Age 64, and Disabled	1.63%	1.73%	1.16%	--	--	1.48%
Presence of 1099-MISC and No Schedule C	7.06%	6.67%	5.65%	5.41%	9.74%	4.57%
Excess Deferred Compensation (>$18,000)	2.66%	1.29%	1.69%	--	--	--
Full- or Part-Time Student	17.21%	6.20%	10.45%	20.88%	18.65%	15.15%
Also Receiving Scholarships or Grants	3.65%	1.21%	1.43%	--	--	1.52%
Child Care Expenses in Household	10.82%	8.13%	6.78%	6.18%	5.65%	6.18%
Adopted Child in Household	1.34%	0.90%	1.36%	--	--	1.44%
Household Employee	3.31%	1.23%	1.90%	7.52%	5.75%	3.85%
Work in Heavily Tipped Industry[1]	13.65%	6.61%	10.57%	19.07%	12.78%	16.90%
Any of the Above Reasons	47.01%	28.47%	33.42%	50.02%	45.39%	41.37%
Share of Tax Units	4.44%		100.00%	7.04%		100.00%
Sample Size of Tax Units	2,700		58,500	350		5,100
Population of Tax Units (Weighted)	5,748,000		129,500,000	754,600		10,720,000
			B. 1040 Wages < W-2 Wages			
Zero 1040 Wages	5.51%	12.92%		11.08%	8.96%	
1040/W-2 Difference Equal to One W-2	65.47%	53.52%		66.32%	56.32%	
1040/W-2 Difference Equal to One or Two W-2s	71.30%	63.36%		71.78%	70.37%	
Share of Tax Units	5.32%		100.00%	10.75%		100.00%
Sample Size of Tax Units	3,000		58,500	500		5,100
Population of Tax Units (Weighted)	6,885,000		129,500,000	1,152,000		10,720,000

* Estimates marked "--"are suppressed due to disclosure risk from small cell sizes

[1] Taxi/limousine service, spectator sports, gambling, traveler accommodations, rooming/boarding houses, restaurants/food services, drinking places, barber shops, beauty/nail salons

Source: 2017 CPS ASEC linked to IRS Forms 1040 and W-2

Notes: This table shows the share of tax units with discrepancies between 1040 and W-2 wages (within $5), as well as dollar discrepancies for these tax units, explained by a number of potential reasons that can be checked in the IRS or survey data. Estimates are calculated over all tax units in the linked CPS sample, dropping non-PIKed and whole imputed individuals in the CPS and adjusting survey weights using inverse probability weighting. W-2 wages correspond to taxable wages on Box 1, and 1040 wages correspond to taxable wages and salaries on Box 7. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A3. Percentiles of Various Income Concepts

	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
Percentile	Survey (1)	CID (2)	Survey (3)	CID (4)	Survey (5)	CID (6)
1	0	5,086	0	3,976	73	8,244
2	1,447	10,780	1,049	10,140	5,566	15,270
3	6,368	14,170	6,029	13,940	10,850	19,100
4	10,080	16,830	10,040	16,990	14,920	21,780
5	13,010	18,900	13,010	18,980	17,420	23,740
6	15,260	20,150	15,540	20,620	19,370	25,750
7	17,340	21,840	17,660	22,410	21,160	27,370
8	18,970	23,530	19,220	23,950	22,790	28,790
9	20,580	25,330	20,850	25,580	24,350	30,220
10	22,240	27,000	22,320	27,050	25,740	31,430
11	23,630	28,500	23,780	28,280	26,890	32,570
12	25,250	30,050	25,080	29,730	28,060	33,710
13	26,740	31,640	26,410	30,930	29,140	35,010
14	28,150	33,200	27,540	32,150	30,270	36,230
15	29,540	34,660	28,650	33,450	31,190	37,110
16	30,970	36,190	29,720	34,650	32,140	38,120
17	32,340	37,740	30,870	35,920	33,050	39,230
18	33,670	39,090	31,830	37,090	33,920	40,150
19	35,000	40,530	32,880	38,190	34,860	41,080
20	36,360	41,980	33,790	39,200	35,770	42,200
21	37,620	43,560	34,820	40,260	36,650	43,060
22	39,000	45,130	35,910	41,360	37,550	44,010
23	40,580	46,610	36,870	42,470	38,410	45,140
24	41,960	48,230	37,860	43,710	39,250	46,080
25	43,170	49,790	38,790	44,850	40,100	47,010
26	44,850	51,130	39,820	46,060	41,000	48,170
27	45,900	52,540	40,810	47,160	41,830	49,030
28	47,540	53,990	41,750	48,290	42,760	50,060
29	49,040	55,550	42,750	49,460	43,790	51,270
30	50,290	57,080	43,830	50,630	44,720	52,470
31	51,780	58,550	44,860	51,790	45,700	53,430
32	53,400	60,060	45,950	53,000	46,760	54,620
33	54,630	61,670	47,070	54,180	47,790	55,750
34	56,110	63,210	48,090	55,360	48,830	56,980
35	57,610	64,740	49,160	56,520	49,890	57,930
36	59,150	66,240	50,240	57,610	50,810	59,090
37	60,570	67,740	51,350	58,830	51,860	60,290
38	62,150	69,310	52,420	59,960	53,020	61,220
39	63,690	71,000	53,600	61,150	54,150	62,410
40	65,160	72,600	54,650	62,360	55,140	63,490
41	66,920	74,260	55,760	63,660	56,250	64,750
42	68,590	75,780	56,850	64,940	57,280	66,010
43	70,010	77,360	58,060	66,300	58,450	67,370
44	71,560	78,910	59,130	67,650	59,490	68,610
45	73,360	80,570	60,290	68,790	60,630	69,950
46	75,000	82,290	61,380	70,080	61,760	71,100
47	76,310	83,900	62,670	71,390	62,980	72,310
48	77,960	85,650	63,780	72,750	64,160	73,560
49	79,820	87,360	65,140	73,990	65,460	74,730
50	81,560	89,130	66,420	75,410	66,710	76,220
Sample Size			145,000			
Population (mil.)			320.3			

Source: 2017 CPS ASEC linked to various administrative records
Notes: Percentiles are calculated over individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Incomes are equivalized using the SPM equivalence scale to be representative of a family with 2 adults and 2 children. Percentiles in Column (6) are calculated using proportional adjustments for admin SNAP based on the 23 states for which we have SNAP data in 2016. All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A4. Percent of Individuals with Incomes Below Absolute Thresholds After Step-by-Step Adjustments (by Multiple of Threshold)

Poverty Measure	Regular (100%) (1)	Deep (50%) (2)	Near (150%) (3)	Twice (200%) (4)
Official Poverty Measure	12.70	5.79	21.17	29.77
Sample, Unit, & Threshold Changes				
Use SPM Sharing Unit	11.42	4.82	19.78	28.32
Use SPM Equivalence Scale	11.29	4.75	19.87	28.49
Remove Whole Imputes & Reweight	11.35	4.61	20.01	28.59
Remove Non-PIKed & Reweight	11.42	4.66	20.13	28.72
Correct Pre-Tax Money Income				
Use DER Earnings	12.84	5.39	21.78	30.63
Use DER & W-2 Earnings	12.59	5.16	21.57	30.45
Use DER, W-2, & 1040 Earnings	11.91	4.57	20.89	29.75
Combine Admin & Survey Earnings	10.16	3.48	18.86	27.68
Use Admin Asset Income	10.08	3.40	18.78	27.54
Use Admin Retirement Income	9.48	3.21	17.56	25.85
Use Admin OASI	9.30	3.06	17.12	25.24
Use Admin DI	9.12	2.99	16.81	24.98
Use Admin SSI	8.93	2.58	16.78	24.99
Use Admin AGI	8.49	2.31	16.20	24.31
Account for Taxes and Expenses				
Add Survey Taxes Before Credits	11.17	3.68	20.40	30.30
Use Admin Taxes Before Credits	9.30	2.54	18.09	27.62
Add Survey EITC	8.01	2.18	16.89	26.89
Use Admin EITC	7.64	2.17	16.56	26.69
Add Survey CTC	7.17	2.10	15.78	25.79
Use Admin CTC	7.15	2.12	15.76	25.77
Subtract Survey Child Support Paid	7.21	2.14	15.84	25.88
Subtract Survey Work Expenses	8.23	2.45	17.54	28.33
Account for In-Kind Transfers				
Add Survey Housing Assistance	7.36	2.09	17.04	28.12
Add Survey SNAP	6.27	1.72	16.18	27.69
Add Survey WIC	6.22	1.70	16.05	27.64
Add Survey School Lunch	5.98	1.66	15.64	27.40
Add Survey Energy Assistance	5.93	--	15.60	27.39
Use Combined Housing Assistance	5.60	1.63	14.88	26.88
Use Admin SNAP	5.29	1.42	14.20	26.49
Use Combined TANF	5.23	1.42	14.09	26.41
Sample Size		145,000		
Population (weighted mil.)		320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights (starting only after the first five steps). Poverty rates correspond to the percent of individuals with incomes below 100%, 50%, 150%, and 200% of the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Approved for release by the Census Bureau’s Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A5. Percent of Individuals with Incomes Below Absolute Thresholds After Step-by-Step Adjustments (by Family Type)

Poverty Measure	Elderly (1)	Single Parent (2)	Multiple Parents (3)	Single Individual (4)	Multiple Individuals (5)
Survey Pre-Tax Money Income	10.03	39.76	10.34	19.13	5.00
Correct Pre-Tax Money Income					
Use DER Earnings	9.86	41.83	12.43	21.76	5.84
Use DER & W-2 Earnings	9.86	41.72	11.96	21.59	5.73
Use DER, W-2, & 1040 Earnings	--	40.19	10.91	21.00	5.37
Combine Admin & Survey Earnings	9.21	37.92	8.73	18.11	4.07
Use Admin Asset Income	8.78	38.00	8.77	18.16	3.95
Use Admin Retirement Income	6.62	37.89	8.59	17.72	3.56
Use Admin OASI	5.67	37.83	8.58	17.59	3.60
Use Admin DI	5.90	37.43	8.40	17.01	3.32
Use Admin SSI	5.79	36.55	8.13	17.41	3.17
Use Admin AGI	5.55	35.34	7.61	16.85	2.91
Account for Taxes and Expenses					
Add Survey Taxes Before Credits	6.36	39.73	10.86	20.57	5.19
Use Admin Taxes Before Credits	5.71	38.07	8.63	17.79	3.36
Add Survey EITC	5.66	31.00	6.61	--	3.22
Use Admin EITC	5.56	28.98	6.17	17.52	3.11
Add Survey CTC	5.56	26.54	5.38	17.52	3.11
Use Admin CTC	5.52	26.18	5.39	17.51	3.10
Subtract Survey Child Support Paid	--	26.18	5.45	--	3.21
Subtract Survey Work Expenses	5.66	29.38	6.59	19.35	3.87
Account for In-Kind Transfers					
Add Survey Housing Assistance	4.46	25.44	6.09	17.70	3.61
Add Survey SNAP	4.01	19.81	4.88	16.76	3.23
Add Survey WIC	4.01	19.69	4.78	16.76	3.23
Add Survey School Lunch	--	18.41	4.40	--	--
Add Survey Energy Assistance	3.91	--	4.36	16.62	3.17
Use Combined Housing Assistance	3.47	17.17	4.23	15.60	3.04
Use Admin SNAP	3.14	15.84	3.93	15.27	2.95
Use Combined TANF	3.12	15.33	3.88	15.19	2.95
Sample Size			145,000		
Population (weighted mil.)			320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Elderly families are defined as being headed by an individual over the age of 65. The other four family types are headed by a non-elderly individual; single parents have one adult aged 18 and over and at least one child below age 18, multiple parents have at least two adults and at least one child, single individual families consist of one individual, and multiple individuals consist of multiple childless adults. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A6. Multipliers Applied to Thresholds to Hold Poverty Rates Fixed After Step-by-Step Adjustments (by Multiple of Threshold)

Poverty Measure	Regular (100%) (1)	Deep (50%) (2)	Near (150%) (3)	Twice (200%) (4)
Survey Pre-Tax Money Income	1.000	1.000	1.000	1.000
Correct Pre-Tax Money Income				
Use DER Earnings	0.915	0.837	0.940	0.942
Use DER & W-2 Earnings	0.928	0.890	0.948	0.947
Use DER, W-2, & 1040 Earnings	0.968	1.018	0.971	0.969
Combine Admin & Survey Earnings	1.078	1.229	1.049	1.029
Use Admin Asset Income	1.084	1.240	1.051	1.033
Use Admin Retirement Income	1.120	1.290	1.099	1.087
Use Admin OASI	1.139	1.314	1.120	1.105
Use Admin DI	1.158	1.354	1.129	1.113
Use Admin SSI	1.167	1.453	1.130	1.109
Use Admin AGI	1.199	1.504	1.156	1.132
Account for Taxes and Expenses				
Add Survey Taxes Before Credits	1.018	1.175	0.992	0.961
Use Admin Taxes Before Credits	1.130	1.432	1.068	1.026
Add Survey EITC	1.207	1.559	1.104	1.043
Use Admin EITC	1.227	1.576	1.117	1.047
Add Survey CTC	1.265	1.603	1.145	1.069
Use Admin CTC	1.268	1.603	1.147	1.071
Subtract Survey Child Support Paid	1.264	1.602	1.143	1.067
Subtract Survey Work Expenses	1.185	1.524	1.078	1.009
Account for In-Kind Transfers				
Add Survey Housing Assistance	1.230	1.603	1.088	1.014
Add Survey SNAP	1.284	1.768	1.110	1.025
Add Survey WIC	1.291	1.779	1.112	1.026
Add Survey School Lunch	1.310	1.810	1.122	1.031
Add Survey Energy Assistance	1.311	1.814	1.123	1.032
Use Combined Housing Assistance	1.340	1.850	1.143	1.043
Use Admin SNAP	1.362	1.895	1.158	1.048
Sample Size		145,000		
Population (weighted mil.)		320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Multipliers correspond to fractions by which poverty thresholds must be multiplied to keep the share of individuals with incomes below 100%, 50%, 150%, and 200% of the absolute poverty line constant at the survey pre-tax money income baseline. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A7. Multipliers Applied to Thresholds to Hold Poverty Rates Fixed After Step-by-Step Adjustments (by Family Type)

Poverty Measure	Elderly (1)	Single Parent (2)	Multiple Parents (3)	Single Individual (4)	Multiple Individuals (5)
Survey Pre-Tax Money Income	1.000	1.000	1.000	1.000	1.000
Correct Pre-Tax Money Income					
Use DER Earnings	1.013	0.939	0.882	0.876	0.878
Use DER & W-2 Earnings	1.013	0.944	0.910	0.886	0.887
Use DER, W-2, & 1040 Earnings	1.016	0.993	0.968	0.907	0.940
Combine Admin & Survey Earnings	1.054	1.040	1.103	1.063	1.132
Use Admin Asset Income	1.069	1.040	1.101	1.063	1.135
Use Admin Retirement Income	1.220	1.041	1.107	1.065	1.200
Use Admin OASI	1.325	1.042	1.108	1.075	1.208
Use Admin DI	1.306	1.051	1.118	1.134	1.246
Use Admin SSI	1.298	1.075	1.134	1.099	1.246
Use Admin AGI	1.325	1.108	1.168	1.136	1.289
Account for Taxes and Expenses					
Add Survey Taxes Before Credits	1.245	1.001	0.966	0.941	0.981
Use Admin Taxes Before Credits	1.308	1.039	1.094	1.074	1.207
Add Survey EITC	1.319	1.190	1.199	1.079	1.229
Use Admin EITC	1.321	1.220	1.225	1.086	1.258
Add Survey CTC	1.323	1.283	1.281	1.086	1.258
Use Admin CTC	1.324	1.285	1.287	1.089	1.259
Subtract Survey Child Support Paid	1.323	1.283	1.286	1.083	1.251
Subtract Survey Work Expenses	1.307	1.222	1.193	0.992	1.152
Account for In-Kind Transfers					
Add Survey Housing Assistance	1.352	1.285	1.221	1.064	1.174
Add Survey SNAP	1.384	1.373	1.282	1.101	1.223
Add Survey WIC	1.384	1.375	1.293	1.101	1.224
Add Survey School Lunch	1.386	1.413	1.318	1.101	1.224
Add Survey Energy Assistance	1.389	1.419	1.320	1.109	1.226
Use Combined Housing Assistance	1.457	1.463	1.331	1.166	1.239
Use Admin SNAP	1.466	1.518	1.353	1.171	1.251
Sample Size			145,000		
Population (weighted mil.)			320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Multipliers correspond to fractions by which poverty thresholds must be multiplied to keep the share of individuals with incomes below the absolute poverty line constant at the survey pre-tax money income baseline. Elderly families are defined as being headed by an individual over the age of 65. The other four family types are headed by a non-elderly individual; single parents have one adult aged 18 and over and at least one child below age 18, multiple parents have at least two adults and at least one child, single individual families consist of one individual, and multiple individuals consist of multiple childless adults. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A8. Percent of Individuals with Incomes Below Relative Thresholds After Step-by-Step Adjustments (by Multiple of Threshold)

Poverty Measure	Regular (100%) (1)	Deep (50%) (2)	Near (150%) (3)	Twice (200%) (4)
Survey Pre-Tax Money Income	11.42	4.66	20.13	28.72
Correct Pre-Tax Money Income				
Use DER Earnings	12.31	5.24	20.78	29.47
Use DER & W-2 Earnings	12.06	5.00	20.62	29.34
Use DER, W-2, & 1040 Earnings	11.55	4.47	20.35	29.07
Combine Admin & Survey Earnings	10.38	3.54	19.27	28.22
Use Admin Asset Income	10.23	3.45	19.12	27.96
Use Admin Retirement Income	10.35	3.46	19.15	27.90
Use Admin OASI	10.30	3.39	18.88	27.67
Use Admin DI	10.15	3.34	18.78	27.60
Use Admin SSI	9.95	2.91	18.68	27.57
Use Admin AGI	9.71	2.67	18.58	27.43
Account for Taxes and Expenses				
Add Survey Taxes Before Credits	9.45	3.34	17.48	26.45
Use Admin Taxes Before Credits	8.55	2.37	16.76	25.91
Add Survey EITC	7.35	2.09	15.61	25.25
Use Admin EITC	7.07	2.07	15.40	25.10
Add Survey CTC	6.75	2.02	14.86	24.65
Use Admin CTC	6.75	2.04	14.82	24.64
Subtract Survey Child Support Paid	6.76	2.06	14.75	24.63
Subtract Survey Work Expenses	7.06	2.22	15.25	25.14
Account for In-Kind Transfers				
Add Survey Housing Assistance	6.21	1.88	14.63	24.88
Add Survey SNAP	5.17	1.59	13.62	24.48
Add Survey WIC	5.14	1.58	13.55	24.42
Add Survey School Lunch	4.99	1.52	13.22	24.13
Add Survey Energy Assistance	4.94	1.51	13.17	24.09
Use Combined Housing Assistance	4.72	1.48	12.64	23.71
Use Admin SNAP	4.49	1.31	12.27	23.50
Sample Size		145,000		
Population (weighted mil.)		320.3		
Threshold as % of Median Income	29.84	14.92	44.76	59.68

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below some fraction of median income, where the fractions are defined such that the starting relative poverty rates correspond to the share of individuals with survey pre-tax money income below 100%, 50%, 150%, and 200% of the absolute poverty line. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A9. Percent of Individuals with Incomes Below Relative Thresholds After Step-by-Step Adjustments (by Family Type)

Poverty Measure	Elderly (1)	Single Parent (2)	Multiple Parents (3)	Single Individual (4)	Multiple Individuals (5)
Survey Pre-Tax Money Income	10.03	39.76	10.34	19.13	5.00
<u>Correct Pre-Tax Money Income</u>					
Use DER Earnings	9.86	39.49	11.84	20.47	5.64
Use DER & W-2 Earnings	9.86	39.41	11.38	20.29	5.54
Use DER, W-2, & 1040 Earnings	9.82	38.65	10.53	19.92	5.30
Combine Admin & Survey Earnings	9.58	39.00	9.13	18.10	4.20
Use Admin Asset Income	9.40	38.84	9.01	18.01	4.02
Use Admin Retirement Income	10.15	38.96	9.08	18.01	3.75
Use Admin OASI	9.55	38.93	9.10	17.88	3.82
Use Admin DI	9.66	38.93	8.92	17.36	3.60
Use Admin SSI	9.69	38.57	8.66	17.66	3.40
Use Admin AGI	9.73	38.54	8.33	17.22	3.25
<u>Account for Taxes and Expenses</u>					
Add Survey Taxes Before Credits	9.07	37.87	8.06	16.80	4.01
Use Admin Taxes Before Credits	8.73	37.97	7.03	15.10	2.58
Add Survey EITC	8.62	35.69	5.17	15.05	2.53
Use Admin EITC	8.56	34.80	4.89	14.95	2.48
Add Survey CTC	8.49	34.47	4.63	14.95	2.48
Use Admin CTC	8.53	34.27	4.61	14.94	2.47
Subtract Survey Child Support Paid	8.55	34.27	4.63	14.95	2.54
Subtract Survey Work Expenses	8.47	34.47	5.04	15.28	2.84
<u>Account for In-Kind Transfers</u>					
Add Survey Housing Assistance	7.43	33.17	4.56	13.72	2.58
Add Survey SNAP	6.93	29.61	3.56	12.32	2.30
Add Survey WIC	6.93	29.44	3.50	12.32	2.30
Add Survey School Lunch	6.91	28.65	3.22	12.32	2.29
Add Survey Energy Assistance	6.85	28.44	3.20	12.26	2.27
Use Combined Housing Assistance	6.18	28.00	3.11	11.91	2.23
Use Admin SNAP	5.90	29.52	2.99	11.58	2.08
Sample Size			145,000		
Population (weighted mil.)			320.3		
Threshold as % of Median Income	33.97	77.25	31.96	33.14	20.48

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below some fraction of median income, where the fractions are defined such that the starting relative poverty rates correspond to the share of individuals with survey pre-tax money income below the absolute poverty line. Elderly families are defined as being headed by an individual over the age of 65. The other four family types are headed by a non-elderly individual; single parents have one adult aged 18 and over and at least one child below age 18, multiple parents have at least two adults and at least one child, single individual families consist of one individual, and multiple individuals consist of multiple childless adults. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A10. Percent of Individuals with Incomes Below 100% of Absolute Thresholds (Regular Poverty) by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
	Survey	CID	Survey	CID	Survey	CID
	(1)	(2)	(3)	(4)	(5)	(6)
All	11.42	8.49	11.44	8.23	8.99	5.29
Elderly	10.03	5.55	10.51	5.66	8.63	3.14
Single Parents	39.76	35.34	34.92	29.38	23.63	15.84
Multiple Parents	10.34	7.61	9.49	6.59	6.99	3.93
Single Individual	19.13	16.85	22.12	19.35	19.44	15.27
Multiple Individuals	5.00	2.91	6.11	3.87	5.39	2.95
Hispanic	18.64	13.28	18.14	12.50	13.60	8.02
White (non-Hisp.)	7.39	5.54	7.60	5.56	6.41	3.87
Black (non-Hisp.)	21.06	16.04	20.96	14.98	14.73	7.52
Asian (non-Hisp.)	9.67	7.30	9.59	7.25	8.32	5.69
Other (non-Hisp.)	25.41	21.92	24.88	21.83	21.51	14.67
Immigrant	15.38	11.41	15.70	11.51	12.86	8.19
Non-Immigrant	10.79	8.02	10.76	7.70	8.38	4.82
Northeast	9.76	8.17	9.28	7.61	6.19	3.91
Midwest	9.47	7.35	9.60	7.17	7.27	4.39
South	13.20	9.51	13.29	9.26	11.06	6.39
West	11.47	8.10	11.62	7.95	9.16	5.24
Age<18	16.32	12.94	14.40	10.83	10.12	6.03
Age 18-64	9.99	7.50	10.66	7.84	8.76	5.53
Age 65+	9.77	5.72	10.10	5.84	8.19	3.18
Urban	11.77	8.77	11.75	8.48	9.02	5.33
Rural	10.00	7.35	10.20	7.21	8.89	5.04
Less than High School	29.22	22.29	28.63	20.37	20.76	11.78
High School Graduate	15.32	11.53	15.35	11.11	12.03	6.94
Some College	9.88	7.42	9.96	7.42	7.92	4.97
BA or More	3.99	2.60	4.14	2.76	3.76	2.18
Student	27.47	23.15	28.60	24.56	25.68	21.63
Non-Student	10.92	8.03	10.91	7.72	8.47	4.78
Sample Size				145,000		
Population (mil.)				320.3		

Source: 2017 CPS ASEC linked to various administrative records

Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below 100% of the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A11. Percent of Individuals with Incomes Below 50% of Absolute Thresholds (Deep Poverty) by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
	Survey	CID	Survey	CID	Survey	CID
	(1)	(2)	(3)	(4)	(5)	(6)
All	4.66	2.31	4.70	2.45	3.29	1.42
Elderly	3.46	0.60	3.55	0.69	3.10	0.36
Single Parents	20.96	12.82	18.85	12.09	8.42	4.49
Multiple Parents	3.24	1.57	3.12	1.52	1.84	0.68
Single Individual	10.52	6.82	11.49	8.02	10.45	6.82
Multiple Individuals	2.06	0.73	2.45	1.00	2.01	0.72
Hispanic	6.46	3.26	6.28	3.39	4.35	1.81
White (non-Hisp.)	2.97	1.47	3.13	1.61	2.46	1.11
Black (non-Hisp.)	9.86	4.38	9.76	4.50	5.17	1.63
Asian (non-Hisp.)	5.01	3.00	4.83	2.99	4.22	2.34
Other (non-Hisp.)	12.56	9.54	12.23	9.92	7.54	5.65
Immigrant	6.39	3.43	6.38	3.67	5.45	2.77
Non-Immigrant	4.39	2.14	4.44	2.25	2.95	1.20
Northeast	4.04	2.04	3.98	2.07	2.53	1.10
Midwest	3.51	1.78	3.61	1.98	2.36	1.05
South	5.64	2.69	5.73	2.84	4.10	1.66
West	4.56	2.39	4.54	2.50	3.36	1.50
Age<18	6.56	3.65	6.06	3.43	3.05	1.29
Age 18-64	4.30	2.26	4.53	2.55	3.46	1.73
Age 65+	3.27	0.51	3.36	0.58	2.99	0.37
Urban	4.81	2.39	4.84	2.54	3.34	1.47
Rural	4.06	2.02	4.15	2.07	3.11	1.24
Less than High School	10.37	5.12	10.27	5.23	5.99	2.24
High School Graduate	5.92	3.00	6.10	3.13	4.08	1.61
Some College	4.29	2.20	4.21	2.43	3.06	1.52
BA or More	2.18	0.98	2.25	1.04	2.01	0.90
Student	16.23	11.78	16.79	12.50	14.85	10.16
Non-Student	4.31	2.02	4.33	2.14	2.93	1.15
Sample Size				145,000		
Population (mil.)				320.3		

Source: 2017 CPS ASEC linked to various administrative records

Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below 50% of the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A12. Percent of Individuals with Incomes Below 150% of Absolute Thresholds (Near Poverty) by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
	Survey	CID	Survey	CID	Survey	CID
	(1)	(2)	(3)	(4)	(5)	(6)
All	20.13	16.20	22.61	17.54	20.82	14.20
Elderly	20.98	12.78	21.96	13.30	20.81	10.61
Single Parents	55.99	53.47	56.33	53.09	48.99	39.48
Multiple Parents	20.13	16.26	22.81	17.41	20.43	13.52
Single Individual	27.48	25.69	32.99	29.59	32.13	27.09
Multiple Individuals	8.83	6.65	11.37	8.31	10.97	7.35
Hispanic	33.47	25.91	37.71	28.03	34.47	22.62
White (non-Hisp.)	13.90	10.95	15.68	12.10	14.70	10.43
Black (non-Hisp.)	33.05	28.52	36.55	29.59	32.68	20.54
Asian (non-Hisp.)	15.65	13.50	17.81	15.03	16.44	12.42
Other (non-Hisp.)	36.55	34.10	39.75	34.71	36.62	29.09
Immigrant	27.01	21.49	31.12	23.64	28.77	19.95
Non-Immigrant	19.04	15.35	21.26	16.57	19.56	13.28
Northeast	16.98	14.38	18.68	14.88	16.13	10.45
Midwest	16.91	13.94	19.38	15.26	17.80	12.37
South	22.82	18.65	25.72	20.20	24.16	16.86
West	20.88	15.56	23.25	17.16	21.42	14.45
Age<18	27.67	23.81	29.59	24.41	26.13	18.40
Age 18-64	17.12	14.18	20.22	16.02	18.88	13.50
Age 65+	20.83	12.80	21.69	13.25	20.57	10.67
Urban	20.49	16.54	23.05	17.93	21.11	14.26
Rural	18.69	14.79	20.87	15.95	19.63	14.01
Less than High School	49.03	39.94	52.98	42.26	48.86	33.74
High School Graduate	27.13	22.05	30.73	23.56	28.32	19.04
Some College	18.27	14.97	20.98	16.51	19.02	13.15
BA or More	7.00	5.06	7.93	5.79	7.50	5.03
Student	38.73	36.29	42.17	39.32	39.49	34.91
Non-Student	19.56	15.57	22.01	16.86	20.24	13.56
Sample Size				145,000		
Population (mil.)				320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below 150% of the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A13. Percent of Individuals with Incomes Below 200% of Absolute Thresholds (Twice Poverty) by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
	Survey	CID	Survey	CID	Survey	CID
	(1)	(2)	(3)	(4)	(5)	(6)
All	28.72	24.31	34.51	28.33	33.83	26.49
Elderly	32.02	20.64	34.20	21.55	33.77	20.01
Single Parents	67.83	66.46	73.35	70.26	71.52	65.18
Multiple Parents	29.80	26.34	36.87	31.46	35.94	29.27
Single Individual	35.34	33.15	44.21	39.80	43.82	38.43
Multiple Individuals	13.45	10.84	18.56	14.29	18.27	13.33
Hispanic	45.33	38.87	53.68	43.94	52.77	41.04
White (non-Hisp.)	21.22	17.19	26.11	20.91	25.70	20.04
Black (non-Hisp.)	44.14	39.56	50.99	43.81	49.39	38.45
Asian (non-Hisp.)	22.18	19.82	27.35	23.26	26.49	22.01
Other (non-Hisp.)	47.11	45.36	52.57	50.21	51.54	46.34
Immigrant	37.09	31.37	44.78	36.19	44.14	34.21
Non-Immigrant	27.39	23.18	32.88	27.08	32.20	25.27
Northeast	24.66	20.44	29.89	23.78	28.89	21.00
Midwest	25.13	21.74	30.98	26.10	30.39	24.75
South	32.30	27.89	38.49	32.07	37.90	30.22
West	29.03	23.56	34.52	27.53	33.84	26.03
Age<18	37.68	34.40	43.99	38.95	42.85	36.12
Age 18-64	24.48	21.40	31.07	26.03	30.50	24.41
Age 65+	32.19	20.73	34.00	21.57	33.58	20.32
Urban	28.93	24.59	34.73	28.58	33.99	26.58
Rural	27.88	23.14	33.62	27.32	33.18	26.12
Less than High School	63.00	55.04	70.47	59.70	69.30	55.57
High School Graduate	38.95	32.67	46.43	37.82	45.55	35.10
Some College	27.63	23.93	34.40	28.84	33.55	27.07
BA or More	10.66	8.24	13.76	10.44	13.54	9.94
Student	50.25	48.30	56.81	53.81	55.25	50.62
Non-Student	28.06	23.56	33.82	27.54	33.17	25.74
Sample Size				145,000		
Population (mil.)				320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below 200% of the absolute poverty line (defined as the official threshold for a two-adult, two-child family adjusted for family size/composition using the SPM equivalence scale). Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A14. Multipliers Applied to Thresholds to Hold Poverty Rates Fixed by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers	
	Survey	CID	Survey	CID	Survey	CID
	(1)	(2)	(3)	(4)	(5)	(6)
All	1.000	1.199	0.999	1.185	1.126	1.362
Elderly	1.000	1.325	0.980	1.307	1.069	1.465
Single Parents	1.000	1.108	1.147	1.222	1.337	1.518
Multiple Parents	1.000	1.168	1.041	1.193	1.158	1.352
Single Individual	1.000	1.136	0.875	0.992	0.988	1.171
Multiple Individuals	1.000	1.289	0.870	1.152	0.955	1.250
Hispanic	1.000	1.214	1.016	1.194	1.141	1.383
White (non-Hisp.)	1.000	1.186	0.982	1.171	1.082	1.298
Black (non-Hisp.)	1.000	1.214	1.004	1.220	1.192	1.485
Asian (non-Hisp.)	1.000	1.172	1.004	1.169	1.124	1.313
Other (non-Hisp.)	1.000	1.145	1.027	1.133	1.147	1.374
Immigrant	1.000	1.199	0.992	1.159	1.104	1.311
Non-Immigrant	1.000	1.199	1.002	1.193	1.131	1.365
Northeast	1.000	1.148	1.035	1.156	1.216	1.465
Midwest	1.000	1.197	0.992	1.165	1.128	1.352
South	1.000	1.204	0.996	1.197	1.105	1.350
West	1.000	1.222	0.994	1.200	1.113	1.355
Age<18	1.000	1.154	1.084	1.216	1.238	1.418
Age 18-64	1.000	1.196	0.957	1.147	1.076	1.299
Age 65+	1.000	1.308	0.984	1.288	1.074	1.443
Urban	1.000	1.203	1.001	1.187	1.140	1.377
Rural	1.000	1.186	0.983	1.182	1.072	1.294
Less than High School	1.000	1.198	1.016	1.195	1.148	1.403
High School Graduate	1.000	1.187	0.999	1.168	1.127	1.346
Some College	1.000	1.180	0.995	1.166	1.109	1.337
BA or More	1.000	1.313	0.969	1.261	1.056	1.358
Student	1.000	1.181	0.951	1.108	1.078	1.224
Non-Student	1.000	1.203	1.001	1.189	1.128	1.368
Sample Size				145,000		
Population (mil.)				320.3		

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Multipliers correspond to fractions by which poverty thresholds must be multiplied to keep the share of individuals with incomes below the absolute poverty line constant at the survey pre-tax money income baseline. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A15. Percent of Individuals with Incomes Below Relative Thresholds by Demographic Subgroup

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./IK Transfers		Threshold as % of Median
	Survey	CID	Survey	CID	Survey	CID	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All	11.42	9.71	8.35	7.06	6.31	4.49	29.84
Elderly	10.03	9.73	9.09	8.47	7.44	5.90	33.97
Single Parents	39.76	38.54	36.46	34.47	31.15	29.52	77.25
Multiple Parents	10.34	8.33	6.43	5.04	4.40	2.99	31.96
Single Individual	19.13	17.22	15.32	15.28	13.96	11.58	33.14
Multiple Individuals	5.00	3.25	4.26	2.84	3.54	2.08	20.48
Hispanic	18.64	16.73	13.61	12.70	10.17	8.59	45.43
White (non-Hisp.)	7.39	6.27	5.35	4.59	4.34	3.12	25.43
Black (non-Hisp.)	21.06	18.23	16.99	14.26	11.76	8.41	43.11
Asian (non-Hisp.)	9.67	9.18	6.67	6.24	5.87	5.15	24.02
Other (non-Hisp.)	25.41	22.62	21.01	19.75	18.18	15.23	44.97
Immigrant	15.38	14.06	11.34	10.88	9.38	8.14	36.93
Non-Immigrant	10.79	9.14	7.88	6.58	5.86	4.03	28.95
Northeast	9.76	9.43	6.46	6.75	4.27	3.49	26.14
Midwest	9.47	7.78	6.72	5.68	4.91	3.23	28.40
South	13.20	10.92	9.94	8.14	7.86	5.53	32.64
West	11.47	10.18	8.49	7.29	6.42	4.87	29.66
Age<18	16.32	14.13	11.07	9.03	7.33	5.13	37.02
Age 18-64	9.99	8.15	7.56	6.12	5.92	4.13	26.83
Age 65+	9.77	9.96	8.73	8.82	7.03	5.95	33.97
Urban	11.77	10.02	8.56	7.29	6.36	4.54	29.71
Rural	10.00	8.52	7.53	6.17	6.16	4.29	30.42
Less than High School	29.22	28.68	25.61	25.34	20.54	20.22	65.42
High School Graduate	15.32	14.16	11.79	10.69	8.88	7.15	39.92
Some College	9.88	8.32	7.34	6.32	5.63	4.11	31.40
BA or More	3.99	2.95	3.01	2.18	2.76	1.79	18.56
Student	27.47	24.09	25.34	22.19	22.95	22.05	49.93
Non-Student	10.92	9.24	7.83	6.61	5.83	4.04	29.48
Sample Size				145,000			
Population (mil.)				320.3			

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Poverty rates correspond to the percent of individuals with incomes below some fraction of median income, where the fractions (in Column 7) are defined such that the starting relative poverty rates correspond to the share of individuals with survey pre-tax money income below the absolute poverty line. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A16. Characteristics of Individuals Remaining in Poverty by All Income Concepts

Population Subgroup	Pre-Tax Cash		Post-Tax/Expenses		Post-Tax/Exp./In-Kind Transfers		
	Survey	CID	Survey	CID	Survey	CID	CID (fixed)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elderly	0.16	0.12	0.16	0.12	0.17	0.11	0.13
Single Parents	0.20	0.23	0.17	0.20	0.15	0.17	0.16
Multiple Parents	0.38	0.38	0.35	0.34	0.33	0.31	0.38
Single Individual	0.16	0.19	0.18	0.22	0.21	0.27	0.20
Multiple Individuals	0.11	0.09	0.13	0.12	0.15	0.14	0.13
Hispanic	0.30	0.29	0.29	0.28	0.28	0.28	0.30
White (non-Hisp.)	0.40	0.40	0.41	0.42	0.44	0.45	0.46
Black (non-Hisp.)	0.23	0.23	0.22	0.22	0.20	0.17	0.17
Asian (non-Hisp.)	0.06	0.06	0.05	0.06	0.06	0.07	0.07
Immigrant	0.18	0.18	0.19	0.19	0.20	0.21	0.20
Northeast	0.14	0.16	0.13	0.15	0.11	0.12	0.12
Midwest	0.18	0.18	0.18	0.18	0.17	0.18	0.18
South	0.44	0.43	0.44	0.43	0.47	0.46	0.45
West	0.24	0.23	0.25	0.23	0.25	0.24	0.24
Age<18	0.33	0.35	0.29	0.30	0.26	0.26	0.30
Age 18-64	0.54	0.54	0.57	0.59	0.60	0.64	0.59
Age 65+	0.13	0.10	0.14	0.11	0.14	0.09	0.11
Rural	0.17	0.17	0.18	0.17	0.20	0.19	0.20
Less than High School	0.28	0.28	0.27	0.27	0.25	0.24	0.26
High School Graduate	0.36	0.36	0.36	0.36	0.36	0.35	0.36
Some College	0.25	0.25	0.25	0.26	0.25	0.27	0.26
BA or More	0.12	0.10	0.12	0.11	0.14	0.14	0.12
Student	0.07	0.08	0.07	0.09	0.09	0.12	0.08
Percent of Population	11.42	8.49	11.44	8.22	8.99	5.29	11.42

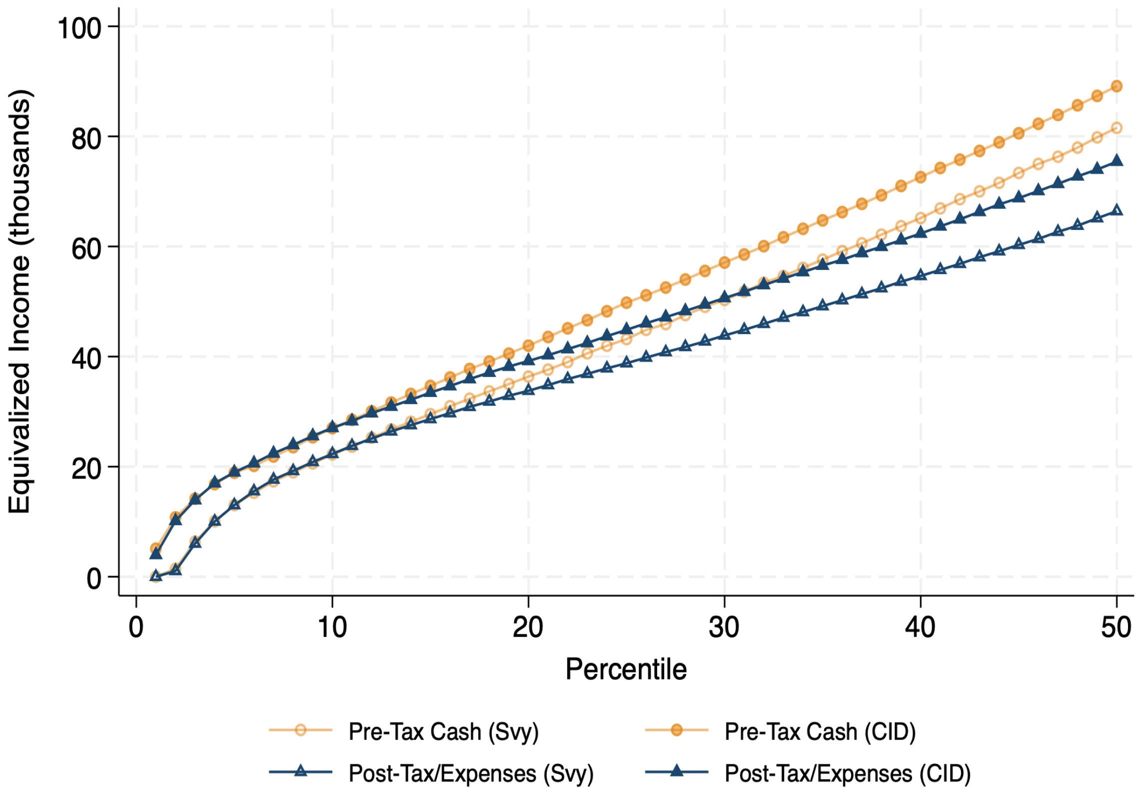
Source: 2017 CPS ASEC linked to various administrative records
Notes: This table shows the characteristics of individuals remaining in absolute poverty for a given income concept. Each row corresponds to the share of poor individuals with a given characteristic. Columns 1 and 2 show the characteristics of those in poverty using survey-reported and CID pre-tax money income, respectively. Columns 3 and 4 show the characteristics of those in poverty using survey-reported and CID money income after taxes and expenses, respectively. Columns 5 and 6 show the characteristics of those in poverty using survey-reported and CID income after incorporating taxes, expenses, and non-medical in-kind transfers, respectively. Column 7 shows the characteristics of those in poverty using the same income concept in Column 6 but scaling thresholds such that 11.42% of individuals remain in poverty (which is the baseline share using the survey income concept in Column 1). The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Table A17. Sample Sizes and Population Counts by Demographic Subgroup

Population Subgroup	Sample Size (1)	Population (Weighted) (2)
All	145,000	320,300,000
Elderly	23,000	57,140,000
Single Parents	9,100	17,970,000
Multiple Parents	72,500	134,400,000
Single Individual	10,000	30,370,000
Multiple Individuals	30,000	80,370,000
Hispanic	28,500	58,950,000
White (non-Hisp.)	88,500	198,700,000
Black (non-Hisp.)	16,500	39,210,000
Asian (non-Hisp.)	9,800	20,950,000
Other (non-Hisp.)	1,800	2,435,000
Immigrant	18,500	43,890,000
Non-Immigrant	127,000	276,400,000
Northeast	21,500	52,920,000
Midwest	27,500	67,850,000
South	54,000	121,600,000
West	42,500	77,900,000
Age<18	40,000	74,120,000
Age 18-64	85,500	196,800,000
Age 65+	20,000	49,370,000
Urban	111,000	256,500,000
Rural	34,000	63,770,000
Less than High School	16,000	34,450,000
High School Graduate	38,000	85,590,000
Some College	42,500	91,880,000
BA or More	49,000	108,400,000
Student	3,800	9,608,000
Non-Student	141,000	310,700,000

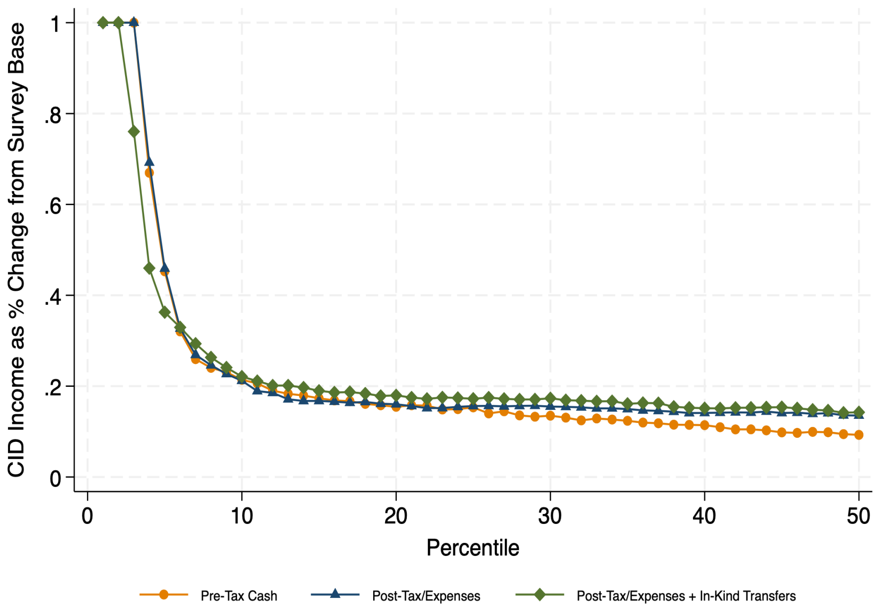
Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Sample sizes in Column 1 consist of the unweighted number of individuals that fall into each demographic group, while population totals in Column 2 consist of the weighted number of individuals that fall into each demographic group. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A1. Bottom Fifty Percentiles of the Income Distribution (Post-Tax/Expenses)

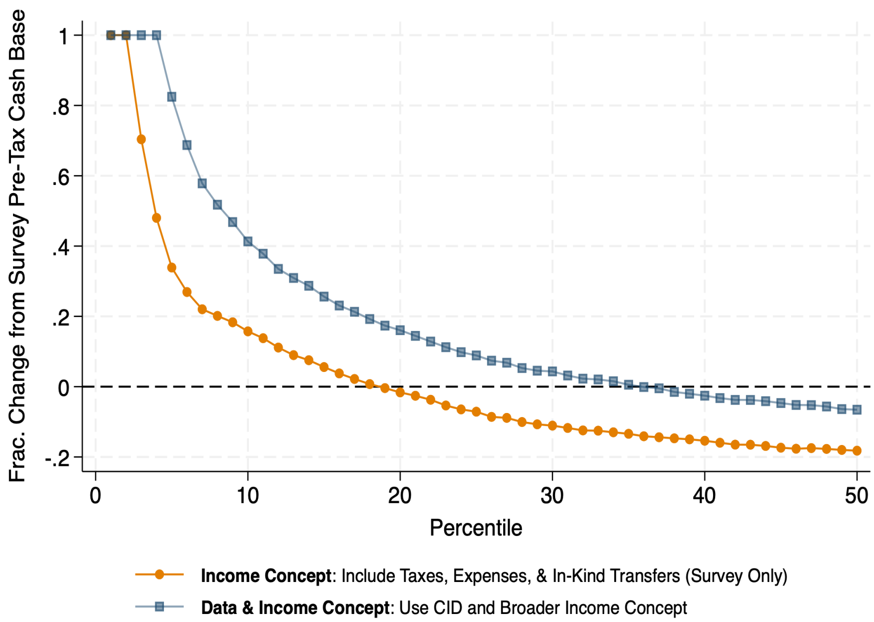


Source: 2017 CPS ASEC linked to various administrative records
Notes: Percentiles are calculated over individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Incomes are equivalized using the SPM equivalence scale to be representative of a family with 2 adults and 2 children. Percentiles for the income concept in Panel B (CID post-tax/expenses plus in-kind transfers, including admin SNAP) are calculated using proportional adjustments for admin SNAP based on the 23 states for which we have SNAP data in 2016. All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A2. Fractional Change in Incomes Due to Adjustments by Percentile



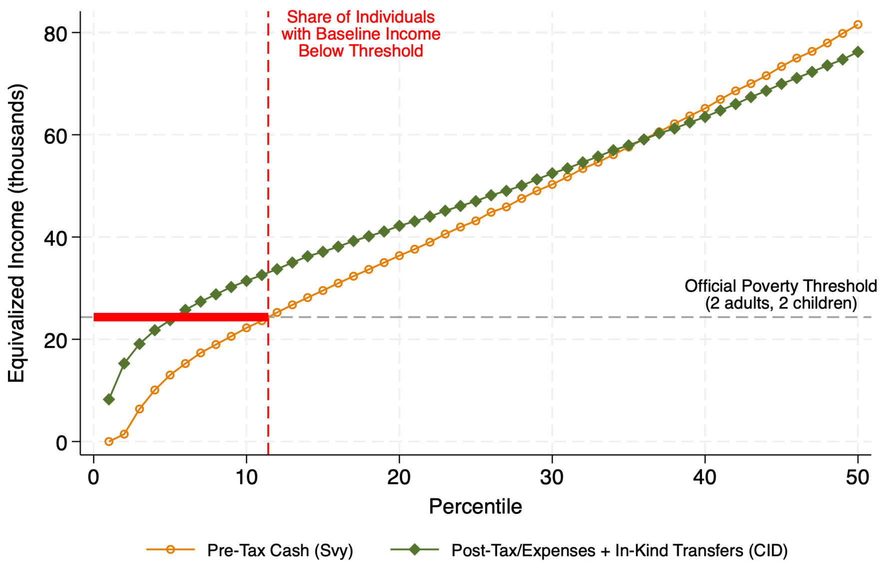
(a) Differences Between Survey and CID (by Income Concept)



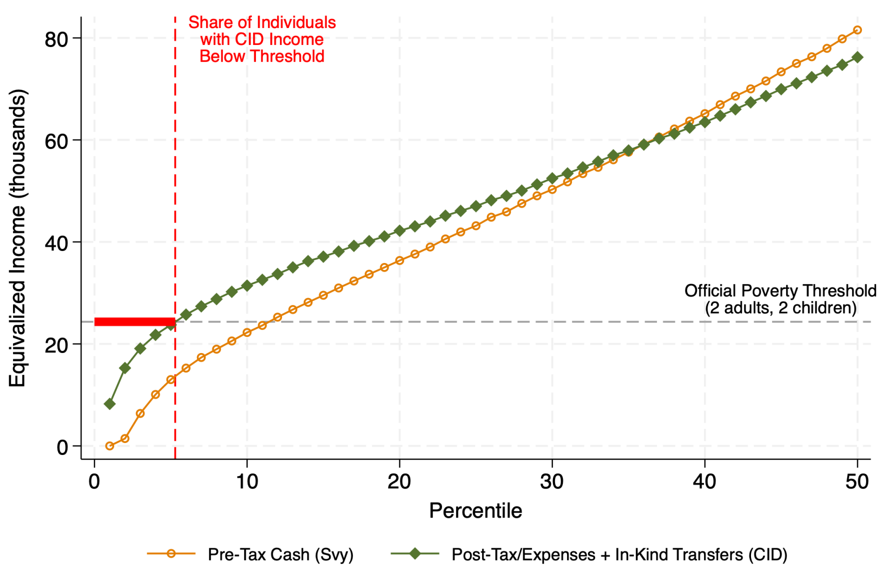
(b) Differences After Income Concept Changes and Better Data

Source: 2017 CPS ASEC linked to various administrative records
Notes: Panel (a) shows the fractional change in income between CID and survey-only sources for each income concept. Panel (b) shows the fractional change in income due to income concept changes and the combination of income concept changes and better data, relative to a survey pre-tax money income baseline. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A3. Share of Individuals with Incomes Below Absolute Thresholds



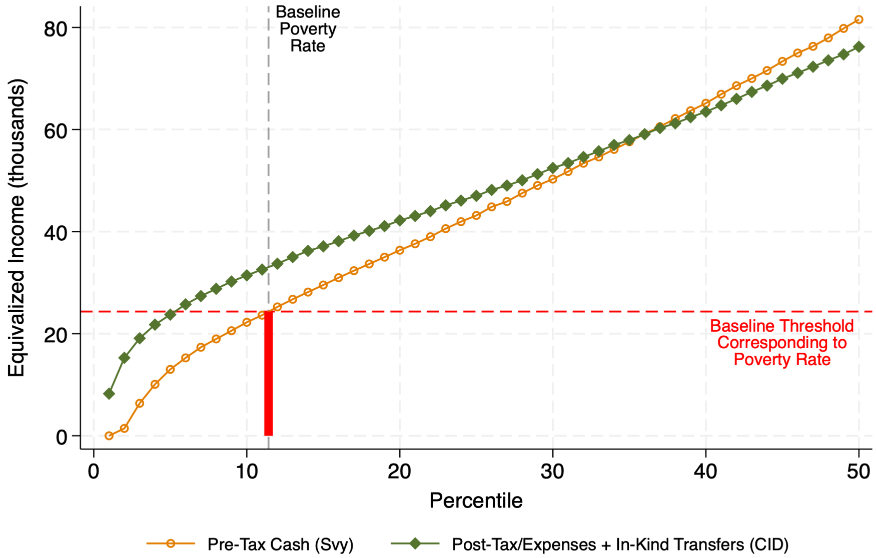
(a) Survey Pre-Tax Money Income



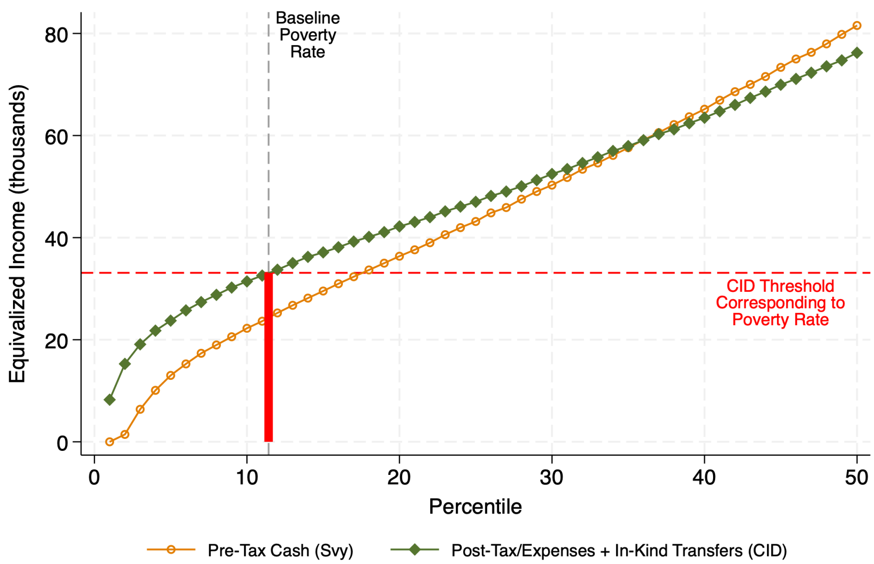
(b) CID Income After Taxes, Expenses, and In-Kind Transfers

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Figures show the share of individuals with equivalized incomes – survey pre-tax money income in Panel (a) and CID income after taxes, expenses, and in-kind transfers in Panel (b) – below the official poverty threshold for a 2-adult 2-child family, treating distributions as inverse CDFs. All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A4. Dollar Thresholds Corresponding to Baseline Poverty Rates



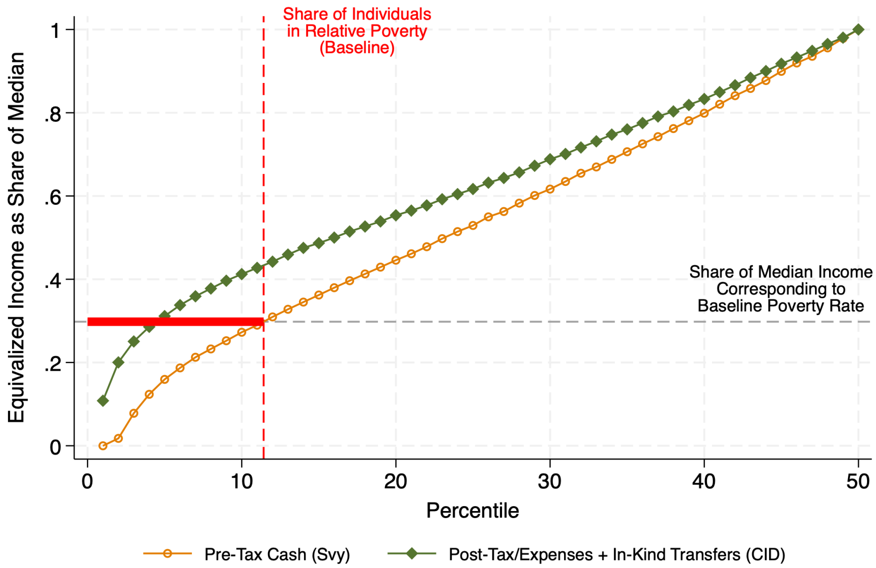
(a) Survey Pre-Tax Money Income



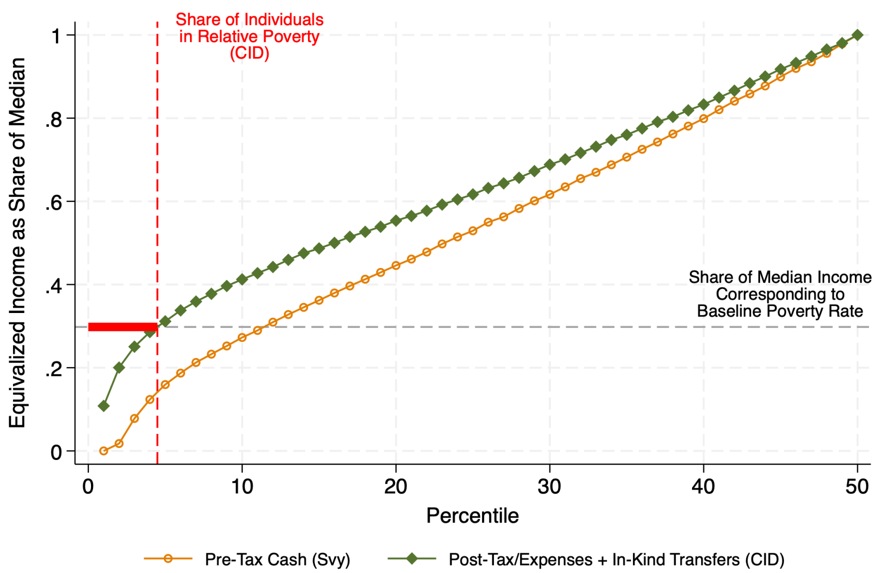
(b) CID Income After Taxes, Expenses, and In-Kind Transfers

Source: 2017 CPS ASEC linked to various administrative records
Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Figures show the dollar value of the equivalized income threshold for which 11.42% of individuals have lower survey pre-tax money income in Panel (a) and CID income after taxes, expenses, and in-kind transfers in Panel (b). All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau’s Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A5. Share of Individuals with Incomes Below Relative Thresholds



(a) Survey Pre-Tax Money Income

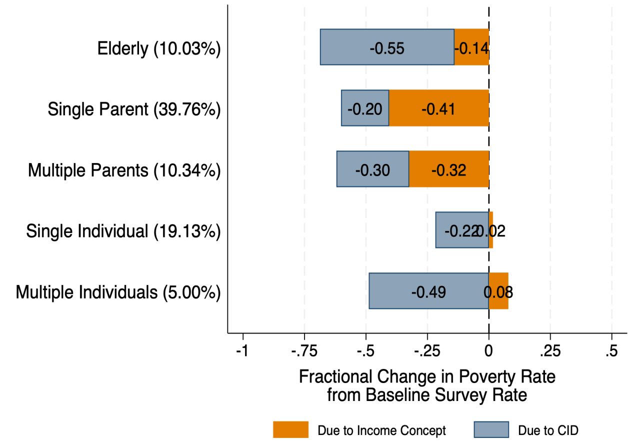


(b) CID Income After Taxes, Expenses, and In-Kind Transfers

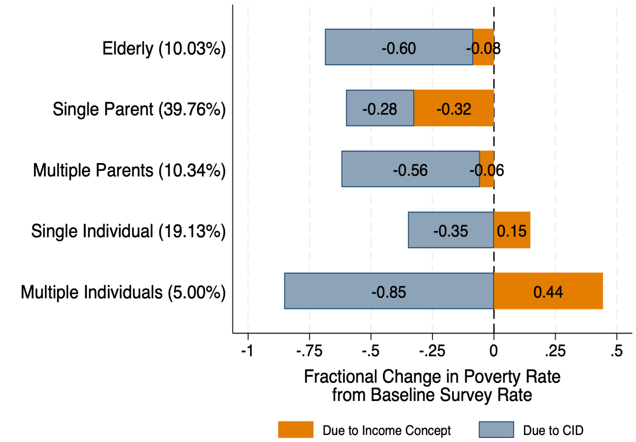
Source: 2017 CPS ASEC linked to various administrative records

Notes: Sample consists of all individuals in the linked CPS sample, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weights. Figures show the share of individuals with equivalized incomes – survey pre-tax money income in Panel (a) and CID income after taxes, expenses, and in-kind transfers in Panel (b) – below 29.84% of median income, treating distributions as inverse CDFs. All percentiles are interpolated using at least 11 unique, non-overlapping observations. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

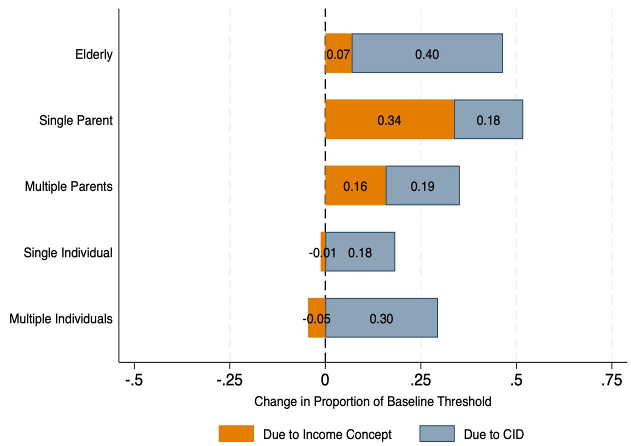
Figure A6. Role of Better Data vs. Income Concept Changes for Prototypical Poverty Analyses (by Family Type)



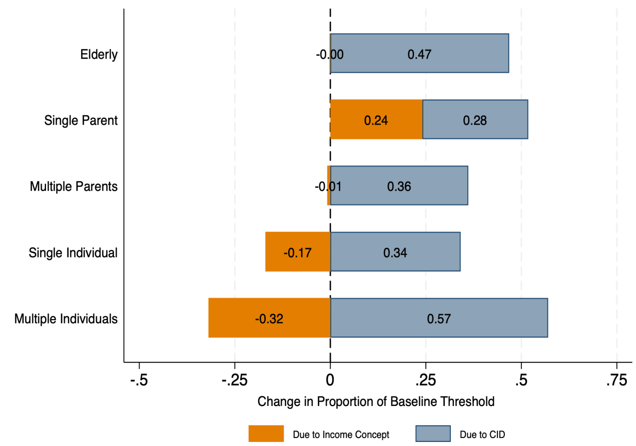
(a) Absolute Poverty: Change Income Concept First



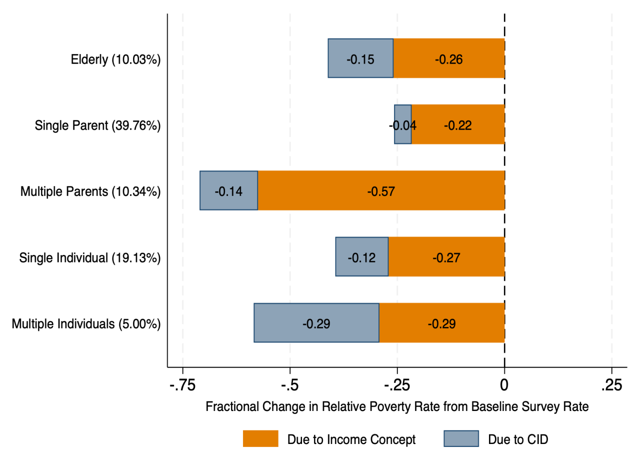
(b) Absolute Poverty: Step-by-Step Adjustments



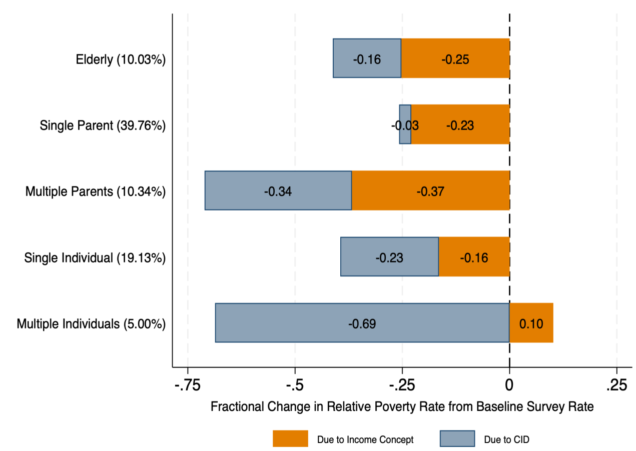
(c) Poverty Thresholds: Change Income Concept First



(d) Poverty Thresholds: Step-by-Step Adjustments



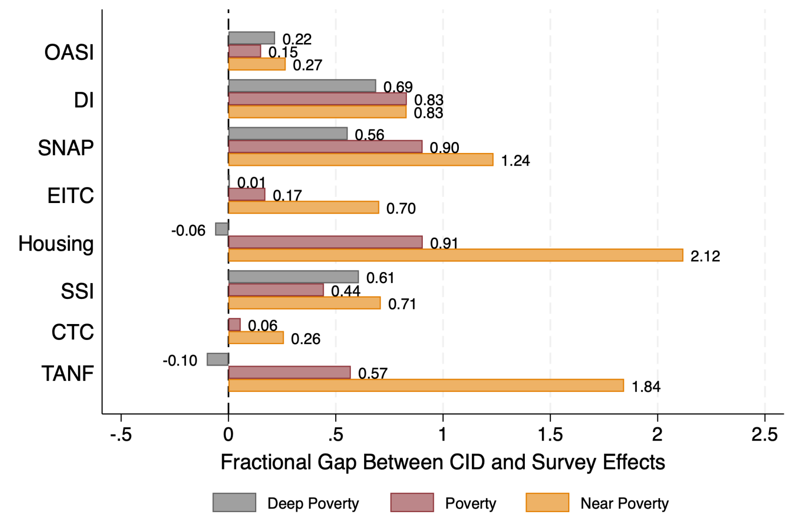
(e) Relative Poverty: Change Income Concept First



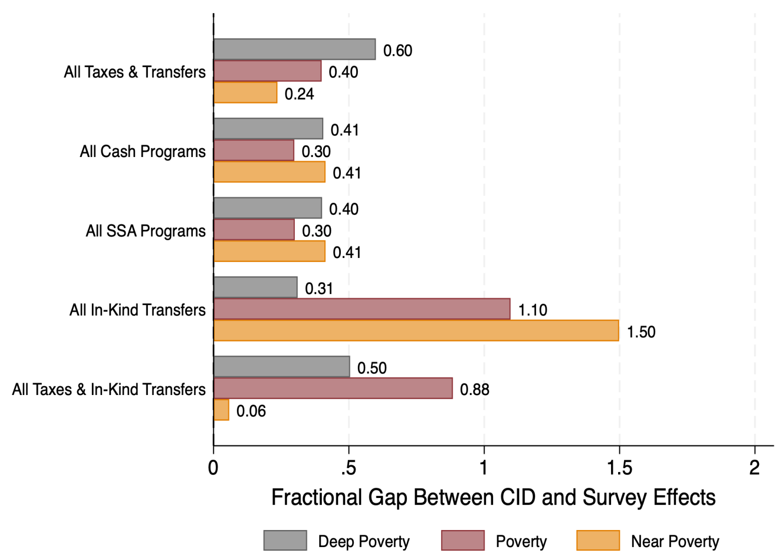
(f) Relative Poverty: Step-by-Step Adjustments

Source: 2017 CPS ASEC linked to various administrative records
Notes: This figure shows the fractional decline in absolute poverty rates (Panels A and B), fractional increase in poverty thresholds needed to hold poverty rates fixed at baseline levels (Panels C and D), and fractional decline in relative poverty rates (Panels E and F) by family type after bringing in conceptual changes to income first and after step-by-step adjustments. The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.

Figure A7. Differences Between Survey and CID Estimates of Poverty Reduction Effects



(a) Individual Programs



(b) Combinations of Programs

Source: 2017 CPS ASEC linked to various administrative records
Notes: These figures show the fractional gap between CID and survey estimates of poverty reduction effects (i.e., how much larger the CID effects are relative to the survey effects). Estimates are calculated using the 23 states for which we have admin SNAP data (except TANF, for which effects are calculated using 18 states with both admin SNAP and TANF data). The sample consists of individuals in the linked CPS data, dropping non-PIKed and whole imputed SPM units and adjusting survey weights using inverse probability weighting. Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-016.