The Use and Misuse of Income Data and the Rarity of Extreme Poverty in the United States*

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Abstract

Recent research suggests that rates of extreme poverty, defined as living on either less than $2 or $4 per-person per-day, are high and rising in the United States. We re-examine the rate of extreme poverty using the rich data in the Survey of Income and Program Participation (SIPP), generally thought to have the most accurate survey income data in the U.S. In addition to income, the SIPP provides information on hours worked, assets, hardships, and other household characteristics. We link these data to IRS Form 1040, W-2 and 1099-R information returns, and program data on SNAP, public and subsidized housing benefits, SSI, and OASDI. We find that accounting for in-kind transfers, errors in earnings reports, errors in transfer reports, and substantial assets means that less than 10% of households with survey-reported money incomes below $2/person/day are actually extreme poor. Of the households remaining in extreme poverty, 90% are single individuals. Several of the largest misclassified groups appear to be at least middle class based on material hardship, housing characteristics, tax data, and other variables. Given the low recent level of extreme poverty, it cannot have risen substantially due to welfare reform as many have argued.

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I. Introduction

There are reasons to be simultaneously concerned and skeptical about recent reports of high and rising rates of extreme poverty in the United States. Several distinguished scholars have argued that millions of Americans – many of them children – live on less than a few dollars per day. Other researchers have reported high rates of "disconnected" people, defined as those with neither earnings nor government benefits. Relying predominantly on survey reports of income, both groups claim that these problems have been rising sharply over time. On the other hand, researchers have long contended that survey reports in the tails of the income distribution have a disproportionate share of errors. Some of these scholars have pointed to evidence of increased under-reporting of income in household surveys or conflicting evidence from consumption data. This paper addresses these questions by bringing to bear a combination of previously under-utilized survey data and new administrative data. These data allow us to re-examine rates of extreme poverty and shed light on other questions, including the targeting of in-kind transfers and the measurement of poverty.

Focusing on 2011 data from the Survey of Income and Program Participation (SIPP), we show that more than 90% of households with survey-reported cash income below $2/person/day are misclassified. Our methodology first implements a series of corrections within the survey, reclassifying households as not extreme poor that receive sufficiently high amounts of in-kind transfers (SNAP, WIC, and housing assistance), earn above $2/person/day in (lower-bound) minimum wage earnings based on reported hours worked, or possess substantial assets. To further examine households not captured by the survey corrections, we take advantage of linked administrative tax data on earnings, asset income, and retirement distributions and program data on OASDI, SSI, SNAP, housing assistance, and the EITC. In the end, our upper bound estimate of the extreme poverty rate is 0.24%, with 90% of the remaining extreme poor households made up of single individuals. Replicating the analysis with the 2012 Current Population Survey (CPS), we estimate that only 0.12% of households are extreme poor over the course of the 2011 calendar year. These estimates are remarkably similar to rates that researchers have calculated using consumption data, suggesting that improved measures of income can reconcile past inconsistencies between income and consumption measures of poverty.

One of this paper's key methodological advances is the use of multiple sources of administrative and survey data to validate the survey corrections. Doing so is pivotal, given that the survey corrections account for 79% of the total decrease in extreme poverty that we calculate. For the groups lifted out due to reported hours worked and substantial assets, we find that 72-98% of these households have incomes from the administrative data above the extreme poverty threshold and 53-76% have incomes above the poverty line. Using rich information from the SIPP's topical modules, we find that these groups have well-being levels (based on measures of material hardship, appliance ownership, and home quality) that are similar to the U.S. average. They are also comparable to the average household on a host of other survey-reported dimensions, such as years of education, health insurance coverage (especially private coverage), and occupation types. Accordingly, the preponderance of evidence suggests that the households lifted out by reported hours worked and substantial assets have survey incomes that are likely to be gross errors. In contrast, the households lifted out by in-kind transfers appear to be significantly worse off than the official poor on multiple dimensions of well-being, implying that these programs are well targeted to the needy. These results are consistent with past findings that those excluded from the poverty rolls under the Census Bureau's Supplemental Poverty Measure (which incorporates in-kind transfers into income and raises some recipients above the poverty line) appear worse off, on average, than the official income poor.

It is important to keep in mind that our best estimate of the extreme poverty rate is not necessarily a final estimate for the population. We miss administrative income data for a number of income sources that are potentially under-reported in the survey, including unemployment insurance, workers' compensation, and veterans' benefits. Thus, our estimates of extreme poverty are overstated. At the same time, the SIPP misses homeless individuals in its survey frame, meaning our estimates of extreme poverty are understated if substantial numbers of the homeless are extreme poor. If anything, these caveats further highlight the imperfect ability of survey data to identify the extreme poor.

More generally, this paper is one of the first from an unprecedented new project that assembles and links survey and administrative data on income, program receipt, and closely related information (Medalia, Meyer, O'Hara, and Wu 2018). The project's goals include 1) improving household surveys and tax administration and 2) better understanding poverty, inequality, and the effects of government transfers. We initially focus on extreme poverty in this paper because the results are so stark and demonstrate the capacity of the linked data to change our understanding of poverty. In future papers, we plan on applying these linked data to re-examine patterns in deep and traditional poverty, as well as other portions of the income distribution. There is great value in linking survey and administrative data, even relative to methods that attempt to formally adjust for misreporting within the survey. A number of studies have found that sophisticated adjustments like TRIM still produce biased poverty estimates, likely because the adjustments themselves are based upon misreported data.[1]

The remainder of the paper is structured as follows.[2] Section II reviews the literature on extreme poverty and discusses why the rates using survey-reported cash income are so high. Section III describes the survey and administrative data used and the process used to link them. Section IV discusses the methodology used to correct for errors in income reports, and Section V describes the results from the SIPP. Section VI replicates the results for the CPS and compares them to the SIPP, and Section VII presents the results of robustness checks and additional caveats. Section VIII concludes.

II. Literature

Past Claims of Extreme Poverty and Conflicting Evidence

In a series of papers and a best-selling book, Kathryn Edin and Luke Shaefer document the prevalence of extreme poverty, which they define as having cash income less than $2/person/day. Using Wave 9 of the 2008 SIPP Panel, Shaefer and Edin (2013) find that 4.3% of all non-elderly households with children (constituting 1.65 million households and 3.55 million children) lived in extreme poverty in a given month in mid-2011. Using the 2012 CPS ASEC, Shaefer and Edin (2017) contend that 1.3 million children lived under $2/day based on annual cash income during the 2011 calendar year.[3] Combining quantitative analyses with ethnographic evidence on the day-to-day lives of the extreme poor, Edin and Shaefer (2015) further shed light on the deprivation faced by such households. Concomitantly, Deaton (2018) uses survey data from the CPS to assert that 5.3 million individuals in the United States lived under $4/day during the 2015 calendar year. These striking

[1] See, for example, Fox, Heggeness, Pacas, and Stevens (2017) and Mittag (2017).
[2] See Table 1 for a list of abbreviations used throughout the paper.
[3] Even though Shaefer and Edin examine reference year 2011 in both of their papers, the counts of children in extreme poverty differ rather dramatically. We think this difference is due to a few reasons. First, the higher number using the SIPP is based only on the fourth reference month of a wave (rather than the monthly average in a wave). Second, as we discuss in Section 6, the SIPP appears to have non-trivial numbers of households with zero earnings but positive reports of hours worked for pay – an inconsistency that does not appear in the CPS. Finally, the lower CPS number relies on the Urban Institute's TRIM micro-simulation model to try to adjust for under-reporting of cash transfers in the survey.

numbers have received a great deal of attention in the policymaking process and the press,[4] and they were recently featured in a prominent United Nations report on the state of poverty in the United States (United Nations 2018).

A related literature has arisen around the plight of "disconnected" individuals and families, who are defined as having little to no earnings and government benefits (usually cash welfare). Most of these studies focus on single mothers. Turner, Danziger, and Seefeldt (2006) use survey data from the Women's Employment Study and find that 9% of single mothers who received cash welfare in February 1997 became disconnected for at least a quarter of the following 79 months (following welfare reform in 1996). Using data from the SIPP and CPS, Blank and Kovak (2009) find that more than 20% of single mothers who live below twice the official poverty line in the mid-2000s have no annual earnings or welfare receipt. These high rates of disconnected single mothers are echoed in Loprest (2011) and Loprest and Nichols (2011), who also utilize the SIPP.

Importantly, a number of these studies argue that rates of extreme poverty and disconnectedness have risen greatly over time in response to welfare reform. Shaefer and Edin (2013) calculate that the number of households with children in extreme poverty grew by 159% between 1996 and 2011. This rate of increase snowballs to 748% between 1995 and 2012 after using TRIM to adjust for under-reporting in the CPS, with Shaefer and Edin (2017) attributing this growth entirely to cuts in cash welfare. Blank and Kovak (2009) also find that the rate of disconnected single mothers nearly doubled between 1995 and 2005 using the CPS, and Loprest and Nichols (2011) calculate a similar increase in the share of disconnected single mothers between 1996 and the 2004-2008 period.

At the same time, a significant literature provides evidence at odds with the results in Shaefer and Edin (2013, 2017) and related papers on disconnectedness. Rather than relying on survey-reported cash income to measure extreme and deep poverty, many of these studies focus on measures of consumption or hardship. Other studies improve the measurement of income by including in-kind transfers and attempting to adjust for survey under-reporting. In an early paper, Mayer and Jencks (1989) find that 43% of a sample of Chicagoans surveyed in the mid-1980s with incomes below the official poverty line reported expenditures on food, housing, and medical care that exceeded their incomes. For disadvantaged single mothers at the 10th percentile in the 1990s,

[4] For example, see https://www.washingtonpost.com/news/wonk/wp/2018/06/25/trump-team-rebukes-u-n-saying-it-overestimates-extreme-poverty-in-america-by-18-million-people/?utm_term=.1f7ba77d349a.

Meyer and Sullivan (2003) also find that expenditures exceeded income by 47% and 24% in the Consumer Expenditure (CE) and Panel Study of Income Dynamics (PSID) surveys, respectively. In subsequent papers, Meyer and Sullivan (2004, 2008, 2012) find that consumption levels at low percentiles rose in the period following welfare reform and that deep consumption poverty has fallen sharply over time.

Additional papers in recent years have used the CE Survey to calculate staggeringly low – indeed, nonexistent – rates of consumption-based extreme and deep poverty (i.e., spending less than \$2/person/day). Chandy and Smith (2014) find that only 0.07% of the U.S. population spent less than \$2/person/day in the fourth quarter of 2011. Hall and Rector (2018) examine all households interviewed in the CE survey since 1980 and similarly find that 0.08% of the U.S. population spent less than \$4/person/day. They also calculate an expenditure-based deep poverty rate of 0.5% in 2017, which is considerably lower than the official income-based deep poverty rate of more than 6% in 2017. Much like the results in Meyer and Sullivan (2012), Hall and Rector find that deep consumption poverty fell sharply from a rate of roughly 2% in the mid-1980s, with this fall being especially precipitous for single parents after welfare reform.

Finally, Winship (2016) re-examines rates of extreme poverty by applying a number of adjustments to reported cash income in the CPS, which include incorporating in-kind transfers (non-medical and medical benefits are separated), taxes and tax credits, and a less biased price index (the PCE deflator) than the CPI-U. Winship also uses TRIM3 to correct for under-reporting of various transfers and divides household income by an equivalence scale to better account for resource sharing. If anything, Winship finds that the adjusted rates of extreme poverty have fallen since welfare reform to approximately 0.1% among all children and closer to 0.01% among children of single mothers in 2012.

Why are Extreme Poverty Rates from Survey-Reported Cash Income So High?

There are several major reasons why the literature has found such high rates of extreme poverty when relying on survey reports of pre-tax cash income. First, these calculations ignore in-kind transfers and tax credits. The majority of means-tested transfer dollars are in-kind, and it is generally accepted that non-medical in-kind benefits should be counted as income (see, for example, Ellwood and Summers, 1985; Citro and Michael, 1995; Blank, 2008). In particular, SNAP and WIC benefits can be plausibly treated as cash payments, since benefit amounts usually fall below the pre-receipt food expenditures of recipient families (Ben-Shalom et al. 2012). The gross rents that are used to calculate housing assistance amounts have also been found to be close to market rents (Olsen 2018). Several studies have even argued that the value of transfer programs may exceed cash earnings, as transfers play an important role in insuring earnings shocks (Blundell, Pistaferri, and Preston 2003; Blundell 2014; Deshpande 2016).

Given that the nature of the safety net in the U.S. has changed dramatically over time, it is important to account for in-kind transfers and tax credits when comparing outcomes over time. While AFDC/TANF payments fell by two-thirds between 1996 and 2011, SNAP payments more than doubled and EITC benefits increased by approximately half during the same time period, both transferring more new dollars than were cut from TANF. Other in-kind transfers like public and subsidized housing followed a similar upward spending trajectory over time. Consequently, focusing on changes in poverty rates based solely on pre-tax cash income becomes anachronistic. These concerns, in large part, motivated the U.S. Census Bureau to start calculating the Supplemental Poverty Measure (SPM) in 2011, which takes into account many of the non-cash programs and tax credits not included in the official poverty measure. To their credit, Shaefer and Edin (2013) find that SNAP, tax credits, and housing subsidies together cut the pre-tax cash extreme poverty rate for households with children by 63% in 2011. But this has not stopped researchers and policymakers from highlighting estimates that exclude these – and other – important government programs.

Another reason for high extreme poverty rates in the literature is that studies almost universally rely on survey income with substantial errors, despite many studies demonstrating significant holes in the income data that arise from survey under-reporting. For example, Meyer and Mittag (2015) find that 63% and 44% of Public Assistance recipients in New York do not report receipt in the CPS and SIPP, respectively, and 43% and 19% of SNAP recipients do not report receipt in the CPS and SIPP. Bee and Mitchell (2017) find that 46% of pension income recipients do not report receipt in the CPS.

While the CPS has generally been found to suffer from more pronounced under-reporting than the SIPP, the latter is not immune to errors. Meyer and Wu (2018) find that, among single parent families, the poverty reduction effects of SSI, OASDI, and Public Assistance from the SIPP are each less than 44% of what the administrative data produce. For all families, the SIPP yields effects on near poverty of SNAP and Public Assistance that are two-thirds and one-half, respectively, what the administrative data generate (Meyer and Wu 2018). These holes in the SIPP income data have also grown over time. Since 2000, there has been a 7 percentage point increase in the share of dollars missed by the SIPP for TANF, unemployment insurance, and workers' compensation (Meyer, Mok, and Sullivan 2015). The share of SIPP dollars that are imputed has also doubled since 1990, and errors in reporting amounts for SSI and OASDI rose sharply between the 1996 and 2008 SIPP panels (Gathright and Crabb 2014).

These errors in survey-reported income are likely most pronounced at the very bottom of the reported income distribution. Many studies have suspected or found errors in income reports at the tails of the distribution (Lillard, Smith, and Welch 1986; Blank and Schoeni 2003; Bollinger, Hirsch, Hokayem, and Ziliak 2018). Especially in the left tail, research has shown that reported expenditures are often a multiple of reported incomes. This pattern has been found not only in U.S. survey data (see Meyer and Sullivan 2004, 2008; Hall and Rector 2018), but in Canadian and British survey data as well. Brzozowski and Crossley (2011) use data from the Canadian Survey of Household Spending and the Family Expenditure Survey to show that total expenditures exceed disposable income by approximately a multiple of five in the bottom decile of the income distribution. Brewer, Etheridge, and O'Dea (2017) use data from the UK Living Costs and Food Survey and find that households in the bottom 1% of the income distribution (who live on less than £75/week) report a median expenditure level of £400/week, equivalent to the population median! The authors find that median expenditures are actually decreasing in income for households living on less than £110/week. They are best able to explain this puzzle by under-reporting of income rather than over-reporting of expenditures or consumption smoothing over time.

III. Data

This section describes the rich sources of survey and administrative data we use in this paper. The section also explains how we link these data and the advantages of the combined data over survey or administrative sources alone.

Survey Data

The survey data primarily come from the Survey of Income and Program Participation (SIPP).[5] Each panel of the SIPP lasts several years, and individuals and households are followed longitudinally within each panel. Specifically, each respondent is interviewed every four months as part of an

[5] In Section VII, we also describe results using the Current Population Survey (CPS).

interview "wave". In each wave, the SIPP collects information about the various types of income and government transfers received during the four months since the last interview wave. Nearly all of these income sources are reported at the month level. Accompanying these income data is rich information on demographics, assets and liabilities, material well-being, and health status (among other details). Many of these characteristics are available in the SIPP topical modules. These sets of questions on a specific subject differ across interview waves and are asked on top of the core questions.

To begin from a known starting point in the literature, we focus on Wave 9 of the 2008 SIPP Panel, whose reference months span January 2011 to July 2011.[6] This sample includes the observations used by Shaefer and Edin (2013). We also link topical modules from Wave 9 and other waves that concentrate on material hardships and housing quality (Wave 9), assets and liabilities (Waves 7 and 10), and disability status (Wave 6).[7] The SIPP sample is intended to be representative of the resident population in the United States, excluding individuals living in institutions and military barracks. Our unit of analysis is a household, of which there are 32,524 unweighted observations in Wave 9. While official poverty estimates use families as the units of analysis (though the U.S. Census Bureau typically calculates inequality at the household level), we use households for two main reasons. First, many of the questions in the SIPP (such as equity values for specific assets and material hardship) are asked at the household level. Second, individuals who are particularly destitute may rely on the additional resources of those outside their immediate families. If so, the household may be the more natural unit for analyzing the circumstances of the extreme poor. In practice, the distinction is not especially important as 92% of all households and 94% of reported extreme poor households have one family (see Appendix Table A.1).

Administrative Data

Our administrative records are derived from a number of sources, which we broadly classify into two categories: tax records from the Internal Revenue Service (IRS) and program participation records

[6] The interview wave spans 7 calendar months because of the staggered nature of the interviews. Respondents are divided into four groups, each of which has a different starting month in the wave. For example, one set of respondents in Wave 9 has reference months spanning January-April 2011. The other three sets of respondents each have reference months spanning February-May 2011, March-June 2011, and April-July 2011.

[7] The proximity of Wave 9 to Waves 6, 7, and 10 presents another advantage of focusing on Wave 9 in our analysis. This is because of both the comparability of the time periods and the smaller role of sample attrition that occurs from wave to wave. An additional benefit of examining Wave 9 is that it spans a single reference year, unlike many other waves. This makes linkage to tax records, which are at the annual level, more convenient.

from various state and federal agencies. Table 2 describes, for each income component, the source of the administrative data, the income unit, the disbursement frequency, and the states covered.

Tax Records

Earnings data covering wage and salary jobs and self-employment are available from the Detailed Earnings Record (DER) database of the Social Security Administration (SSA). The DER itself is derived from IRS W-2 Forms (for wage and salary jobs) and Schedule SE of IRS 1040 Forms (for self-employment). We also have data on various forms of asset income from IRS 1040 Forms, including taxable dividends, taxable and tax-exempt interest, and taxable income from rents and royalties. Data on retirement distributions come from IRS 1099-R Forms, which cover gross distributions from employer-sponsored plans (defined benefit and defined contribution plans) and IRA withdrawals. Finally, we calculate eligible EITC amounts based on filing status, earned income, and qualifying dependents in the prior year's IRS 1040 Forms.

As Table 2 indicates, the tax data contain universe records spanning the entire United States. These data are at the level of the tax unit, which consists of a single individual or married couple filing together with any eligible dependents. Note that the tax unit is conceptually distinct from a household, even if the two units are equivalent for most people. Furthermore, we convert annual data from the administrative tax records to monthly amounts by dividing the total amounts by twelve and distributing them evenly across all months in the calendar year.

Program Participation Records

Administrative records for Social Security (OASDI) come from the SSA's Payment History Update System (PHUS) file, with our preferred measure of total benefits including any amounts that are deducted for medical insurance premiums. Data on Supplemental Security Income (SSI) come from the SSA's Supplemental Security Record (SSR) file and include all federally-administered payments that are initially split into federal payments and federally-administered state payments. OASDI and SSI benefits are paid to individuals on a monthly basis. For housing assistance, our administrative data come from the Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification System (TRACS) files. These data cover almost all public and subsidized housing assistance programs under the jurisdiction of the Department of Housing and Urban Development (HUD). We calculate the benefit amount for a household as the difference between the gross rent and actual tenant payment.[8] Supplemental Nutrition Assistance Program (SNAP) records come directly from various state agencies, and we have records for eleven states in 2011. Housing assistance and SNAP benefits are disbursed to households on a monthly basis.

Combining Survey and Administrative Data

Data Linkage Process

We link the administrative data to the SIPP using Protected Identification Keys (PIKs) created by the U.S. Census Bureau's Person Identification Validation System (PVS) (Wagner and Layne 2014). Over 99% of most administrative records are associated with a PIK, and nearly 97% of households in Wave 9 of the SIPP contain at least one member associated with a PIK. To account for the likely small bias arising from non-random missing PIKs conditional on observed characteristics in the survey, we divide the household survey weights by the predicted probability that at least one member of the household has a PIK (see Wooldridge 2007). The appendix provides a fuller discussion of the inverse probability weighting adjustment. We link all benefit dollars from an administrative case to a survey household as long as there is a common individual between each unit. If an administrative case links to multiple survey households, we distribute benefit dollars from the administrative case proportionally to the number of individuals linked to each household.[9]

Alignment of Survey and Administrative Values

On their own, the administrative data incompletely cover certain income components in the survey data. In these cases, combining the survey and administrative data delivers the most comprehensive and accurate estimates of income amounts. First, our preferred measure of earnings is the maximum of the survey and administrative values. This choice is motivated by the administrative tax records only including tax reported amounts for these income sources, while the survey measure may include earnings from off-the-books and non-standard jobs that are not reported to the IRS (see Abraham, Haltiwanger, Sandusky, and Spletzer 2013, 2017). Even so, there are good reasons to believe that the non-tax earnings in the survey are themselves under-reported (Hurst, Li, and Pugsley

[8] Because the administrative data do not include gross rent amounts for public housing units (which constitute less than a quarter of all households in the administrative data), we impute the market rent for these units based on the average rent by five-digit zip code, household size, and year. If rent is still missing, we impute by three-digit zip code, household size, and year – and subsequently by five-digit zip code and year and by three-digit zip code and year if needed. We consider a household to be receiving subsidized housing for the twelve months since the most recent certification date as long as the period is prior to any termination date.

[9] For the EITC, we link individuals in survey households only to primary and secondary filers from the tax data.

2014; Hokayem, Bollinger, and Ziliak 2015). Similarly, we take the maximum of the survey and administrative values to construct our preferred measure of asset income. For SSI, we only have administrative data on federally-administered benefits, even though states can separately administer benefits themselves. Thus, our preferred measure of total SSI benefit amounts sums administrative values for federally-administered SSI and survey values for state-administered SSI. Finally, the administrative data for housing assistance cover only HUD-administered programs while the SIPP asks about any type of housing assistance, including those provided by the Department of Agriculture, states, and localities. We therefore treat as true respondents all survey respondents reporting receipt that do not appear in the administrative data. Section VI discusses how these adjustments may impact our analyses.

IV. Methods

To begin, we define our baseline measure of extreme poverty (based on survey reports of cash income) and explain the decisions involved in constructing this measure. We then describe how we can improve on this reported measure *within the survey*. These corrections involve incorporating non-medical in-kind transfers, undertaking conservative corrections for errors in reported earnings, and accounting for substantial assets. Next, we illustrate how bringing in the administrative data further improves the measurement of extreme poverty beyond what is possible in the survey. Lastly, we validate each of the survey corrections by examining the administrative incomes and survey-reported material hardships, housing circumstances, and demographics of the groups removed from extreme poverty by the corrections. Through confirming that those characterized as not extreme poor are well-off according to other indicators, the resulting measure reflects multiple dimensions of material well-being.

Defining Extreme Poverty and Sample Construction

A number of different definitions of extreme poverty or "disconnectedness" have been used in the literature. As discussed in Section II, one of the written about standards considers a household to be in extreme poverty if the household's income is less than or equal to $2 per-person, per-day. Various papers use slightly different cutoffs or differ in what is included in income and the period over which income is measured, though most report results for multiple definitions.[10] We start from pre-tax money income, which includes earnings, asset and retirement income, cash transfers, and other money income that members of the household may receive.[11] Crucially, it ignores in-kind transfers such as SNAP and tax credits like the EITC that have grown in prominence over the last two decades. Subsequently, we show the degree to which this baseline measure of reported cash extreme poverty (hereafter referred to as "reported extreme poor") holds up against various corrections.

In this paper, we define extreme poverty at the *wave* level, though the results are very similar at the month level.[12] In particular, we consider a household to be in extreme poverty if its average monthly income over the reference months in a wave is less than $2/person/day. There are several reasons to analyze extreme poverty at the wave level. First, a wave provides a more comparable time period than a month to use when linking with annual tax records. Second, to keep our results comparable to measures in other surveys such as the CPS, we want to use a single retrospective interview rather than the multiple interviews needed to construct calendar quarters or years.

While previous analyses have focused on households with children (see Shaefer and Edin 2013, 2017), we study all households and investigate how the prevalence of extreme poverty differs across five mutually exclusive and exhaustive household types. This disaggregation is informative given that eligibility for transfer programs is often dependent on household composition (e.g., elderly status, having children). These household types include households headed by someone aged 65 or older (elderly) and four non-elderly household types: single parents, multiple parents, single individuals, and multiple adults without children.[13]

Corrections Using Survey and Administrative Data

Survey Data

Here, we describe the corrections made within the survey to improve upon the reported extreme poverty rate. We first incorporate the following in-kind transfers: SNAP, WIC (Special Supplemental Nutrition Program for Women, Infants, and Children), and housing assistance. We

[10] Deaton (2018) uses a $4 per-person, per-day cutoff. Blank and Kovak (2009), in their study of disconnected single mothers, set three alternative cutoffs of 1) no earnings or welfare receipt over an entire year, 2) an annual cutoff of $2000 per family in earnings or $1000 in cash welfare, or 3) Cutoff (2) plus annual SSI income of $1000. United Nations (2018) relies on Deaton.

[11] "Other money income" can include sources like child support, income assistance from charitable groups, money from friends or relatives, etc.

[12] See Appendix Table A.2 for the month-level results and Table 3 for the wave-level results.

[13] As we note in the appendix, there are some very rare cases where we classify individuals under 18 as adults – e.g., a 17-year-old single mother living on her own with her children.

follow the methodology in Shaefer and Edin (2013) to account for in-kind transfers. Specifically, we lift a household out of extreme poverty if 1) its total cash income plus survey-reported values of SNAP and WIC benefits exceeds $2/person/day or 2) it receives any form of housing assistance.[14]

We next calculate lower-bound earnings based on survey reports of hours worked under the assumption workers at least earn the federal minimum wage ($7.25/hour). As documented in Section VII, the vast majority of this group reports no earnings at all. Among those still in extreme poverty after incorporating in-kind transfers, we lift households out of extreme poverty if their minimum wage earnings exceed $2/person/day.[15] We first identify the households lifted out by lower-bound earnings using only reported wage and salary hours. Second, we identify households lifted out using lower-bound earnings for reported hours worked in self-employment jobs as well. One might worry that this algorithm applies less robustly to off-the-books and/or self-employment jobs where the federal minimum wage may not be a theoretical lower bound on hourly earnings. Nonetheless, we can verify using administrative income sources and various measures of survey-reported well-being that the households lifted out by these corrections are nearly all not extreme poor. The appendix provides a thorough discussion of how we calculate these lower-bound earnings, caveats associated with our methodology, and the occupations associated with households removed by these corrections.

Our last entirely survey-based correction accounts for households holding substantial assets. Among those still left in extreme poverty after incorporating in-kind transfers and lower-bound earnings, we consider households to not be in extreme poverty if their reported real estate equity exceeds $25,000, liquid assets exceed $5,000, or total assets exceed $50,000.[16] We include the restriction that households must have positive total assets to be lifted out by this correction. We

[14] The assumption behind including housing assistance in this way is that the monetary value of public or subsidized housing is worth at least $2/day per person. For this not to be true, the assistance amount for a two-person household would have to be less than $120/month, which seems implausible. As a robustness check, we impute average housing assistance amounts from the administrative data based on county, household size, and year (and county and year if still missing) and designate a household as being lifted out of extreme poverty if its total cash income + survey-reported SNAP and WIC benefits + imputed housing assistance amount is greater than $2/person/day. The results are identical.
[15] Alternatively, we could add these lower-bound earnings to survey-reported cash income plus in-kind transfers less reported earnings – and compare the resulting amount to $2/person/day. We choose to use our more conservative correction because the extreme poverty threshold is so low and, as is, very few hours are required to lift a household above the extreme poverty threshold. For example, a single person needs to work only 9 hours in a month to earn above $2/day. If we layer these calculated earnings on top of in-kind transfers, just a couple hours worked could potentially pull a household out of extreme poverty, and these very low reports of hours are likely to be errors themselves.
[16] Real estate equity includes home equity and equity in any other real estate, including mobile homes. Liquid assets include checking accounts, savings accounts, money market accounts, bonds, securities, mutual funds, debt or margin accounts, certificates of deposits, and stocks. Total assets include liquid assets, retirement accounts, real estate equity, vehicle equity, business equity, and the value of other financial investments (i.e., “equity in other assets”).

extract information on asset amounts from the topical modules corresponding to Waves 7 and 10 from the SIPP. While we acknowledge that assets are not technically part of cash or in-kind income, we believe that households with sizeable assets that can be drawn upon should not be considered to be in extreme poverty (see Ruggles 1990 for a discussion on this and other options such as spreading the asset stock over a small number of years).

Administrative Data

Given the under-reporting of many types of income such as government transfers and private pensions, we bring in administrative data to further refine the extreme poverty rate. Among those still in extreme poverty after all survey corrections, we consider households to not be in extreme poverty if their incomes from the administrative data exceed $2/person/day. The administrative data can help account for false negatives among recipients of transfer programs and gross errors in income reports, among other survey errors. We first incorporate only the administrative data on earnings, asset incomes, and retirement distributions. We hereafter refer to these income sources collectively as "tax income". We can calculate this share over all states, as we have administrative tax records for the universe of taxpayers in the U.S. Next, we incorporate income from the administrative data on five transfer programs (OASDI, SSI, housing assistance, SNAP, and the EITC). We hereafter refer to these income sources collectively as "transfer income".[17] Because we only have administrative SNAP records for 11 states, we calculate the extreme poverty rate after including all administrative data by multiplying the rate after including substantial assets (calculated over all states) by the share of households lifted out of extreme poverty by the administrative data (calculated over 11 states).

Validating the Survey Corrections

We recognize that our survey corrections may come with flaws. For example, some earnings (especially those that are off-the-books) are not subject to the minimum wage. Moreover, the survey reports of hours worked and assets may themselves be misreported. Consequently, we thoroughly validate the appropriateness of each survey correction using information from the administrative data and rich measures of well-being from the SIPP topical modules. First, for each subgroup of the

[17] Note that we designate the EITC as falling under "transfer" rather than "tax" data, even though EITC amounts are calculated from IRS 1040 tax returns.

reported extreme poor lifted out by a survey correction, we directly calculate the share of households with incomes above \$2/person/day based on the administrative data. To investigate the extent of gross errors, we also calculate the share of households in each subgroup with incomes above half the poverty line, the poverty line, and twice the poverty line based on the administrative data.

As additional checks on the validity of the survey corrections, we compare the groups lifted out of extreme poverty to the official poor and all households based on survey-reported measures of hardship and housing quality. For material hardships, we examine survey answers (yes/no) to nine separate questions on a range of topics, from whether a household was able to pay the full amount of rent to whether a household member needed to see a doctor but could not go. We also examine ownership of eight appliances, including air conditioners, color televisions, and in-unit washers. We further investigate whether a household faces any of seven home quality issues, including problems with pests, leaking roofs, and plumbing problems. The appendix provides a more detailed description of the specific hardship and material well-being variables used. Finally, we assess additional demographic and economic characteristics reported in the SIPP – such as student status, educational attainment, health insurance coverage, and asset ownership – to obtain an even better picture of each group lifted out of extreme poverty.

V. Results

Changes in Extreme Poverty After Corrections

All Households

Table 3 displays the number and share of households and individuals that are left in extreme poverty after incorporating each correction. The first column starts with survey-reported cash income and finds that 3% of all households report having less than \$2/person/day of cash income. However, nearly a third of these households are lifted out of extreme poverty by survey-reported in-kind transfers (Column 2), with the extreme poverty rate for households falling to 2.08%. Nearly 95% of the impact of in-kind transfers is attributable to SNAP (see Appendix Table A.3). Columns 3 and 4 correct for errors in reported earnings based on reported hours worked for pay. Accounting only for reported wage and salary hours decreases the extreme poverty rate for households to 1.86%. Further accounting for reported self-employment hours worked decreases the extreme poverty rate for households to 1.33%. All told, correcting for errors in reported earnings lifts an additional 36% of households out of extreme poverty. Accounting for substantial assets again reduces the extreme poverty rate by over a third, leaving us with 0.87% of households remaining in extreme poverty.

While improved use of the survey data eliminates most of extreme poverty, the administrative tax and program data provide additional information. Applying just the administrative tax data removes an additional 58% of those remaining in extreme poverty and cuts the extreme poverty rate to 0.36% (Column 6). After incorporating the administrative data on transfer programs, we find that the extreme poverty rate further decreases to 0.24% (Column 7). Of the households lifted out of extreme poverty by the combined data, nearly 50% have incomes above half the poverty line and 40% above the poverty line according to the administrative data. This finding suggests that there are still non-trivial gross errors in the extreme poverty rate after only the survey corrections. Together, these corrections slash the extreme poverty by 92% from a reported rate of 3%. More than three-quarters of the total reduction is due to corrections using the survey data alone.

We observe a similar pattern for individuals, with in-kind transfers cutting the extreme poverty rate the most (both proportionally and absolutely) and each of the other corrections also lifting a sizable portion of individuals out of extreme poverty. When looking at only reported cash income, we find that 2.62% of individuals live on less than \$2/day. After accounting for in-kind transfers, reported hours worked, and substantial assets, the extreme poverty rate for individuals falls by more than three-quarters to 0.59%. Bringing in the administrative tax and transfer data further reduces the extreme poverty rate to 0.11%. The extreme poverty rates for individuals are lower than those for households because extreme poor households tend to have fewer members.

Results by Household Type

We now analyze how extreme poverty differs by household type. Shaefer and Edin focus on two of the five household types (those with children), while the "disconnected families" literature focuses on those with a single parent. We first consider elderly households, which always have the lowest extreme poverty rate among all household types. The elderly begin with a reported extreme poverty rate of 0.47%, less than one-sixth the rate for all households (Figure 1a). After incorporating each of the survey corrections, a mere 0.14% of elderly households remain in extreme poverty. Bringing in the administrative tax data lifts 54% of the remaining extreme poor out of extreme poverty, and adding in administrative transfer data reduces the extreme poor share by nearly 90% (Table 4, Column 2).[18] Perhaps not surprisingly, the role of the administrative data is driven entirely by improved measures for three income sources: retirement distributions, OASDI, and SSI. The final estimate of the elderly extreme poverty rate is 0.01%.

We next consider single parent households, whose reported extreme poverty rate of 9.23% is more than three times the rate for all households. However, about two-thirds of single parent households are lifted out of extreme poverty by reported in-kind transfers. The extreme poverty rate for single parent households then declines at a similar rate as for all households across the remaining survey corrections, ending with 1.52% of single parent households in extreme poverty after accounting for substantial assets. After bringing in the administrative data, the extreme poverty rate of the sample of single parents astoundingly falls to zero. Among single parent households in the remaining extreme poor prior to including administrative data, 75% have positive earnings from the tax records and 96% receive at least one transfer – usually SNAP or the EITC – per the administrative data (Table 4, Column 3).

Unlike single parent households, multiple parent households start with a reported extreme poverty rate of 2.05% that is below that of all households. In-kind transfers noticeably decrease their extreme poverty rate by 41%, and the subsequent corrections for reported hours worked and assets bring down their extreme poverty rate to 0.29%. Like for single parents, incorporating the administrative data brings the estimated extreme poverty rate for multiple parent households down to zero. This correction is driven again by the role of earnings and transfers, with more than 70% of the remaining extreme poor after survey corrections having positive earnings and 79% receiving a transfer (Table 4, Column 4).

Single individuals start at a lower extreme poverty rate than single parent households, though their reported extreme poverty rate of 6.9% is still 2.3 times higher than that of all households. Single individuals are not nearly as impacted by the corrections and therefore have the highest extreme poverty rate of any household type after every correction. We are left with 2.9% of single individual households in extreme poverty after the survey corrections, which is almost as high as the overall reported extreme poverty rate. Bringing in the administrative data also has a smaller effect on single individuals, lifting out only 61% of single individuals remaining in extreme poverty after survey corrections. This relatively smaller reduction is due to several factors. First, single individuals

[18] We omit SNAP from the calculation for the elderly given that elderly households rarely receive SNAP and we already have a smaller sample size over the 11 states with administrative SNAP data.

appear to be the most disconnected from the safety net, with only 28% of the remaining extreme poor receiving at least one transfer. Second, the majority of these single individuals do not have positive earnings (Table 4, Column 5). We are therefore left with a final extreme poverty rate of 1.13% for single individuals, which is markedly higher than that of any other household type.

Multiple childless adult households have a reported extreme poverty rate (1.91%) not far from that of multiple parent households. The survey corrections for in-kind transfers, reported hours worked, and substantial assets together decrease their extreme poverty rate by more than three-quarters to 0.46%. Adding in administrative tax and transfer data cuts the extreme poverty rate for multiple adults to 0.07%. Among the remaining extreme poor after survey corrections, multiple adults are actually as under-served by the safety net as single individuals, with less than 30% receiving at least one transfer (Table 4, Column 6). However, earnings and asset incomes play a considerably larger role for these multiple adult households, with 83% having positive earnings and 42% having non-zero asset income. Consequently, 84% of multiple adult households among the remaining extreme poor after survey corrections are lifted out by the administrative data (compared to only 61% of single individuals).

The patterns of extreme poverty for individuals in Figure 1b are nearly identical to those for households in Figure 1a. Figure 2 also shows changes in extreme poverty with corrections, as measured by population-weighted individual counts. For the elderly, there are initially 215,000 individuals reported in extreme poverty, with this number falling to less than 4,000 after all corrections. Based purely on survey-reported cash income, there are also 2.9, 1.8, 1.6, and 1.5 million extreme poor individuals in single parent, multiple parent, single individual, and multiple adult households, respectively. After all corrections, the extreme poverty estimates are zero for single and multiple parents and a mere 43,000 individuals in multiple childless adult households. Importantly, there are still 255,000 single individuals remaining in extreme poverty after all corrections. In summary, the combined survey and administrative data indicate that extreme poverty is extremely rare for the elderly and families with children, rare for multiple adult households, and uncommon for single individuals.

Distribution of Household Types

To clarify the heterogeneous impacts of these corrections, we next examine the share of those in extreme poverty who are of each household type. Among the reported extreme poor, single individuals make up the largest share at nearly 44% (Figure 3a). Households with children make up the next largest shares, with single parent households and multiple parent households together making up about 36% of the reported cash income extreme poor (about 18% each). Multiple adult households also make up about 17% of the reported extreme poor, while elderly households contribute only a little over 3%. However, as we add each correction, single individual households constitute an increasingly larger share. About 63% of the remaining extreme poor households after the survey corrections are those with single individuals. After incorporating the administrative tax and transfer data, single individuals make up more than 90% of all extreme poor households.

While single individuals constitute a disproportionate share of the households in extreme poverty, we may also want to consider the composition of extreme poverty in terms of the share of individuals who are extreme poor (Figure 3b). When analyzing extreme poverty at the individual level, we find that only about 19% of the reported extreme poor are single individuals, while 59% are members of households with children (about 23% single parent and 36% multiple parent). Multiple adults make up another 19%, and the elderly contribute 2.7%. Nonetheless, we see with each correction the same, albeit less dramatic, pattern that we saw with households, as single individuals make up an ever-larger share of extreme poor individuals. Specifically, single individuals make up 36% of the remaining extreme poor individuals after the survey corrections, and they make up more than 84% of extreme poor individuals after all corrections.

Characteristics of Subgroups of the Reported Extreme Poor

We now describe the results obtained from validating each of the survey corrections against income levels from the administrative data and survey reports of material well-being and selected demographics. Throughout this subsection, the "remaining extreme poor" subgroup refers to households that are left in extreme poverty after the survey corrections.

Incomes from Administrative Data

We first examine the shares of households in each extreme poor subgroup lifted above $2/person/day (and other income thresholds) according to the administrative data. While there are still large holes in the administrative data,[19] they are the closest we can get to measures of truth. Figure 4 shows that

[19] We are missing administrative data on TANF, unemployment insurance, workers' compensation, VA benefits, the child tax credit, and other benefits.

62% of households among the reported extreme poor have incomes above $2/person/day when looking at just tax income from the administrative data. When we add in administrative data on transfer income, 85% have incomes above the extreme poverty threshold. Furthermore, nearly half of all reported extreme poor households have incomes above the poverty line and over a quarter have incomes above twice the poverty line. Thus, it is clear that there is a vast amount of error associated with classifying households as extreme poor based solely on their survey-reported cash income.

Looking separately across subgroups of the reported extreme poor gives a sense of the validity of each correction. Over 98% of households lifted out of extreme poverty by survey-reported in-kind transfers have incomes above $2/person/day according to the administrative tax and transfer data. As expected, the administrative transfer data play a relatively large role for this subgroup, with less than half of its households lifted out of extreme poverty by just the administrative tax data. The small percentage of households not raised above $2/person/day by the administrative data is possibly due to incomplete linkage or false positives. The survey correction for reported wage and salary hours is similarly robust, with 98% of households lifted out having incomes from the administrative data confirmed above the extreme poverty threshold. The vast majority of these households are lifted out of extreme poverty by the administrative tax data alone. This subgroup also appears to have substantial gross errors, with over three-quarters of households having incomes above the poverty line and nearly half having incomes above twice the poverty line.

There is slightly more more slippage in the survey corrections for reported self-employment hours and substantial assets. Among the households lifted out due to reported self-employment hours, 78% have incomes above $2/person/day using just the administrative tax data and 81% have incomes above the threshold using the administrative tax and transfer data. While these shares are still large, they are smaller than those for the groups lifted out by in-kind transfers and wage and salary hours. This discrepancy could be due in part to the under-reporting of self-employment earnings on tax returns (Internal Revenue Service 2016). Alternatively, this gap could be a result of self-employed individuals having hourly earnings below the minimum wage, in which case our correction assumes too high of a lower bound for self-employment earnings.[20] Similarly, among the households lifted out of extreme poverty due to substantial assets, only 66% are not extreme poor based on the administrative tax data and 72% are not extreme poor based on the administrative tax

[20] However, given the relatively high-earning self-employment occupations and industries reported for this group in Appendix Tables A.6 and A.8, it is unlikely that this is the primary contributor to the gap.

and transfer income. However, note the high fraction of gross errors in this subgroup, with 53% of households having incomes above the poverty line and 34% above twice the poverty line.

We therefore find strong evidence that these survey corrections are by and large confirmed by the administrative data. The corrections for in-kind transfers and reported wage and salary hours are particularly robust, with nearly every included household having incomes above $2/person/day per the administrative data. The corrections for reported self-employment hours and substantial assets are slightly less powerful but still strongly supportive of our reclassification. It is important to remember that our administrative data do not completely cover all income sources and do not cover assets at all, meaning the shares in Figure 8 should be treated as lower bounds.

Survey-Reported Material Well-Being

As yet another test of the validity of our survey-based corrections, we examine the mean number of material hardships, appliances owned, and housing problems reported by the households lifted out by each survey correction. In Table 5a, we also report the percent of households with at least one hardship, appliance, or problem (and for material hardships, the percent of households with five or more material hardships). We discuss only changes in the mean number because each of these measures reveals similar patterns of well-being among subgroups of the reported extreme poor. Looking first at the number of hardships, a clear pattern appears. The reported extreme poor experience 1.22 hardships on average. This count is slightly below the average number of material hardships (1.29) experienced by official poor households. Given that we would expect the truly extreme poor to experience more hardships than the official poor, this suggests that there is some amount of classification error in the reported extreme poor. Indeed, we see sharp differences between subgroups of the reported extreme poor that add up to the overall result.

First, households that are lifted out of extreme poverty by in-kind transfers experience 53% more hardships than official poor households, with their members clearly among the worst-off Americans. This pattern importantly suggests that these transfer programs are well-targeted. On the other hand, the groups lifted out of extreme poverty by wage and salary hours, self-employment hours, and substantial assets experience about the same number of hardships as a typical household in the U.S. Specifically, those lifted out by wage and salary hours have 13% fewer hardships than the average over all households, while those lifted out by self-employment hours and substantial assets have 10% and 7% more hardships, respectively. Thus, rather than being in extreme poverty or even poverty, these households appear to be close to middle-class or better! The remaining extreme poor average 1.21 hardships, which is similar to the average number of hardships experienced by the official poor and suggests that some substantial errors still remain. This result makes sense, since the remaining extreme poor still include those households that are not in extreme poverty when incorporating the administrative data. Similar patterns emerge when we analyze the shares of households reporting having at least one hardship and having five or more hardships.

Examining home quality issues and appliance ownership reveals patterns that are similar but less dramatic than those for material hardships. The reported extreme poor again have an average number of home quality problems similar to the official poor, and they also report owning 5.98 appliances, or about 1% more than the official poor's 5.91. Those households that are lifted out of extreme poverty due to in-kind transfers have more home problems than any other subgroup (7.5% more than the official poor), and they own 7% fewer appliances than the official poor. Again, the good targeting of in-kind transfers is apparent.

On the other hand, the households that are lifted out of extreme poverty due to reported hours worked or substantial assets have a mean number of home problems not far from the overall average: households lifted out by wage and salary hours worked and by substantial assets have 22% and 30% more problems than all households (which is also 30% and 25% fewer problems than the official poor), while those lifted out by self-employment hours have on average exactly the same number of problems as all households. The households lifted out by self-employment hours also own the most appliances, and the households lifted out by wage and salary hours or substantial assets have a similar number of appliances on average as all households (4% and 2% fewer, respectively). Finally, the remaining extreme poor again have a mean number of home problems similar to the official poor, but they own almost 10% fewer appliances than the official poor.

We also find that these patterns are robust across all household types (Figures 4, 5, 6, and 7), although there are a few additional findings worth noting.[21] In every subgroup except for those lifted out by in-kind transfers, single parents are more likely than the average household type to report experiencing at least one hardship. Additionally, while there are a few outliers associated with some household types for the number of home problems (e.g., single individuals lifted out by reported wage and salary hours, multiple adults lifted out by substantial assets, and multiple parents in the

[21] We exclude elderly households from this part of the analysis because there are so few unweighted observations of extreme poor elderly households that analyzing subgroup characteristics cannot give us meaningful results.

remaining extreme poor), the patterns in well-being are quite consistent across groups.[22] For material hardship and appliances owned, we see for every household type that those lifted out by in-kind transfers are worse off than the reported extreme poor and those lifted out by the earnings and asset corrections are better off. Lastly, single individuals have fewer hardships than any other household type among the remaining extreme poor, suggesting that they contain a significant share of individuals who are well-off.

Survey-Reported Demographics

To get a clearer picture of *who* are the households in the reported extreme poor and each of its subgroups, Table 5b explores demographic details available in the SIPP. First, note that 12% of the reported extreme poor are students, higher than the 7.19% of official poor households and 2.63% of all households. We disaggregate this number across subgroups and find that the remaining extreme poor have the highest rate of student status, with full-time students heading 18% of its households. Student status could proxy for access to other sources of financial support that we do not account for, such as financial aid (cash or in-kind), unreported assistance from parents, and student loans. Indeed, more than half of student-headed households among the remaining extreme poor report receiving educational assistance not included in cash income.[23]

The patterns in educational attainment across each of the extreme poor subgroups also reflect the patterns observed for material well-being. The household heads for the reported extreme poor have an average of 12.90 years of education, which is roughly midway between the level of the average official poor (12.25) and the overall average (13.59). Households that are lifted out of extreme poverty due to in-kind transfers have the lowest years of education (11.98). The households lifted out by self-employment hours and substantial assets have even more education than the average household (13.70 and 13.90 years, respectively). Those lifted out by wage and salary hours have 12.99 years of education and the remaining extreme poor have 12.84 years of education, both roughly midway between the levels for the official poor and all households (Appendix Table A.9).

[22] For single individuals, there is less of a difference between the average number of hardships reported for those lifted out of extreme poverty by self-employment hours or substantial assets and the hardships reported for the remaining extreme poor.

[23] None of our income measures include educational assistance, with the exception that cash income does include GI bill education benefits. See pages 3-7 of the SIPP Users' Guide: https://www2.census.gov/programs-surveys/sipp/guidance/SIPP_2008_USERS_Guide_Chapter3.pdf

We observe similar patterns in reported health insurance coverage. The households that are lifted out of extreme poverty by in-kind transfers have the highest rate of Medicaid coverage, with their household heads covered at over 1.5 times the rate of official poor households. Conversely, those households that are lifted out by reported hours or substantial assets have very high rates of *private insurance* coverage, with near or above 50% of these households covered. While these rates are not as high as that of private insurance coverage across all households (69.73%), they are much higher than the rates for official poor households (25.7%). The households remaining in extreme poverty have the lowest rate of health insurance coverage, but over a quarter of their heads still have some form of health insurance coverage (mostly private insurance).

Table 5b also examines ownership rates of several assets, including homes, vehicles, and liquid assets. The households lifted out of extreme poverty by in-kind transfers and those remaining in extreme poverty tend to have the lowest asset ownership rates. In contrast, those households lifted out by wage and salary earnings have similar asset ownership rates to the official poor, while the households lifted out by self-employment earnings own assets at rates similar to the average for all households. Appendix Table A.9 provides an expanded version of Table 5b and looks at a broader set of demographic and economic characteristics of these subgroups. Appendix Table A.10 also includes imputation rates by subgroup for most of the income sources and transfer programs in the survey.

VI. Comparison to Current Population Survey Results

While we focus on the SIPP in this paper, we are also interested in examining whether our results generalize to the Current Population Survey Annual Social and Economic Supplement (CPS). In addition to serving as the official source of poverty and income statistics in the United States, the CPS is one of the most widely used surveys. Because the CPS collects a sparser set of information on income and well-being than the SIPP, we can only incompletely replicate our analysis.

Data & Methodology

We use the 2012 CPS, which interviewed 74,383 households in March 2012 about their annual incomes in the previous calendar year. Thus, the reference period for the CPS includes the seven months that comprise Wave 9 of the 2008 SIPP but is broader than the SIPP's reference period. We employ a similar set of corrections as those used for the SIPP but proceed in a slightly different order.[24] We start with households living on less than $2/person/day over the course of 2011 according to their survey-reported cash income. We first correct for under-reported earnings based on reported hours worked. We multiply a household's annual hours worked (as reported in the survey) by the federal minimum wage and lift households out of extreme poverty if these lower-bound earnings are above the extreme poverty threshold. This is done separately for wage and salary hours and for total hours worked (which include self-employment hours).

Next, we incorporate in-kind transfers by lifting a household out of extreme poverty if 1) its total cash income plus survey-reported SNAP benefits exceeds $2/person/day or 2) it receives housing subsidies.[25] We subsequently account for substantial assets in the CPS in a slightly different manner than in the SIPP. The CPS does not contain as detailed information as the SIPP on the specific amounts of various types of assets, but it does indicate whether or not a household has a mortgage and how high its property value is. We therefore lift a household out of extreme poverty if it has *no* mortgage and a property value greater than $25,000, or if a household has a mortgage and a property value greater than $100,000. Finally, we lift a household out of extreme poverty if its annual income from cash and in-kind transfers from the administrative data exceeds $2/person/day. The reference period of the CPS actually aligns better than the SIPP with the administrative tax records because both are for the calendar year. We follow these alternative methods here in the SIPP as well as the CPS to allow a close comparison.

Results

Table 6 reports the extreme poverty rate after each correction in the CPS and compares these numbers to the rates after the same (aligned) corrections in the SIPP. Note that the reported extreme poverty rate in the CPS is 2.12%, which is less than the corresponding rate of 3% in the SIPP (Column 1). Correcting for reported wage and salary hours reduces the gap in the estimates between surveys, with the extreme poverty rate declining by 9% to 2.72% in the SIPP and falling by a mere 2% to 2.08% in the CPS (Column 2). Correcting for reported self-employment earnings errors

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[24] The alternative order in which we introduce corrections allows us to better compare and contrast the estimates of extreme poverty in the CPS and SIPP.

[25] We do not include WIC payments because WIC amounts are not reported in the CPS. We assume that if a household reports receiving housing assistance, then it receives housing assistance for all 12 months of 2011. This follows the assumption that the U.S. Census Bureau makes when calculating the Supplemental Poverty Measure (Johnson, Renwick, and Short 2011).

remarkably closes this gap, with the extreme poverty rate dropping to 2.10% in the SIPP and remaining mostly unchanged at 2.07% in the CPS (Column 3).

Including SNAP and housing assistance cuts the extreme poverty rate by approximately a third in both surveys, yielding identical extreme poverty rates of 1.34% in the CPS and SIPP (Column 4). Note that SNAP and housing assistance are by far the most important in-kind transfers, since including WIC (as the original corrections for in-kind transfers do) decreases the extreme poverty rate by only an additional 0.01 percentage points. Accounting for substantial assets further reduces the extreme poverty rate to 1.01% in the SIPP and 0.82% in the CPS (Column 5).[26] After bringing in the administrative tax data, the extreme poverty rate falls to 0.42% in the SIPP and 0.36% in the CPS (Column 6). After incorporating the administrative transfer data, we obtain a final extreme poverty rate among households of 0.12% in the CPS and 0.28% in the SIPP (Column 7).

Consequently, the results for the two surveys are far more alike than they initially seem. The sizeable errors that we find in the left tail of the SIPP income distribution appear with almost the same frequency in the CPS. The primary difference is that households almost never report positive hours worked and extremely low earnings in the CPS, while such a pattern is relatively common among the reported cash extreme poor in the SIPP.[27] Our final estimates of the extreme poverty rate in Column 7 are also consistent with the idea that poverty over the course of an entire year (CPS) should be less frequent than poverty over the course of four months (SIPP). The larger impact of the administrative transfer data on the CPS estimate is also in line with work showing greater under-reporting of transfer programs in the CPS relative to the SIPP.

VII. Robustness Checks and Caveats

Robustness Checks

We conduct a series of robustness checks to examine the sensitivity of our results to a wide set of alternative specifications. First, we calculate estimates of extreme poverty at the level of the fourth reference month, which is regarded as having the most accurate survey reports (Moore 2008) and

[26] Due to the more limited asset information available in the CPS, the correction for substantial assets that we utilize here is narrower than what we utilize for the main SIPP results. Specifically, the extreme poverty rate in the SIPP after accounting for assets is 1.01% using this more limited correction, compared to 0.87% using the original correction (which also accounts for liquid and total assets).

[27] In the CPS, all households that report 0 earnings also report 0 hours worked across all members. In the SIPP, 7.94% of all households that report 0 earnings report positive average monthly hours worked. Also in the SIPP, 72% of households lifted out of extreme poverty by wage and salary hours reported 0 earnings, as did 88% of households lifted out of extreme poverty by self-employment hours.

follows the reference period in Shaefer and Edin (2013). Appendix Table A.2 displays estimates after each survey-based correction using the fourth reference month and finds that they are only slightly higher than our wave-level estimates. For example, the reported extreme poverty rate of 3.82% using the fourth reference month is 27% higher than the comparable wave level rate, and the extreme poverty rate of 1.09% after accounting for substantial assets using the fourth reference month is 25% higher than the comparable wave-level rate. The similarity of the estimates across the month and wave reference periods reflects the tendency of survey responses to be strongly correlated when taken within the same interview (Moore, 2008). While we would also like to replicate our estimates over the course of a calendar year, we do not do so in the SIPP because of attrition across interview waves and the fact that responses would be taken across three or four interviews (rather than one), making it less comparable to one shot interview surveys like the ACS and CPS ASEC. However, the results in the CPS strongly suggest that the patterns and levels of annual estimates mirror those of wave-level estimates in the SIPP.

We also examine whether our extreme poverty results extend to a higher income cutoff – specifically $4/person/day (see Allen 2017; Deaton 2018). Appendix Table A.4 shows that they do. As expected, the extreme poverty rates are larger when measured using a higher income threshold. The reported rate of 3.7% using $4/person/day is 23% higher than the rate using $2/person/day, and the rate of 1.02% after incorporating substantial assets using $4/person/day is 17% higher than the rate using $2/person/day. These differences are not large and are consistent with a relatively large mass of households reporting zero incomes, many of which are likely to be gross errors. The survey-based corrections also cut the reported extreme poverty rate by 72% when using the $4/person/day threshold, which is nearly identical to the 71% cut by the survey-based corrections when using the $2/person/day threshold.

Because our best estimate of the extreme poverty rate is calculated over the eleven states for which we have administrative SNAP data for reference year 2011, we validate the representativeness of these states for the entire country. Appendix Table A.11 compares these eleven states (hereafter referred to as SNAP states) with all fifty states on a number of demographic and economic characteristics and finds that they are extremely similar to the full sample. Fewer households in the SNAP states receive OASDI and SSI, and more receive SNAP, Public Assistance, and housing assistance than those in the full sample (with differences being miniscule for all programs except SNAP and housing assistance). Households in the SNAP states are also nearly indistinguishable from the full sample in terms of poverty status, having a marginally higher extreme poverty rate, but smaller deep, official, and near poverty rates (measured based on cash income).

In addition, we test whether the differences in material well-being between the groups lifted out of extreme poverty by the survey corrections are statistically significant and robust to the inclusion of demographic covariates. To do so, we regress an indicator of well-being (mean number of hardships, appliances, or home problems) on a dummy for whether a household is poor based on pre-tax cash income, separate dummies for whether a household is lifted out of extreme poverty by a given survey correction, and covariates for the age of the household head and the number of children and adults in the household. We run these multivariate regressions without a constant, meaning the coefficient on the poor dummy should be interpreted as the mean level of well-being for poor households that are not reported extreme poor (hereafter referred to as P-NREP households) and the coefficient on the extreme poor subgroup dummies should be interpreted as relative to poor households that are not reported extreme poor.

Appendix Table A.12 shows the results of these regressions. Column 1 shows the results with average number of hardships as the dependent variable and no covariates, finding that P-NREP households have an average of 1.31 hardships. The households lifted out of extreme poverty by in-kind transfers have 0.68 more hardships than P-NREP households, while the households lifted out by the earnings and asset corrections have 0.63-0.77 fewer hardships than P-NREP households. The households remaining in extreme poverty after survey corrections have similar hardship numbers as P-NREP households. After we include covariates in Columns 2 and 3 (coded continuously in Column 2 and categorically in Column 3), we find that the poor coefficient is slightly attenuated but the coefficients on the extreme poor subgroups are remarkably similar and statistically significant. Consequently, controlling for these covariates yields coefficients on the dummies for earnings and asset corrections that are almost as negative as the poor dummy is positive. In other words, the households lifted out of extreme poverty by the earnings and asset corrections have hardship numbers not far from those of the average non-poor household after incorporating covariates. Columns 4 to 6 and 7 to 9 show analogous results using the number of appliances and home problems as dependent variables, respectively. The patterns in both sets of regressions are similar to those in Columns 1 to 3, although the coefficients on the extreme poor subgroup dummies tend to be less precise when using the number of home problems as the outcome. Note that the signs on the extreme poor subgroup dummies are reversed when using the number of appliances as the outcome, because more appliances (unlike more hardships or home problems) is indicative of greater well-being.

We also examine more closely the households lifted out of extreme poverty due to reported hours worked. Appendix Tables A.5 and A.6 show the top 10 occupations of workers in households lifted out by wage and salary hours and by self-employment hours, respectively (Appendix Tables A.7 and A.8 show the top 10 industries of these workers). Most of these occupations are not exempt from the federal minimum wage and, in fact, have average earnings that are generally far above minimum wage. For example, almost 9% of workers in households lifted out of extreme poverty by wage and salary hours are computer scientists or engineers (compared to less than 2% of all wage and salary workers). Additionally, while 1.41% of workers in this subgroup are waiters and waitresses (an occupation that could conceivably earn less than minimum wage), a higher rate (1.82%) of all wage and salary workers are waiters and waitresses. Additionally, the three most common occupations for workers in households lifted out of extreme poverty by self-employment hours are various kinds of managers (14% of such workers, as compared to 11.55% of all self-employed workers). To get a sense of the extent to which these subgroups are likely to have error-ridden earnings reports, Appendix Table A.13 also displays the share of households in these subgroups with zero or single-digit reported average monthly earnings. We find that 72% of households lifted out of extreme poverty by wage and salary hours report zero earnings and that 78% report zero or single-digit earnings. Of the households lifted out of extreme poverty by self-employment hours, 88% report zero earnings and 89% report zero or single-digit earnings.

Additional Caveats

In this subsection, we discuss some additional caveats and the degree to which they are likely to affect the results. We begin by discussing a number of issues with the administrative data. First, we use eligible EITC amounts calculated based on the administrative tax data rather than actual amounts. While this will overstate the true amount of the EITC disbursed, the upward bias associated with eligible EITC amounts is likely substantially smaller than the downward bias in survey-based imputations of EITC receipt and amounts.[28] Second, when combining survey and administrative data, we may overstate certain income sources if we erroneously treat false positives as true

[28] We find that the actual EITC dollars disbursed (from publicly available IRS totals) are 90% of the total eligible dollars that we calculate. In contrast, aggregate EITC dollars imputed in the CPS understate disbursements by approximately 30% (Meyer 2017).

recipients or if amounts reported in the survey are overstated. On the other hand, these income amounts may be understated since there may be false negatives and/or under-reported survey amounts associated with non-HUD housing assistance, state-administered SSI, and non-taxable sources of earnings and asset income. On net, we suspect these income components are understated based on comparisons of the survey amounts to aggregate payments (Meyer, Mok, and Sullivan 2009; Meyer and Wu 2018).

We are also still missing administrative data for a number of income sources, such as Temporary Assistance for Needy Families, General Assistance, the Child Tax Credit, unemployment insurance, workers' compensation, and veterans' benefits.[29] Figure 9 shows that we miss $216 billion from the four largest transfer programs not in our administrative data, with $107 billion attributable to unemployment insurance alone. Based on 2011 government expenditures, the programs covered by our administrative data encompass 79% and 48% of all transfer programs and all non-OASDI transfers (excluding Medicare and Medicaid), respectively. We likely also miss income from sources like off-the-books employment and money from relatives (Jencks 1997). Incorporating administrative sources for these other income components may lead to further reductions in the extreme poverty rate. In fact, we find that more than 20% of the remaining extreme poor after all corrections are veterans, which may be due in part to our administrative data missing information on veterans' benefits (including disability compensation).

The SIPP and CPS survey frames also cover resident households, meaning they miss homeless individuals. Given that there were 636,000 homeless individuals in 2011 (based on HUD estimates) and that the homeless are among the most destitute members of our communities, our final estimate of the extreme poverty rate may be an understatement for the entire population.[30] While the extreme poverty estimates in the literature discussed in Section II also rely on surveys that do not include the homeless, a broader view of extreme poverty would include them. Moreover, if homeless individuals are more likely than the non-homeless to be single childless individuals, incorporating the homeless might further increase the already large share of extreme poor individuals that are single and childless.

[29] While we have access to administrative TANF data and have used them in other work (see Meyer and Wu 2018), we only have these data for 30 states and are hesitant to base our extreme poverty estimates on the seven states for which we have both administrative SNAP and TANF data.

[30] See https://www.hudexchange.info/resources/documents/2011AHAR_FinalReport.pdf.

There are also caveats associated with the linkage of SIPP topical modules to the Wave 9 core file. First, the information on assets and disability status is collected from topical modules corresponding to a different reference period than Wave 9 (Waves 7 and 10 for assets and Wave 6 for disability). Second, because of survey attrition and slight changes in household composition across waves, not all households that appear in Wave 9 match to topical modules from the other waves (especially later waves).[31] Therefore, any households that do not link to the topical modules for Waves 7 or 10 are not lifted out of extreme poverty by substantial assets. In fact, one-sixth of the un-weighted households left in extreme poverty after accounting for substantial assets cannot be linked to the Wave 7 or 10 topical modules. This missing data problem leads to an understatement of the survey-based asset correction and therefore leads to an overstatement of the final extreme poverty rate.

Finally, we do a series of checks to make sure that imputed values in the survey only have a minor effect on our estimates. For example, 59% of households lifted out by in-kind transfers in the survey have SNAP amounts imputed, but only 3% have receipt imputed (see Appendix Table A.10a). Yet, 98% of these households have incomes above $2/person/day based on the administrative data. We also find that 47% and 54% of households lifted out by wage and salary hours and by self-employment hours, respectively, have imputed values for overall hours worked (see Appendix Table A.10b). Once again, 98% and 81% of these households have incomes above the extreme poverty threshold based on the administrative data. This finding is not surprising since the vast majority of the hours imputations rely on information from past waves that is likely to be of good quality.

VIII. Conclusions

Through closely examining the SIPP and augmenting the survey data with administrative tax and transfer data, we find that less than 0.24% of households in the United States live on $2/person/day or less. Our methodology yields a similarly low rate of extreme poverty in the CPS, with less than 0.12% of households living on $2/person/day or less over the course of an entire year. This is a far cry from the 3% and 2.12% of households in the SIPP and CPS, respectively, that would otherwise

[31] 92.55% of the households (weighted) we use in Wave 9 link to the Wave 6 topical module. 97.88% of households we use in Wave 9 link to either Wave 10 or Wave 7: we link 90.83% to Wave 10 and 7.05% to Wave 7 (we only link households to Wave 7 if we could not link them to Wave 10).

be classified as extreme poor based on survey-reported cash income. Many of the households included in extreme poverty under this naïve classification appear to be better off than the average American household based on numerous indicators of material well-being. These results are therefore consistent with the literature showing that survey data at the very bottom of the income distribution are error-ridden and likely to be outliers. The results also reflect the very low rates of extreme and deep consumption poverty that various studies have found (Meyer and Sullivan 2004, 2008; Hall and Rector 2018). Importantly, we may yet overstate the true rate of extreme poverty, because our administrative data miss a number of important income sources for which we cannot correct for under-reporting. Furthermore, we measure extreme poverty in 2011, during the midst of the recovery from the worst economic crisis since the Great Depression and when poverty was particularly pronounced.

This paper's analyses further demonstrates that the face of extreme poverty is quite different from what the literature has previously emphasized. Among the 286,000 households left in extreme poverty, 90% are made up of single individuals. Households with elderly heads and multiple childless individuals make up the other 10% of the extreme poor. Incredibly, after implementing all corrections, not a single SIPP-interviewed household with children has an income below $2/person/day. This result lies in stark contrast to the focus in academic and policy circles on the plight of extreme poor households with children. This result also indicates that extreme poverty among such households cannot have risen due to welfare reform because there is effectively no room for it to have risen. It is worth re-emphasizing that these dramatic results hold even in the absence of administrative data for TANF, which is targeted towards single-parent households and is heavily under-reported in surveys.

Our results also indicate that means-tested transfers – especially in-kind benefits – are well-targeted to the needy, as the households lifted out of extreme poverty by in-kind transfers appear to be considerably worse off than those in official poverty. We therefore provide an explanation for the poor ability of the U.S. Census Bureau's Supplemental Poverty Measure to select those with low material well-being (see Meyer and Sullivan 2012): it likely reclassifies as non-poor those receiving in-kind transfers, who are very needy, and leaves as poor those who are misclassified because of substantial assets or unreported income. This puzzle merits additional examination, with a focus on comparing the degrees to which cash and in-kind transfer dollars (and dollars for specific programs) target the needy.

This paper leaves room for a number of extensions. First, we might consider examining post-tax measures of extreme poverty. While this paper does calculate the EITC from administrative tax records, it does not account for all tax credits (like the Child Tax Credit) and tax liabilities. Second, we plan on bringing in more complete administrative data as they become available (e.g., on veterans' benefits, unemployment insurance, and workers' compensation) to further improve the measurement of extreme poverty. In part, doing so will help us understand how many of the single individuals we categorize as extreme poor are misclassified because of missing administrative data. In the meantime, we intend to analyze more deeply the well-being of the significant number of extreme poor single individuals. Third, we hope to incorporate the homeless into our analysis of extreme poverty. While survey frames often do not cover the homeless, several administrative datasets (such as the SNAP and Medicaid files) include information identifying homeless recipients. We can also link the administrative homeless to surveys over time to better understand the extent to which extreme poor households move in and out of homelessness.

More generally, we lay out a novel methodology for how income data can be better used to measure poverty. We show that our survey-based corrections go a long way in addressing survey errors, accounting for 79% of the change in extreme poverty due to the combination of survey- and administrative-based corrections. Although this paper focuses on extreme poverty, we can apply a similar methodology to address survey errors at higher income cutoffs defining other portions of the income distribution. These cutoffs include deep and official poverty thresholds. By combining the accuracy of the administrative data with the richness of the SIPP data, we aim to better understand the barriers to success faced by households that are truly poor. We also plan to link these data across time periods to assess how the picture of the poor has evolved over time.

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Tables and Figures

Table 1. Abbreviated Terms Used throughout the Article

AFDC	Aid to Families with Dependent Children
ASEC	CPS Annual Social and Economic Supplement
CE	Consumer Expenditure Survey (Bureau of Labor Statistics)
CPI-U	Consumer Price Index for All Urban Consumers (Bureau of Labor Statistics)
CPS	Current Population Survey (Bureau of Labor Statistics, U.S. Census Bureau)
DER	Detailed Earnings Record (SSA)
EITC	Earned Income Tax Credit
HUD	U.S. Department of Housing and Urban Development
IPW	Inverse Probability Weighting
IRA	Individual Retirement Account
IRS	Internal Revenue Service
LIHEAP	Low Income Home Energy Assistance Program
LIS	Luxembourg Income Study
Numident	Numerical Identification File (SSA)
OASDI	Old Age, Survivors, and Disability Insurance Program (Social Security)
PA	Public Assistance
PCE	Personal Consumption Expenditure
PHUS	Payment History Update System (SSA)
PIC	Public and Indian Housing Information Center (HUD)
PIK	Protected Identification Key
P-NREP	Poor households that are not reported extreme poor
PSID	Panel Study of Income Dynamics (University of Michigan)
PVS	Person Identification Validation System
SIPP	Survey of Income and Program Participation (U.S. Census Bureau)
SNAP	Supplemental Nutrition Assistance Program
SPM	Supplemental Poverty Measure (U.S. Census Bureau)
SSA	Social Security Administration
SSI	Supplemental Security Income
SSR	Supplemental Security Record (SSA)
TANF	Temporary Assistance for Needy Families
TRACS	Tenant Rental Assistance Certification System (HUD)
TRIM	Transfer Income Model (Urban Institute)
UI	Unemployment Insurance
WC	Workers' Compensation
WIC	Special Supplemental Nutrition Program for Women, Infants, and Children

Table 2. Administrative Data Sources

Income Source	Administrative Source	Income Unit	Income Frequency	States Covered
Earnings	DER (SSA)	Individual	Annual	All
Asset Income	Form 1040 (IRS)	Tax Unit	Annual	All
Retirement Distributions	Form 1099-R (IRS)	Individual	Annual	All
OASDI	PHUS (SSA)	Individual	Monthly	All
SSI	SSR (SSA)	Individual	Monthly	All
EITC	Form 1040 (IRS)	Tax Unit	Annual	All
SNAP	State Agencies	Household	Monthly	11 States
Housing Assistance	PIC & TRACS (HUD)	Household	Monthly	All

Notes: This table shows – for each income source in the administrative data – the source of the data, the unit at which the dollar amounts are reported, the frequency at which the dollars are reported, and the states/years covered. Note that all of the administrative data, with the exception of SNAP, cover the universe of recipients in the United States.

Table 3. Estimates of Extreme Poverty for All Households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sources Included in Income							
Cash	x	x	x	x	x	x	x
SNAP, WIC, housing assistance		x	x	x	x	x	x
Minimum wage earnings calculated from hours worked for pay (wage/salary jobs only)			x	x	x	x	x
Minimum wage earnings calculated from hours worked for pay (wage/salary + self-employment jobs)				x	x	x	x
Other Adjustments							
Substantial assets*					x	x	x
Income from administrative tax data						x	x
Income from administrative tax + transfer data							x
Weighted number of households	3,565,000	2,466,000	2,211,000	1,575,000	1,033,000	432,000	286,000
Share of households	3.00%	2.08%	1.86%	1.33%	0.87%	0.36%	0.24%
Unweighted number of households	900	600	550	400	250	100	70
Weighted number of individuals	8,005,000	4,926,000	4,292,000	2,868,000	1,806,000	691,000	326,000
Share of individuals	2.62%	1.61%	1.40%	0.94%	0.59%	0.23%	0.11%
Unweighted number of individuals	2,000	1,200	1,000	700	400	150	70

*Owns real estate equity > $25,000, liquid assets > $5,000, or total assets > $50,000.

Notes: Wave 9 of the 2008 SIPP panel, covering January-July 2011. Only includes households present in the survey in reference month 4. Households are weighted by the weights they are assigned in reference month 4. Households in "extreme poverty" are those with average income across the four months of the wave less than or equal to $2/person/day. Households with negative incomes in any month in the wave are defined as not being in extreme poverty. When including housing assistance, all households that receive public housing or housing subsidies are defined as not being in extreme poverty. The number of hours that each person in the household worked each month is calculated as [average hours per week worked this reference period in a paid job] × [number of weeks worked the month in a paid job]. Hours worked in a month are then multiplied by the federal minimum wage ($7.25) to estimate income for the month, and the estimated income for all household members is summed. If the total household estimated income per person per day is greater than $2, the household is considered not in extreme poverty. We do not include unpaid family workers in this calculation. Assets are as reported in the wave 10 topical module (or wave 7, if a household does not match to wave 10).

Table 4. Income Receipt for Remaining Extreme Poor Households (Administrative Data)

	(1) All	(2) Elderly	(3) Single Parents, Non-Elderly	(4) Multiple Parents, Non-Elderly	(5) Single Individuals, Non-Elderly	(6) Multiple Adults, Non-Elderly
Earnings	56.55%	15.57%	75.03%	70.17%	48.30%	83.13%
Asset Income	26.39%	15.57%	20.78%	10.57%	26.68%	41.61%
Retirement Dist.	11.61%	42.69%	6.51%	3.79%	12.58%	7.97%
OASDI	6.21%	58.26%	0.00%	7.21%	5.19%	1.63%
SSI	2.89%	35.97%	0.00%	14.17%	0.00%	2.75%
Housing	3.61%	20.75%	1.18%	10.93%	2.82%	0.00%
EITC	26.73%	0.00%	64.49%	42.28%	20.09%	28.16%
SNAP	19.76%		63.54%	73.69%	3.77%	22.37%
Any Transfer	40.69%	89.60%	96.07%	79.14%	28.32%	29.76%

Notes: These shares reflect the percent of households and individuals in each group that receive each source of income (per the admin data). For the elderly, we omit SNAP (meaning "any transfer" refers to OASDI, SSI, housing assistance, or the EITC).

Table 5a. Material Well-Being for Extreme Poor Subgroups and Comparison Households

	Reported Cash Extreme Poor (1)	Lifted Out by In-Kind Transfers (1)-(2)[1]	Lifted Out by Wage/Salary Earnings Based on Hours (2)-(3)[2]	Lifted Out by Self-Employment Earnings Based on Hours (3)-(4)[3]	Lifted Out by Substantial Assets (4)-(5)[4]	Remaining Extreme Poor (5)	Official Poor	All Households
<u>Material Hardship</u>								
Over the past 12 months, there was a time someone in the household…								
…did not meet all essential expenses	31.77%	55.25%	18.88%	15.30%	15.82%	28.45%	32.35%	16.07%
…did not pay full amount of rent or mortgage	17.68%	28.06%	8.32%	9.28%	7.45%	19.49%	16.91%	8.06%
…was evicted for not paying rent or mortgage	2.03%	2.21%	0.63%	0.00%	1.28%	3.83%	1.33%	0.51%
…did not pay full amount of energy bills	21.11%	37.05%	8.69%	9.73%	7.67%	21.25%	23.10%	10.54%
…had energy service disrupted	4.62%	7.42%	0.63%	2.98%	2.84%	4.58%	4.49%	1.74%
…had telephone service disconnected	9.61%	14.69%	2.19%	5.38%	7.03%	9.98%	10.38%	3.81%
…needed to see a doctor but did not go	13.06%	17.58%	7.27%	11.55%	9.82%	12.30%	14.40%	7.93%
…needed to see a dentist but did not go	14.36%	19.38%	6.52%	11.33%	8.84%	15.71%	18.01%	9.89%
…had not enough food (past 4 months)	7.59%	16.34%	0.00%	1.70%	3.97%	5.69%	7.77%	2.88%
Number of hardships	1.22	1.98	0.53	0.67	0.65	1.21	1.29	0.61
Any hardships	40.57%	64.70%	26.21%	26.98%	24.09%	35.45%	45.01%	24.25%
Five or more hardships	7.45%	12.26%	2.53%	3.98%	3.96%	7.52%	7.59%	2.92%
<u>Housing Characteristics</u>								
Home does not have…								
Microwave	9.85%	9.19%	4.20%	4.50%	2.62%	19.03%	6.84%	3.21%
Dishwasher	47.99%	61.55%	37.59%	29.67%	31.18%	56.23%	55.03%	30.75%
Air conditioning (room or central)	16.36%	14.49%	6.74%	11.40%	11.78%	26.18%	16.59%	11.32%
Color television	8.02%	3.62%	5.53%	8.39%	4.21%	15.08%	3.90%	1.71%
Computer	35.17%	50.25%	28.32%	13.67%	26.30%	38.69%	41.81%	22.04%
Washer in unit	32.65%	43.81%	23.15%	12.32%	18.01%	43.31%	31.26%	14.82%
Dryer in unit	35.25%	46.75%	24.44%	15.74%	18.69%	46.38%	34.63%	16.60%
Cell phone	16.52%	21.38%	6.40%	6.05%	14.58%	21.29%	19.10%	11.03%
Number of appliances owned	5.98	5.49	6.64	6.98	6.73	5.34	5.91	6.89
Own at least one appliance	96.61%	99.57%	100.00%	100.00%	98.94%	89.33%	98.96%	99.78%
Problems with Home Quality								
Problem with pests	11.57%	13.23%	8.95%	8.27%	12.07%	12.23%	14.92%	8.74%
Leaking roof	7.79%	7.39%	5.65%	5.86%	4.95%	11.41%	7.49%	4.71%
Broken windows	3.71%	6.39%	2.89%	1.23%	3.07%	2.92%	5.22%	3.05%
Exposed electrical wires	1.60%	2.32%	1.23%	0.83%	0.00%	2.24%	1.19%	0.62%
Plumbing problems	4.05%	3.83%	4.86%	3.66%	3.82%	4.46%	3.87%	2.15%
Cracks or holes in the walls or ceiling	5.39%	7.49%	3.53%	2.77%	5.59%	5.13%	5.35%	2.91%
Holes in the floor	1.52%	2.21%	1.23%	0.00%	0.93%	2.09%	1.65%	0.70%
Number of problems with home	0.36	0.43	0.28	0.23	0.30	0.40	0.40	0.23
Have at least one problem	20.93%	21.71%	11.03%	16.82%	17.56%	26.82%	23.07%	15.15%

1. Extreme poor in Table 3 column 1 but not in column 2.
2. Extreme poor in Table 3 column 2 but not in column 3.
3. All wage/salary hours and self-employment hours. Extreme poor in Table 3 column 3 but not in column 4.
4. Extreme poor in Table 3 column 4 but not in column 5.

Table 5b. Selected Demographics for Extreme Poor Subgroups and Comparison Households

	Reported Cash Extreme Poor (1)	Lifted Out by In-Kind Transfers (1)-(2)[1]	Lifted Out by Wage/Salary Earnings Based on Hours (2)-(3)[2]	Lifted Out by Self-Employment Earnings Based on Hours (3)-(4)[3]	Lifted Out by Substantial Assets (4)-(5)[4]	Remaining Extreme Poor (5)	Official Poor	All Households
Household Characteristics								
Someone in household is…								
…unemployed	26.09%	38.32%	5.77%	5.29%	24.33%	31.82%	18.23%	8.59%
…a displaced worker	1.22%	1.93%	5.34%	0.00%	0.77%	0.45%	1.73%	1.41%
…a child with a severe disability	1.69%	3.71%	0.00%	0.00%	2.11%	0.66%	3.17%	1.87%
…severely disabled	19.50%	27.26%	3.77%	11.70%	23.47%	17.41%	33.68%	25.29%
…severely disabled (mental/emotional)	6.84%	10.97%	2.46%	6.86%	5.39%	4.03%	9.93%	5.97%
…a care provider for an ill or disabled person	4.48%	3.49%	4.52%	7.74%	6.36%	2.54%	4.86%	5.84%
Education of Household Head								
Full time student	12.00%	13.68%	4.67%	1.14%	13.13%	18.12%	7.19%	2.63%
Full or part time student	13.48%	16.26%	8.46%	1.63%	13.13%	19.24%	10.07%	5.00%
Receives educational assistance if a student	52.74%	57.70%	26.71%	23.72%	54.79%	51.90%	57.99%	51.48%
Years of education	12.90	11.98	12.99	13.70	13.90	12.84	12.26	13.59
Health Insurance of Household Head								
Medicaid	19.07%	49.93%	1.87%	4.41%	3.20%	7.83%	32.01%	9.40%
Private Insurance	28.62%	4.12%	57.49%	49.87%	53.77%	21.31%	25.70%	69.73%
Medicaid or Medicare or Private Insurance	48.08%	53.46%	60.24%	55.40%	58.20%	29.55%	62.98%	84.76%
Assets								
Own a home	33.95%	14.24%	32.37%	69.21%	72.90%	9.14%	31.25%	61.73%
Total real estate equity > $25,000	26.31%	9.95%	27.43%	48.41%	74.68%	0.00%	24.38%	50.08%
Own a car, van, or truck	64.69%	47.40%	69.28%	89.71%	78.49%	58.30%	63.57%	84.37%
Liquid assets > $5,000	11.68%	1.15%	6.15%	20.65%	43.17%	0.00%	8.50%	33.05%
Total assets > $50,000	32.28%	10.87%	31.92%	68.90%	84.33%	0.00%	26.44%	57.29%
Weighted number of households	3,565,000	1,099,000	255,000	636,000	542,000	1,033,000	17,710,000	118,700,000
Share of households	3.00%	0.93%	0.21%	0.54%	0.46%	0.87%	14.92%	100.00%
Unweighted number of households	900	300	70	150	150	250	4,800	32,500

1. Extreme poor in Table 3 column 1 but not in column 2.
2. Extreme poor in Table 3 column 2 but not in column 3.
3. All wage/salary hours and self-employment hours. Extreme poor in Table 3 column 3 but not in column 4.
4. Extreme poor in Table 3 column 4 but not in column 5.

Notes: Wave 9 of the 2008 SIPP panel, covering January-July 2011. Only includes households present in the survey in reference month 4. Households are weighted by the weights they are assigned in reference month 4. Numbers in parentheses in headings refer to income measure columns in Table 3. See notes to Table 3 for definition of "extreme poor" for each income measure. See the appendix for a description of the linkage to topical modules and a full description of the variables used.

Table 6. Comparison of CPS and SIPP Extreme Poverty Estimates for All Households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sources Included in Income							
Cash	x	x	x	x	x	x	x
Minimum wage earnings calculated from hours worked for pay (wage/salary jobs only)		x	x	x	x	x	x
Minimum wage earnings calculated from hours worked for pay (wage/salary + self-employment jobs)			x	x	x	x	x
In-kind transfers*				x	x	x	x
Other Adjustments							
Substantial assets**					x	x	x
Income from administrative tax data						x	x
Income from administrative tax + transfer data							x
Share of households (CPS)	2.12%	2.08%	2.07%	1.34%	0.82%	0.36%	0.12%
Share of households (SIPP – aligned corrections)	3.00%	2.72%	2.10%	1.34%	1.01%	0.42%	0.28%
Share of households (SIPP – original corrections)	3.00%	2.72%	2.10%	1.33%	0.87%	0.36%	0.24%

*SNAP, WIC, and housing assistance in SIPP (original corrections). SNAP and housing in CPS, SIPP (aligned corrections).
**For SIPP (original corrections), owns real estate equity > $25,000, liquid assets > $5,000, or total assets > $50,000. For CPS and SIPP (aligned corrections), household has property value > $25,000 and has no mortgage, or has property value > $100,000 and has a mortgage.

Figure 1a. Share of Households in Extreme Poverty After Corrections, by Household Type

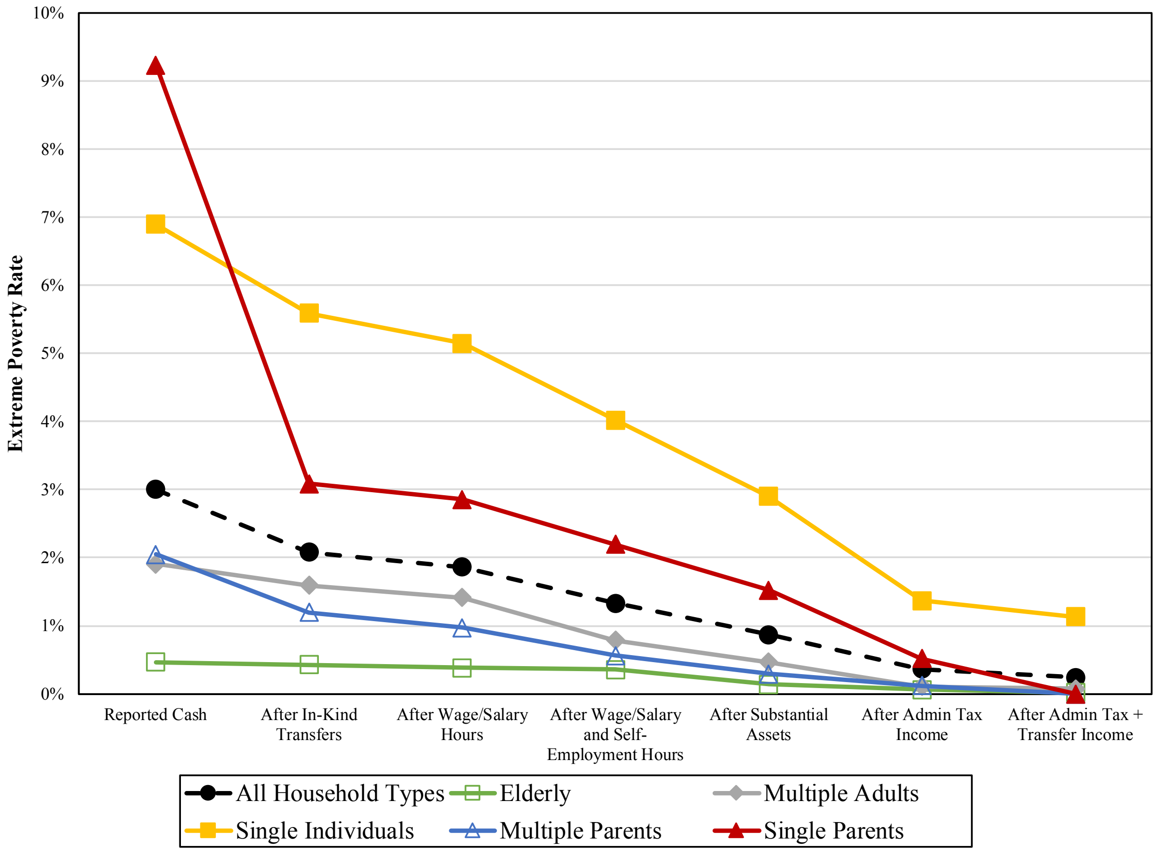


Figure 1b. Share of Individuals in Extreme Poverty After Corrections, by Household Type

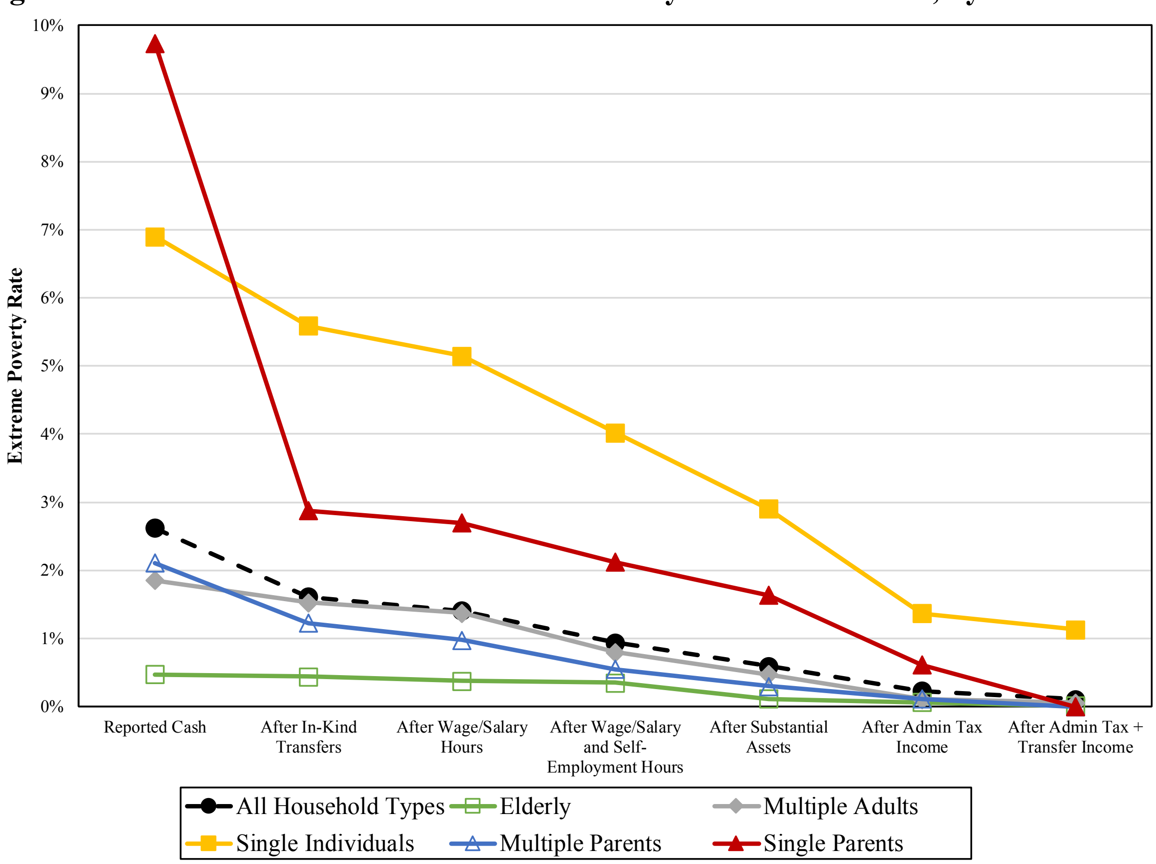


Figure 2. Number of Individuals in Extreme Poverty After Corrections, by Household Type

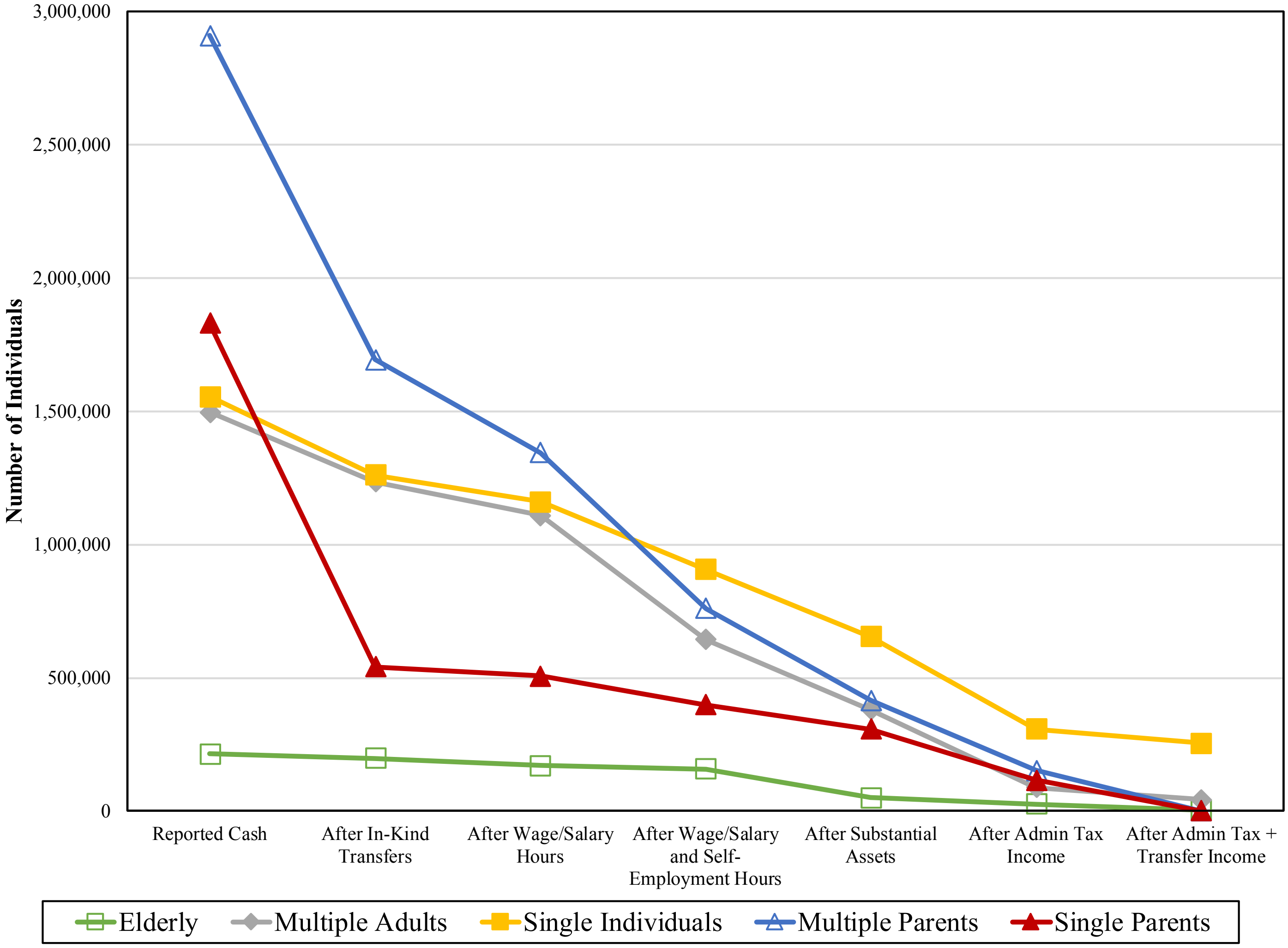


Figure 3a. Household Type Distribution of Extreme Poor Subgroups After Corrections
Share of Households

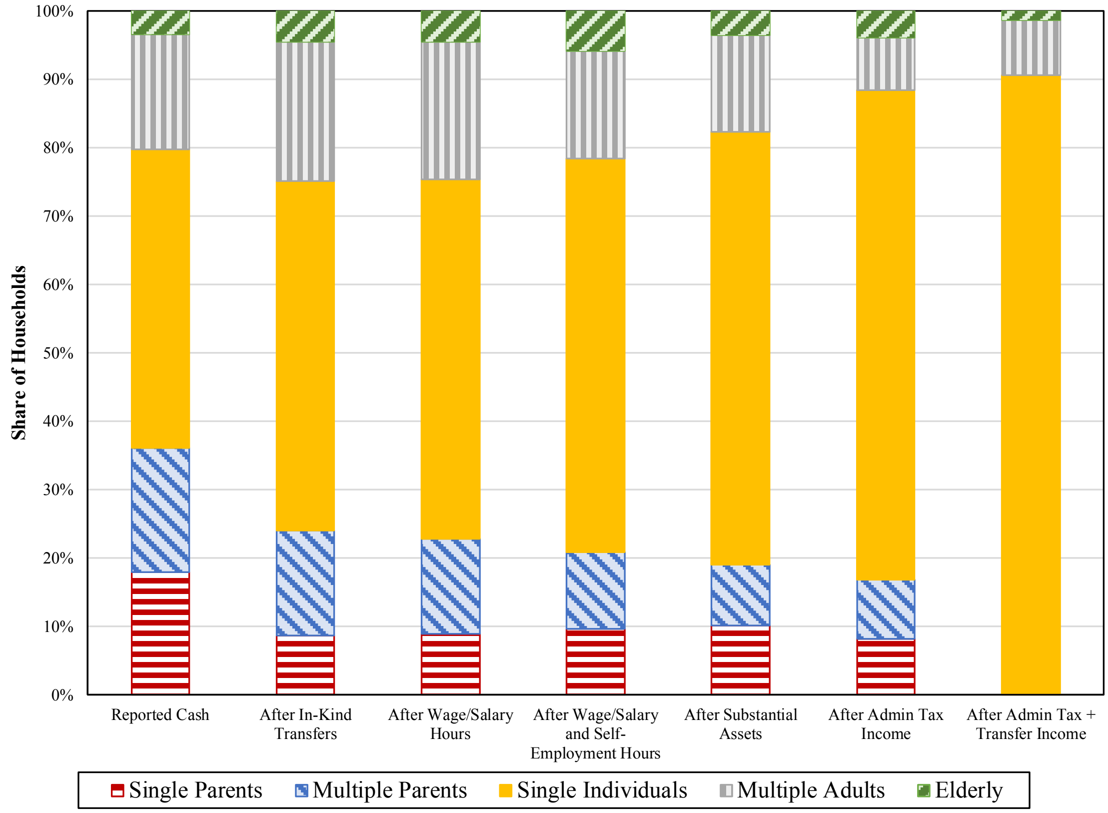


Figure 3b. Household Type Distribution of Extreme Poor Subgroups After Corrections
Share of Individuals

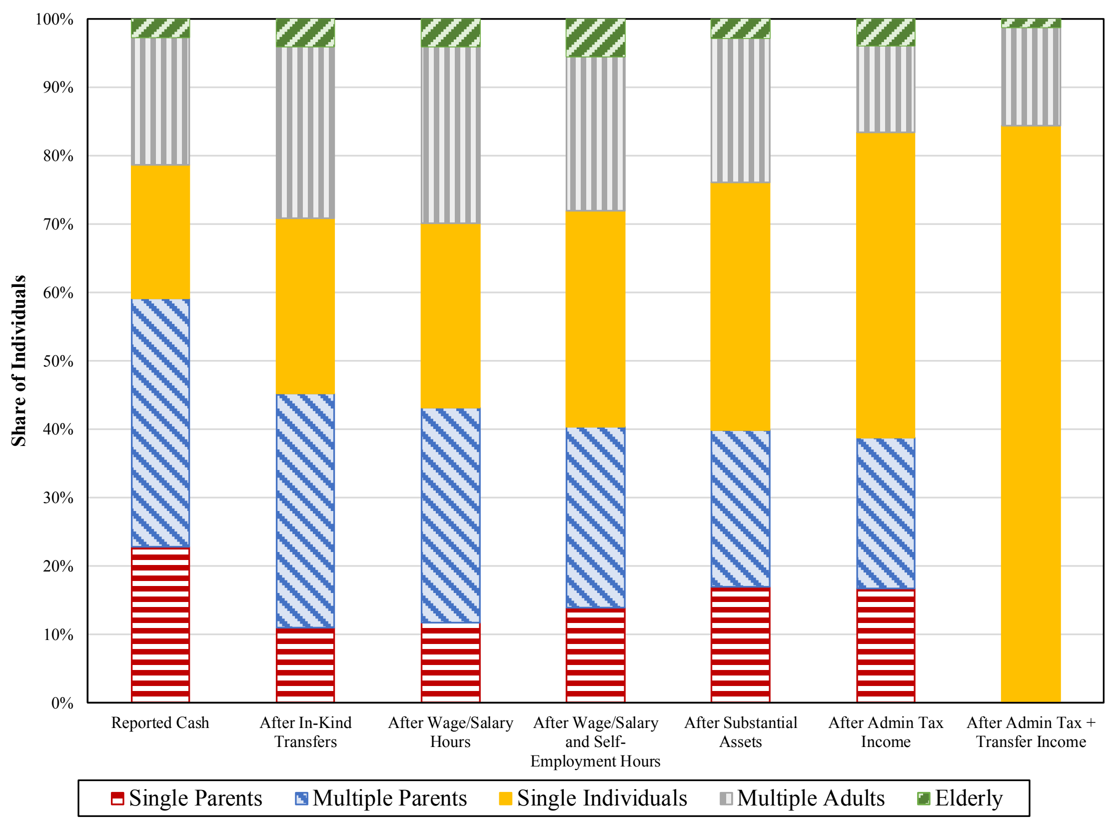


Figure 4. Share of Households in Extreme Poor Subgroups Raised Above Income Thresholds by Administrative Data

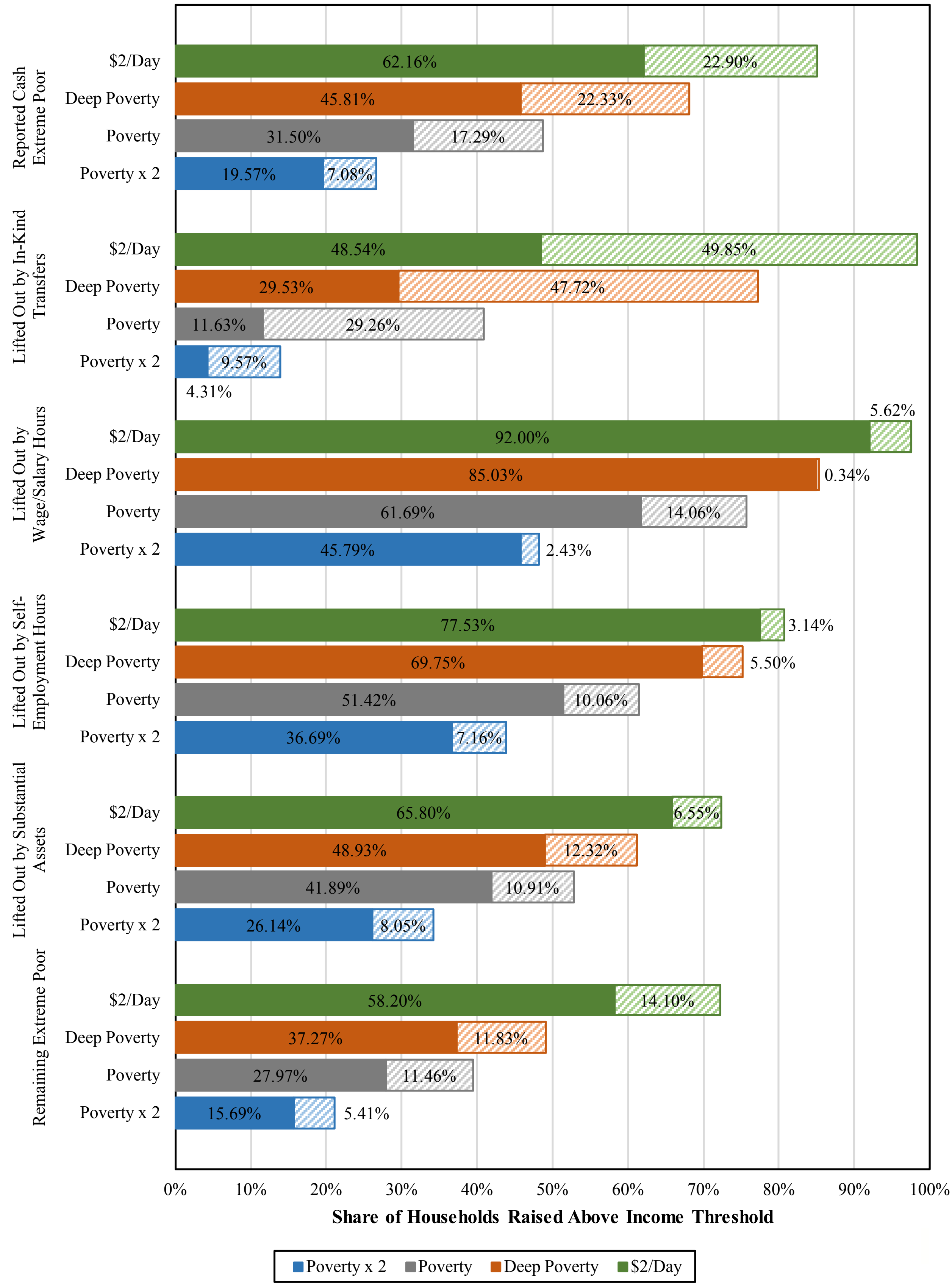


Figure 5. Number of Material Hardships for Extreme Poor Subgroups, by Household Type

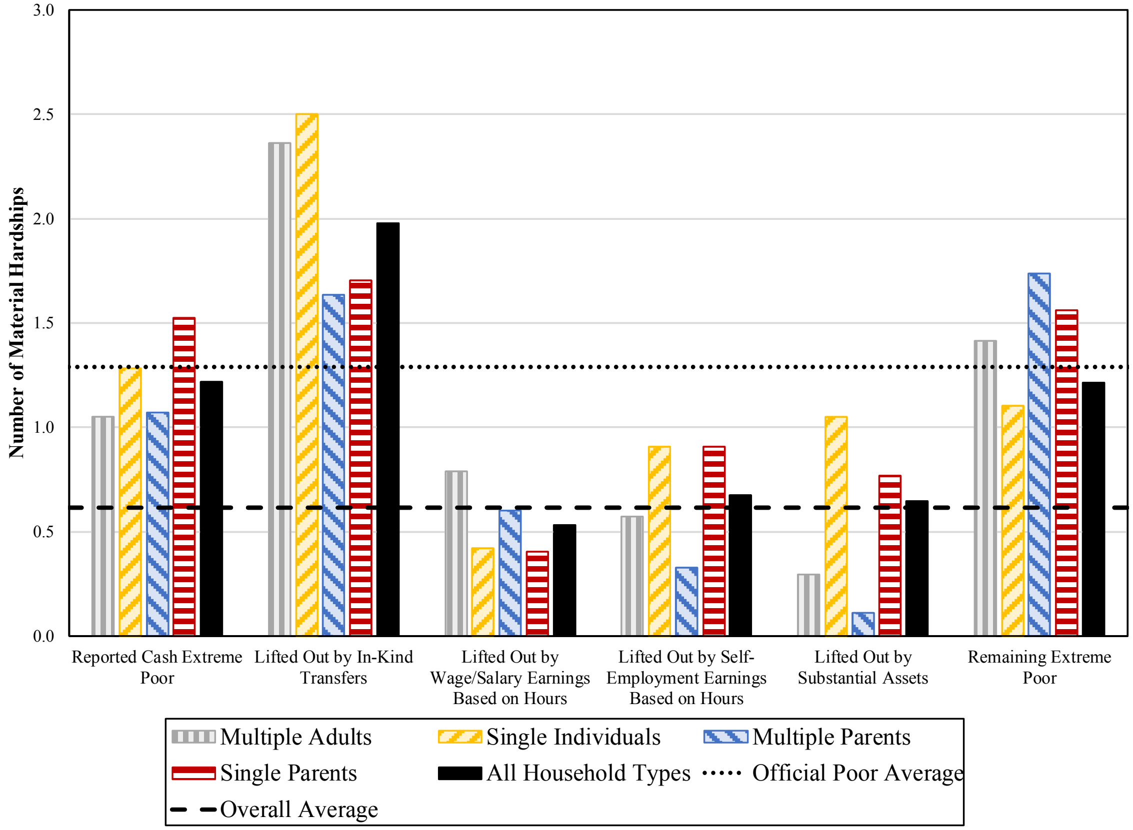


Figure 6. Share of Households with Any Material Hardship for Extreme Poor Subgroups, by Household Type

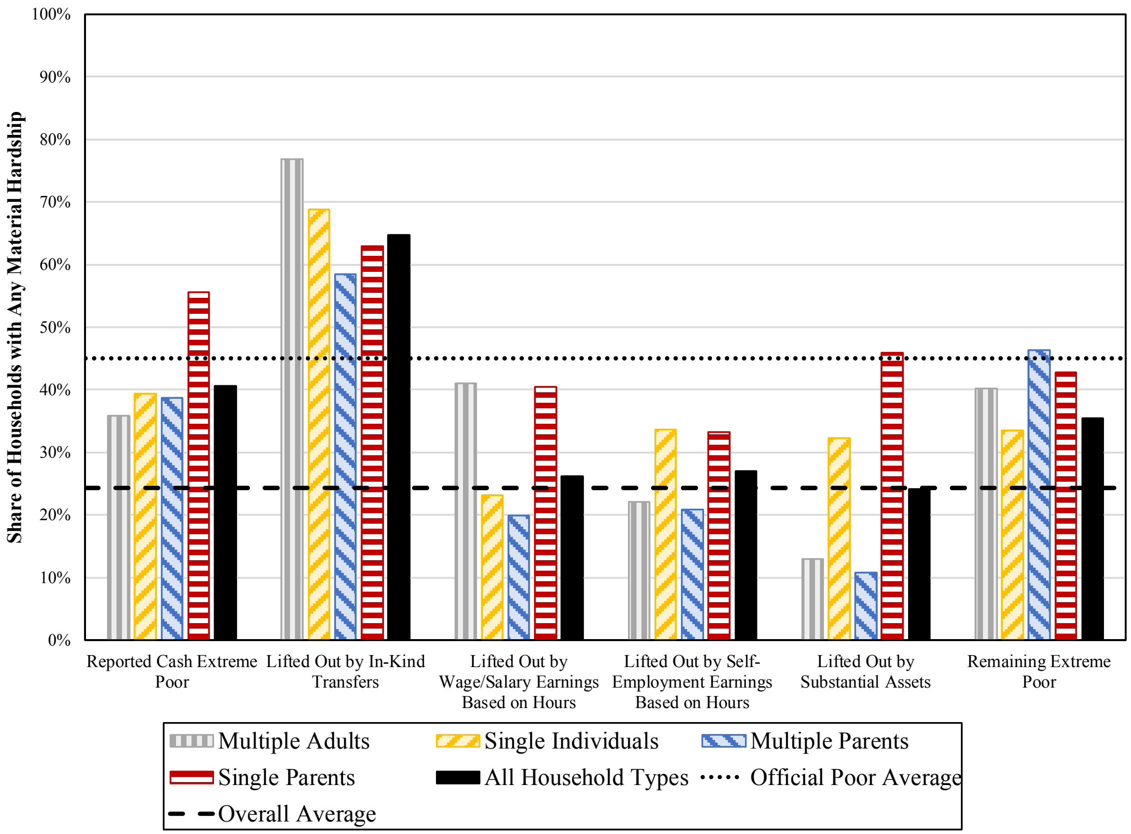


Figure 7. Number of Home Problems for Extreme Poor Subgroups, by Household Type

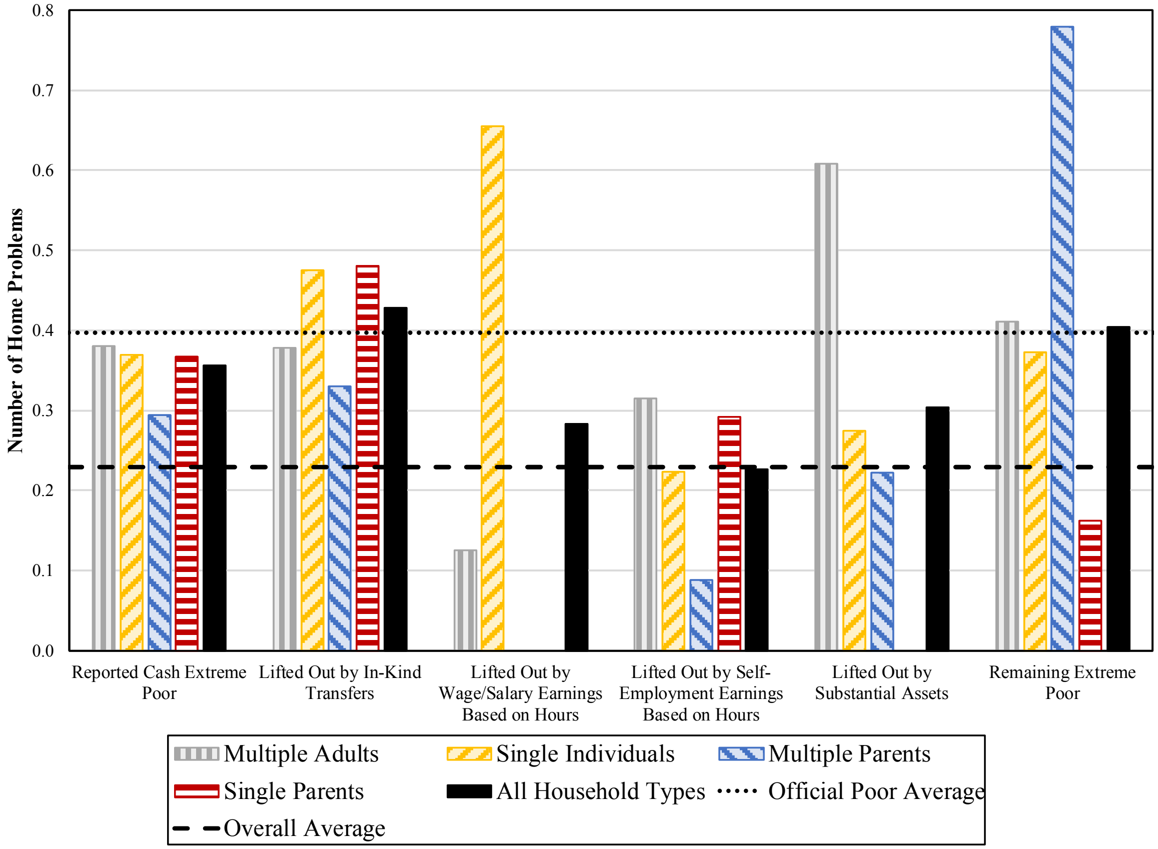


Figure 8. Number of Appliances Owned by Extreme Poor Subgroups, by Household Type

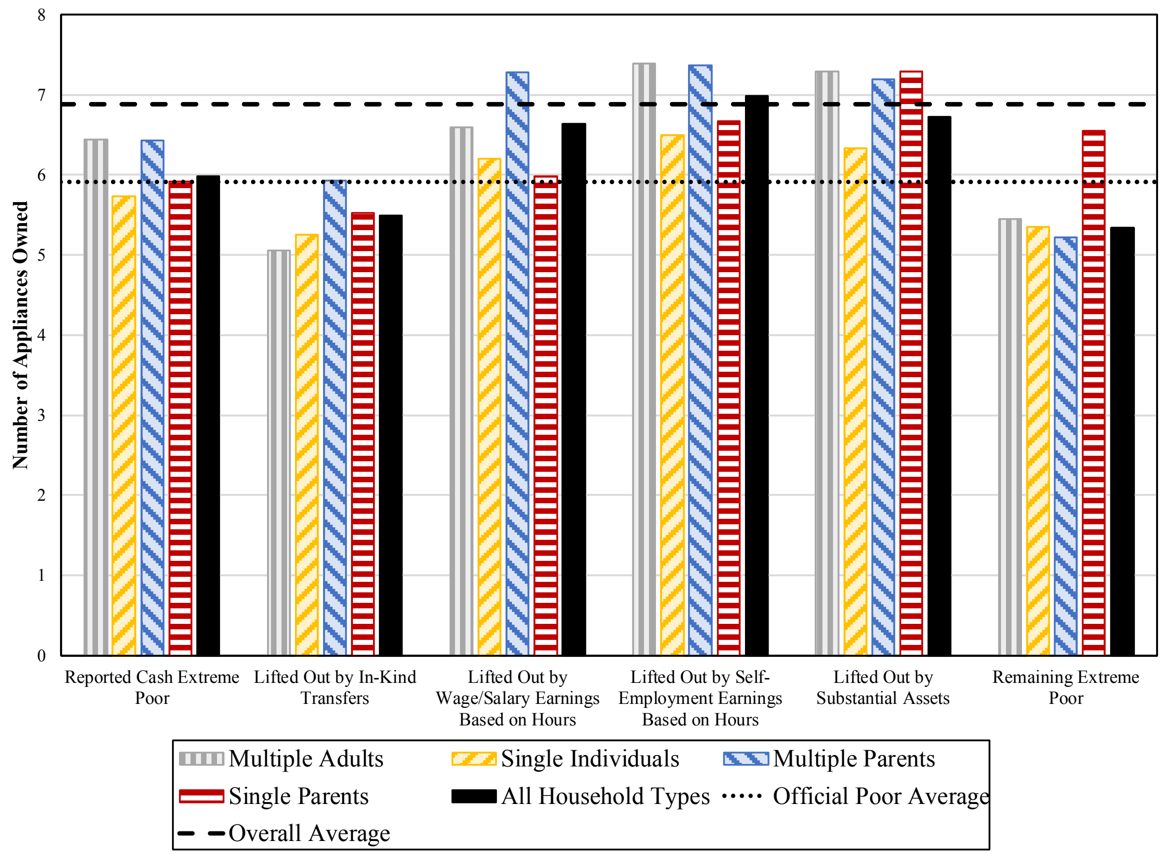
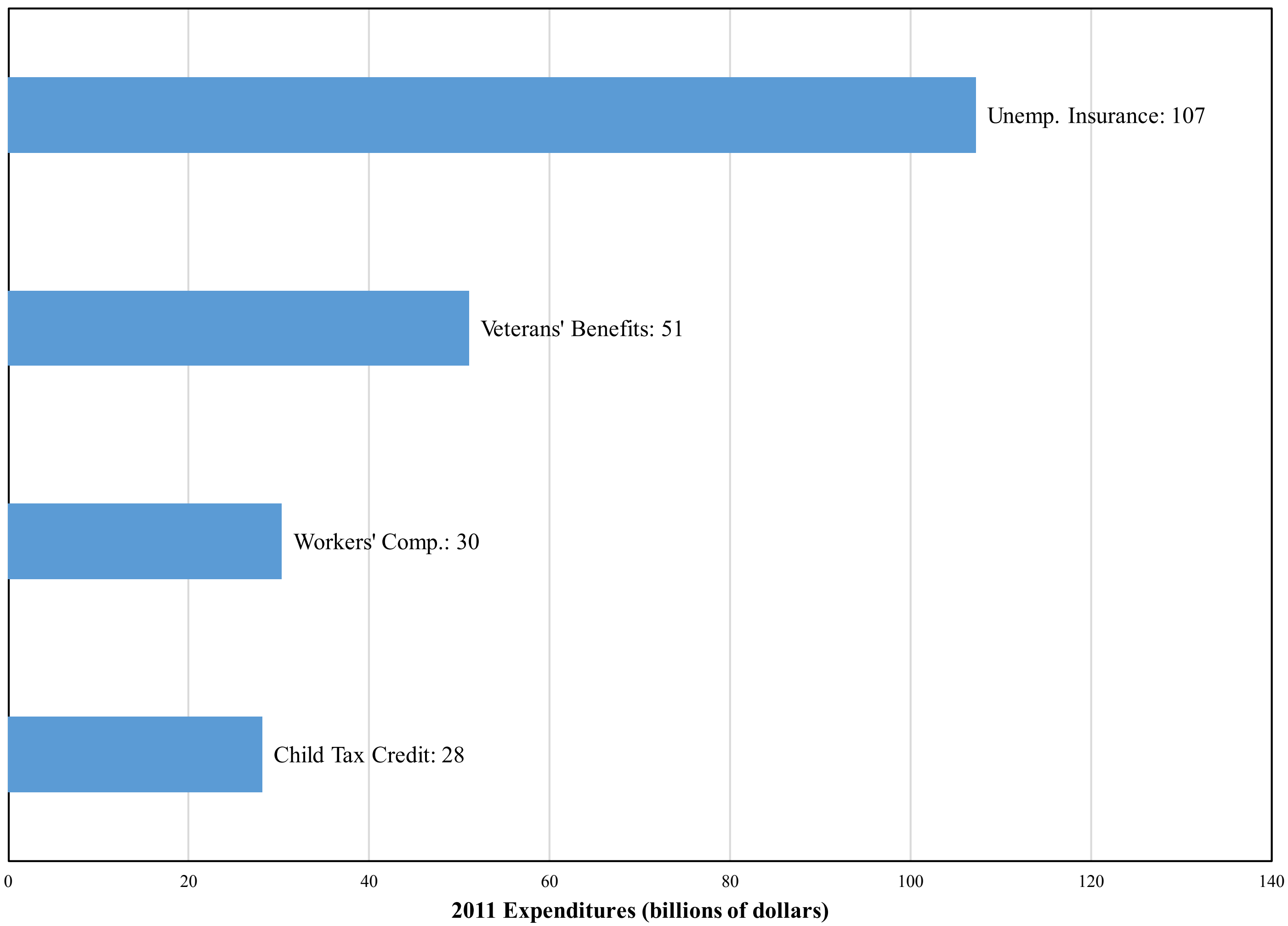


Figure 9. Expenditures on Four Largest Transfer Programs Not in Administrative Data



Notes: Does not include Medicare and Medicaid. OASDI, EITC, SSI, housing assistance, and SNAP are in the administrative data. Unemployment insurance, veterans' benefits, workers' compensation, child tax credit, public assistance, school food programs, WIC, and LIHEAP are *not* in the administrative data. Expenditures data from National Income and Product Account Table 3.12 and other sources; see appendix.