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THE POVERTY REDUCTION OF SOCIAL SECURITY AND MEANS-TESTED TRANSFERS

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ABSTRACT

Many studies examine the anti-poverty effects of social insurance and means-tested transfers, relying solely on survey data with substantial errors. We improve on past work by linking administrative data from Social Security and five large means-tested transfers (SSI, SNAP, Public Assistance, the EITC, and housing assistance) to 2008-2013 Survey of Income and Program Participation data. Using the linked data, we find that Social Security cuts the poverty rate by a third – more than twice the combined effect of the five means-tested transfers. Among means-tested transfers, the EITC and SNAP are most effective. All programs except for the EITC sharply reduce deep poverty (below 50% of the poverty line), while the impact of the EITC is more pronounced at 150% of the poverty line. For the elderly, Social Security single-handedly slashes poverty by 75%, more than 20 times the combined effect of the means-tested transfers. While single parent families benefit more from the EITC, SNAP, and housing assistance, they are still relatively underserved by the safety net, with the six programs together reducing their poverty rate by only 38%. SSI, Public Assistance, and housing assistance have the highest share of benefits going to the pre-transfer poor, while the EITC has the lowest. Finally, the survey data alone provide fairly accurate estimates for the overall population at the poverty line, although they understate the effects of Social Security, SNAP, and Public Assistance. However, there are more striking differences at other income cutoffs and for specific family types. For example, the survey data yield 1) effects of SNAP and Public Assistance on near poverty that are two-thirds and one-half what the administrative data generate and 2) poverty reduction effects of SSI, Social Security, and Public Assistance that are 34-44% of what the administrative data produce for single parent families.

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A online appendix is available at http://www.nber.org/data-appendix/w24567

1 Introduction

The majority of government expenditures go towards social insurance and means-tested transfers. Social insurance programs are available to all individuals who have experienced unfortunate circumstances or are aged. These programs include Social Security retirement and disability insurance, unemployment insurance, and Medicare. Means-tested transfers, on the other hand, provide cash or in-kind assistance to only those with the lowest incomes. These programs include the Supplementary Nutrition Assistance Program (SNAP, formerly called food stamps), Supplemental Security Income (SSI), and Public Assistance, as well as certain tax credits, housing assistance, and Medicaid. All told, these programs constituted 57% of all federal outlays in 2015, in addition to a large share of state spending.[1] Given the purposes of these programs, two first-order questions are the following: 1) Does the money go to those whose current incomes are low, and 2) How effective are these programs in lifting recipients out of poverty? Using combined survey and administrative data, this paper analyzes the poverty reduction of social insurance and means-tested transfer programs and the extent to which their dollars are targeted to the poor.

There is a long literature on the distributional and poverty-reducing effects of transfer programs. Unfortunately, a major difficulty for this literature is that survey data alone are not up to the task of capturing these transfers. Most programs in most survey data are sharply under-reported. Meyer et al. (2015a) find that in recent years, the Current Population Survey (the source of official income and poverty statistics) missed 50% of Public Assistance dollars, 42% of SNAP dollars, and 16% of SSI spending.[2] For other key benefits or tax credits, surveys often do not ask about receipt or the amount of the benefit received. Because of these impediments, in this paper we rely on administrative microdata on Social Security (including retirement and disability benefits) and five of the largest means-tested transfer programs (SNAP, TANF, SSI, housing benefits, and the Earned Income Tax Credit or EITC).[3] We link these administrative data to 2008-13 data from the Survey of Income and Program Participation, the household survey that previous research has found to provide the most accurate and complete information on transfer programs (see Meyer et al., 2015b).

[1] See Table 3.1 of the Office of Management and Budget's Historical Tables: https://obamawhitehouse.archives.gov/omb/budget/Historicals
[2] Specifically, these numbers refer to the 2000-2012 period.
[3] We use data on actual benefits paid for all programs except for the EITC, for which we calculate the credit amount for all those the IRS believes are eligible tax units.

Linking survey and administrative data combines the accuracy of the administrative measures with the rich demographic detail and population representativeness of the survey. While the available administrative data are currently incomplete in program, geographic, and chronological coverage, there is still great value in combining sources – especially given that misreporting on surveys is getting worse over time and carefully validated imputation methods are not available (Meyer et al., 2015a). Furthermore, since the administrative data on their own sometimes incompletely cover certain transfers in the survey data (e.g., Public Assistance and housing assistance), combining the data sources allows the most accurate and complete estimates of program effects. While administrative program data have been linked to surveys in the past, we have greater program and population coverage than any past research. Where possible, we contrast the results obtained from the combined data with those using survey data alone. This paper is one of the first steps in a larger project that seeks to improve income measurement by linking administrative income sources to household surveys whenever possible. We call this larger project the Comprehensive Income Dataset project, and it is described in Medalia et al. (2018).

We first survey the literature on the anti-poverty effects of these programs, noting that social insurance has larger impacts than means-tested transfers on the poverty rate but that means-tested transfers have a relatively larger impact on reducing the poverty gap. Social Security consistently produces the largest anti-poverty effect among all transfers (targeting elderly and disabled beneficiaries across the entire income distribution), while the EITC has the largest effect among means-tested transfers (targeting employed families with children, often those around the poverty line). While many means-tested programs heavily target their dollars to the pre-transfer poor, they often phase out at income levels significantly below the poverty line – tempering their anti-poverty effects. However, comparisons of poverty reduction estimates across programs and papers are complicated by differences in methodologies, surveys used, and time periods examined.

Using a pre-tax, pre-transfer measure of base income, our results show that Social Security singlehandedly cuts the poverty rate by a third and the poverty gap by 45%, more than twice the combined effect of the five means-tested transfers. Among means-tested transfers, the EITC and SNAP are most effective at reducing the poverty rate, although SSI, SNAP, Public Assistance, and housing assistance are most targeted to the pre-transfer poor. All programs except for the EITC have relatively larger effects on deep poverty (50% of the poverty line), with the impacts on the poverty rate rather uniform across means-tested transfers excluding Public Assistance. The EITC generates a more pronounced reduction in near poverty (150% of the poverty line), and the impacts on the poverty gap are now more uniform among means-tested transfers excluding Public Assistance.

While the SIPP does rather well in yielding average estimates similar to those from the combined data, it understates the poverty reduction of Social Security, SNAP, and particularly Public Assistance. The survey also overstates the extent to which SNAP targets the pre-transfer poor. There are more striking contrasts for particular income cutoffs and family types. The survey data yield effects of SNAP and Public Assistance on near poverty that are, respectively, two-thirds and one-half what the combined data generate. For single parent families, the poverty reduction of Social Security, Public Assistance, and SSI calculated from the survey data are 34%, 38%, and 44%, respectively, of what the combined data produce.

Section 2 provides background on these transfer programs, and Section 3 discusses the findings in the literature and quality of the data used in these studies. Section 4 describes the data and methodology, and Section 5 presents the results. Section 6 discusses the implications of these results, and Section 7 concludes.

2 Background on Transfer Programs

Among the transfer programs on which this paper focuses, four are cash transfers (Social Security, Supplemental Security Income, Public Assistance, and the Earned Income Tax Credit) and two are in-kind transfers (the Supplemental Nutrition Assistance Program and housing assistance). This section briefly describes the benefits and eligibility requirements of each of these six programs, as well as the major social insurance and means-tested transfers less extensively examined in this paper. Figures 1a and 1b indicate, based on 2008 expenditures, that Social Security is by far the largest social insurance program and that the four largest means-tested transfer programs are among the five studied in this paper. In particular, Social Security constituted 84% of all social insurance transfers in 2008 (excluding Medicare), while the five means-tested programs in this study constituted 79% of all means-tested transfers in 2008 (excluding Medicaid). Together, these six programs comprised 83% of all transfers in 2008 (excluding Medicare and Medicaid).

Social Security (OASDI)

Social Security, also known as the Old Age, Survivors, and Disability Insurance Program (OASDI), is a composite of two programs administered by the Social Security Administration (SSA): the Old-Age and Survivors Insurance Program (OASI) and the Disability Insurance Program (DI). As a social insurance program, Social Security provides monthly payments designed to partially offset the loss of income due to retirement or death (for the case of OASI) or disability (for the case of DI). The earliest age at which retired individuals are eligible for OASI benefits is 62, with full retirement benefits available starting at age 65-67 (depending on the retiree's date of birth). Qualifying retirees must have worked for a certain number of "credits" (typically 40 quarters or 10 years of work). Surviving spouses can also receive OASI benefits upon the death of a worker covered by Social Security. Finally, individuals are eligible for DI if they have recently worked long enough (based on certain criteria) and are deemed to have a long-term disability that inhibits them from continuing in their previous jobs.

Supplemental Security Income (SSI)

The Supplemental Security Income (SSI) program is a federal cash assistance program specifically targeting individuals with low incomes and who are also aged (65 or over), blind, or disabled. The Social Security Administration administers the federal SSI program. In addition to the federal program, states can augment benefits through their own supplementation programs (Daly and Burkhauser, 2003). Individuals must meet several criteria to be eligible for federally-administered SSI. First, given that SSI is a means-tested transfer, they must meet separate income and asset limits. Income limits are indexed to inflation and are in general slightly lower than the official poverty thresholds from the U.S. Census Bureau. Asset limits are set at $2,000 and $3,000 for non-elderly individuals and couples, respectively (Duggan et al., 2016).[4] Eligible individuals must also meet residency and citizenship standards. Finally, individuals might have to meet additional criteria to obtain state-administered SSI payments.

Public Assistance

Public Assistance broadly refers to benefits (often in the form of cash welfare) offered by state and local governments to needy families and individuals. An especially prominent program is the

[4] See also https://www.ssa.gov/ssi/text-resources-ussi.htm.

Temporary Assistance for Needy Families (TANF) program, which is federally-funded but run by states and targeted to low-income families with children. Formerly known as Aid to Families with Dependent Children (AFDC), TANF is funded through a block grant to states, which have flexibility to set their own benefit levels and types, income and asset limits, etc. (Moffitt, 2003). As a result, there is often significant variation across states in how the grant money is spent and what types of families are eligible. Nevertheless, families receiving TANF tend to have single parents or no parents at all.[5] However, there are certain eligibility criteria that are specified at the federal level. Adults cannot receive TANF payments for more than sixty months over their lifetimes, although states can exempt this requirement for twenty percent of caseloads (Ziliak, 2016). Furthermore, 50 percent of all TANF families must work for at least 30 hours per week, and 90 percent of all two-parent TANF families must engage in work – usually for 35 hours per week.[6]

Earned Income Tax Credit (EITC)

The Earned Income Tax Credit (EITC) is given to individuals and couples with positive earnings, especially those with qualifying children. Eligible families can only claim the credit if they file a tax return. The EITC can be used to offset positive tax liabilities, but the majority of families receive it as a lump sum refund given that it usually exceeds these liabilities (Nichols and Rothstein, 2016). The IRS generally issues these refunds within a few weeks of the tax returns being filed. A number of states also augment the credit by building the EITC into their own income tax systems, with these benefits typically equal to a given percentage of the federal EITC amount (Hotz and Scholz, 2003).

Eligibility for the EITC is contingent on several factors. First, the generosity of the credit increases with the number of qualifying children (i.e., younger than 19, with exceptions for full-time students and disabled children) in the tax unit. Second, only those with earnings receive the credit. The EITC schedule consists of several segments, with the credit initially being proportional to earnings, then remaining at a maximum level for a range of earned income, and finally decreasing with additional earnings until the credit completely phases out. Third, filers must also have an adjusted gross income (AGI) under a given threshold to be eligible, with a higher threshold for joint (married) filers than single (unmarried) filers.[7]

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[5] See https://www.acf.hhs.gov/ofa/resource/character/fy2010/fy2010-chap10-ys-final.
[6] See https://www.cbpp.org/research/policy-basics-an-introduction-to-tanf.
[7] In 2016, this threshold was $53,505 for a family of three or more qualifying children with the parents filing jointly.

Supplemental Nutrition Assistance Program (SNAP)

The Supplemental Nutrition Assistance Program (SNAP) is the largest of the food and nutrition assistance programs provided by the U.S. Department of Agriculture (USDA). Formerly known as the Food Stamp program, SNAP benefits consist of in-kind vouchers (now EBT cards) that recipient households can use to purchase items from grocery stores (Currie, 2003). Unlike most of the transfer programs discussed in this section, SNAP is widely available to all low-income households regardless of age, employment status, presence of children, etc. In particular, households are eligible for SNAP as long as their gross monthly income is at or below 130 percent of the poverty line, net income (defined as pre-tax cash income after deductions) is at or below the poverty line, and countable assets are less than $2,250 (or $3,500 if the household has an elderly or disabled member).[8] There are work requirements for most able-bodied adults without dependents. Benefit amounts are decreasing in net income and tied to the cost of a market basket of foods intended to provide a nutritious diet at minimal cost (Hoynes and Schanzenbach, 2016). In 2017, the estimated average monthly benefit for a household size of two was $253.[9]

Housing Assistance

Federal agencies as well as states and localities offer a wide variety of housing assistance programs. At the federal level, the Department of Agriculture and particularly the Department of Housing and Urban Development (HUD) support the largest programs (see Olsen, 2003). Public housing programs provide rental houses or apartments that are managed by local housing agencies and funded by HUD (Collinson et al., 2016). The Section 8 Housing Choice Voucher Program provides vouchers to tenants who are free to choose any housing that meets minimum health and safety standards. With Section 8 project-based rental assistance, private landlords contract directly with HUD to offer lower rents to tenants. While these are the largest federal low-income housing assistance programs, states and local areas often provide additional rental assistance programs for low-income families.

Public housing and housing choice voucher programs specifically target low-income families, senior citizens, and disabled individuals. Eligibility for public housing is based on several factors, including whether a case falls into one of the three aforementioned categories, annual gross

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[8] See https://www.fns.usda.gov/snap/resources-rules-resource-limits.

[9] See https://www.cbpp.org/research/a-quick-guide-to-snap-eligibility-and-benefits.

income, and citizenship or immigration status. In particular, eligible applicants for public housing must have earnings below 80 percent of the median income for the county or metropolitan area of intended residence.[10] The eligibility criteria for housing choice vouchers are similar to those of public housing, with the exception being that the family's income may not exceed 50 percent of the median income for the county or metropolitan area of intended residence.[11] However, a local housing authority is obligated to provide 75 percent of its vouchers to families whose incomes fall under 30 percent of the area median income.

Other Safety Net Programs

There are several other welfare programs on which this study does not focus but which we briefly discuss here. Unemployment insurance (UI) programs, which are run by individual states, provide benefits for workers who have become unemployed through no fault of their own. Workers' compensation is another state-level social insurance program and provides wage replacement and medical benefits to individuals who are injured or fall ill during employment. Veterans' benefits constitute a wide variety of compensation types for veterans (and their dependents and survivors), including disability compensation, pensions, educational assistance, etc.

Among means-tested transfers, the child tax credit is available to tax units with children under the age of 17 and adjusted gross income below a given threshold ($110,000 for joint filers and $75,000 for a single filer).[12] School food programs (i.e., the School Breakfast Program and National School Lunch Program) provide free or subsidized school meals to low-income children, and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides in-kind assistance on a variety of fronts (e.g., nutritious foods, nutrition education, health care referrals). The Low Income Home Energy Assistance Program (LIHEAP) is another means-tested transfer that assists low-income households with paying for their utility costs.

Finally, in terms of expenditures, Medicare is the second-largest social insurance program (behind Social Security) and Medicaid is the largest means-tested transfer. Medicare provides hospital insurance and supplemental medical and prescription drug coverage for the elderly and non-elderly disabled, while Medicaid assists with medical costs for low-income and disabled individuals. For several reasons, we do not include Medicare and Medicaid in the programs we analyze here.

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[10] See https://www.hud.gov/topics/rental_assistance/phprog.
[11] See https://www.hud.gov/topics/housing_choice_voucher_program_section_8.
[12] See https://www.irs.gov/newsroom/ten-facts-about-the-child-tax-credit.

These publicly provided health coverage programs are valued very differently by different people depending on their health status and the availability of other sources of care. This heterogeneity, combined with lack of fungibility and divergent perspectives on how to assess their value (e.g., cost to the government, willingness-to-pay of recipients, etc.), leads us to leave them for later work.

3 Prior Literature

A long literature has examined the poverty reduction due to these safety net programs over different time periods and for different types of families. In this section, we focus on the major findings regarding the direct effects of these programs on incomes and various poverty measures.[13] We also discuss the quality of the data used in these studies and the extent to which the literature has corrected for measurement error in the data.

The official poverty measure in the United States compares a family's pre-tax cash income to poverty thresholds that vary by family size and composition. One widely recognized shortcoming of this measure is that it omits taxes, tax credits, and non-cash benefits from the definition of a family's resources (see Citro and Michael, 1995; Meyer and Sullivan, 2012a). As a result, an analysis of the official poverty rate (which has shown virtually no long-term trend over time) overlooks the major expansion in recent decades of tax credits like the EITC and in-kind benefits like food stamps and housing assistance. While a number of studies have assessed the anti-poverty effects of such transfers (in addition to cash assistance programs), they often vary in how they define base income. For example, the Census Bureau's Supplemental Poverty Measure (SPM) classifies base income as post-tax and post-transfer, and calculates the effect of a transfer by subtracting it from the base income (Fox, 2017). Other studies utilize pre-tax cash income as the base income, adding to it tax credits and in-kind transfers and subtracting from it pre-tax cash assistance (Hoynes et al., 2006). Finally, some studies classify base income as pre-tax and pre-transfer, and compute the effect of a transfer by adding it to the base income (Scholz et al., 2009; Ben-Shalom et al., 2012). As a result, these methodological differences complicate comparisons of poverty reduction estimates across programs and papers.

[13] The literature has tended to focus on TANF when discussing cash welfare, but we focus on a broader measure (Public Assistance) that encompasses TANF, General Assistance, and other forms of state and local cash assistance.

Direct Effects of Transfer Programs

Table 1 lists the transfer programs included in some of the key studies analyzing the anti-poverty effects of multiple programs. Scholz et al. (2009) find that social insurance and means-tested transfers (incorporating Medicare and Medicaid) reduced the poverty rate in 2004 by 38% and 22%, respectively. They also find that social insurance and means-tested transfers filled the poverty gap by 48% and 36%, respectively. Even though social insurance dollars are less targeted to the pre-transfer poor, they have a larger anti-poverty impact than means-tested program dollars (in absolute terms) because of the sheer size of Social Security. However, means-tested transfers have a relatively larger impact on reducing the poverty gap than the poverty rate, because many means-tested transfers begin to phase out at income levels significantly below the poverty line.

Other studies have observed similar patterns. Hoynes et al. (2006) find that means-tested cash and non-cash transfers reduced the non-elderly poverty rate in 2003 by 7% and 13%, respectively, while social insurance cash transfers reduced the non-elderly poverty rate by 18%. However, Scholz and Levine (2001) estimate that means-tested cash and non-cash benefits make up more than three quarters of the total effect of all transfers in filling the non-elderly poverty gap. Between 1993 and 1999, means-tested transfers had double the effect of social insurance programs in reducing the poverty gap (Blank, 2002). These patterns are also consistent with means-tested transfers having larger effects on deep poverty rates than on the traditional poverty rate (Fox et al., 2015; Tiehen et al., 2015; Meyer and Mittag, 2017).

There is also significant variation in program effects within social insurance and means-tested transfers. As previously alluded to, Social Security is responsible for by far the largest poverty reduction among all transfers – not merely social insurance programs. Scholz et al. (2009) find that OASI and DI reduced the total poverty rate by 26% and 7%, respectively. No other transfer program decreased the poverty rate by more than 12%. At least in recent years, the relative importance of Social Security has been remarkably stable. Short (2012) finds that OASDI's effect on the poverty rate in 2011 was 3 times as large as the anti-poverty effect of the next most important transfer (excluding Medicare and Medicaid): refundable tax credits. In 2016, the effect of OASDI was still 3.2 times as large as that of refundable tax credits (Fox, 2017).

Among means-tested transfers outside of Medicaid, the literature has consistently shown the EITC to have the largest effect on reducing the poverty rate, with the impact swelling over time as the EITC grew in importance. In 1992, the EITC decreased the poverty rate by 5%, which was identical to the effect of SNAP and nearly twice as large as the effect of housing assistance (Iceland et al., 2001). Meyer (2010) finds that the EITC reduced the poverty rate by 10% in 2007, and Short (2012) calculates a reduction of 17% in the poverty rate associated with refundable tax credits in 2011 (which encompass both the EITC and the child tax credit). Indeed, Fox (2017) finds that the effect of refundable tax credits on the poverty rate was more than double that of each of the next most important means-tested transfers (SNAP, SSI, and housing subsidies). As studies like Liebman (1998) and Meyer (2010) have noted, the recipients of the EITC tend to be closer to – and therefore more likely to be moved across – the poverty line.

There is less variation in the magnitudes of the anti-poverty effects of other programs (excluding Medicare and Medicaid), but SNAP plays a relatively important role. Scholz et al. (2009) and Fox (2017) both find that it yields the second-largest poverty reduction among means-tested transfers, and Short (2012) and Tiehen et al. (2015) calculate the effect of SNAP on the poverty rate to be 9.3% and 8%, respectively, in 2011. SSI and housing assistance have slightly smaller anti-poverty effects than SNAP, while the effects of TANF have diminished greatly since welfare reform in the 1990s. The role of UI is highly countercyclical, as it had a static anti-poverty effect similar to that of SNAP in 2010 and 2011 (when unemployment benefits were extended at the height of the Great Recession) while its poverty reduction was substantially smaller and similar to TANF's in 2016 (Short, 2012; Fox, 2017).

Several studies have also explored how to incorporate Medicare and Medicaid into measures of poverty. Scholz et al. (2009) value Medicare at 2.5 times the average cost of a fee-for-service plan and Medicaid at the cost of a typical HMO policy. They find that Medicare decreases the pre-transfer poverty rate for all families by 10% (second in importance only to OASDI among social insurance programs) and Medicaid by 11% (larger than any other single means-tested transfer). More recent work by Korenman and Remler (2016) develops and implements a health-inclusive poverty measure that adds a need for health insurance to the Census Bureau's SPM threshold and incorporates government and employer health insurance benefits into household resources. Under this measure, Medicare and Medicaid decrease the pre-transfer poverty rate for individuals under age 65 by approximately 7% and 11%, respectively (Remler et al., 2017).

Program Effects by Family Type

Since social insurance and means-tested transfers are often intended for certain types of recipients, many studies also emphasize their effects on those families most targeted by these transfers. Here, we concentrate on what the literature has found regarding the effects of transfer programs on poverty and incomes of the following family types: elderly families, disabled families, and families with children (who can in turn be divided into single parent and multiple parent families).

Elderly Families and Disabled Families

Elderly families receive most of their transfer dollars from OASI, while the disabled receive a large portion of their benefits from DI and SSI. Unlike transfers designed to cover only food expenses or medical care, Social Security (which encompasses OASI and DI) is intended to cover all expenses and is therefore associated with considerably higher benefit amounts than most other programs (Moffitt, 2015; Ben-Shalom et al., 2012). Consequently, average transfer expenditures in 2004 were at least twice as large for elderly families and disabled families as they were for unemployed families and single parent families (Ben-Shalom et al., 2012).

The decline in the official poverty rate for the elderly since the late 1960s generally coincides with increases in Social Security benefits over this time period (Hoynes et al., 2006), and Engelhardt and Gruber (2006) find causal evidence that changes in Social Security benefits can explain virtually the entire decline in poverty. Short (2012) and Fox (2017) find that Social Security singlehandedly reduced the SPM poverty rate for the elderly by 70% in 2011 and 72% in 2016, respectively. For context, the second- and third-most important programs for the elderly in 2016 were housing assistance and SSI, whose effects on the poverty rate were each 1/25th the magnitude of Social Security's effect. Nevertheless, it is important to remember that Social Security is a social insurance program that benefits higher-income elders as well as lower-income elders (Engelhardt and Gruber, 2006). As a result, these large poverty reductions are simply a direct result of the tremendous size of the OASDI program.

Overall, the safety net yields large reductions in poverty for the elderly and disabled, especially in comparison to other types of families. Ben-Shalom et al. (2012) find that, in 2004, all transfers together (including cash assistance, in-kind transfers, and tax credits but excluding Medicare and Medicaid) decreased the poverty rate for the elderly and disabled by 83% and 73%, respectively. In contrast, these effects were only 17% and 41% for unemployed families and single parent families, respectively.

Families with Children

Unlike the elderly and disabled, non-elderly parents with children are much more likely to receive means-tested transfers. Prior to the 1990s, single parent families were especially dependent on cash welfare (Blank, 2002; Haveman et al., 2015). However, welfare reforms in the 1990s substantially reduced AFDC/TANF caseloads and expanded the EITC in the hopes of creating a more work-based income support system. As a result of a more generous EITC and the expansion of the economy in the 1990s, single parent families on average saw rising incomes despite the reduction in cash welfare (Meyer and Rosenbaum, 2001; Grogger, 2003). Hoynes and Patel (2015) find that the 1993 EITC expansion led to a 7.9 percentage point decrease in the poverty rate for single-mother families. However, not all single parent families benefited from these reforms. In fact, several studies have found that the poorest quintile of single-mother families saw decreases in their reported incomes in the late 1990s (Jencks et al., 2001; Haskins, 2001). These were families who had trouble finding employment (inhibiting them from reaping EITC benefits) and saw reductions in cash welfare.[14] On average, multiple parent families saw even larger increases in incomes as a result of these reforms, since they tended to have higher earnings and more children (Moffitt, 2015). However, this pattern may have been influenced by the under-reporting of transfers that we have emphasized in this paper, which tends to be worse in surveys besides the SIPP. Meyer and Sullivan (2004, 2008) note that the relative well-being of single mothers (both average and the least well-off) did not decrease relative to their single childless or married counterparts when examining consumption patterns.

Meyer (2010) estimates that the EITC reduced the child poverty rate by 16% in 2007. Short (2012) and Fox (2017) estimate that refundable tax credits diminished the child poverty rate by 26% and 28% in 2011 and 2016, respectively. In addition to the EITC, SNAP decreased the child poverty rate and gap by an average of 6.2% and 16.4% from 2000 to 2011 (Tiehen et al., 2015). Indeed, Fox et al. (2015) determine that the EITC and nutritional assistance programs together played a larger role in reducing child poverty in 2012 than cash welfare did at its peak in the 1980s. Shaefer and Edin (2013) also find that, in 2011, SNAP reduced the rate of extreme poverty among households

[14] Moreover, many of these families saw reductions in food stamps along with TANF, since losing TANF typically meant losing automatic eligibility for food stamps (Moffitt, 2015).

with children by 48% (where extreme poverty is associated with living in a household earning $2/day/person or less). Furthermore, housing assistance programs have a notable impact on children, especially those of single parents who are often given preference for a restricted number of available slots (Scholz et al., 2009). Finally, TANF decreased the child poverty rate by less than 3% in 2016, which – while nontrivial – falls short of the impacts of the aforementioned means-tested transfers (Fox, 2017). These relatively weak effects for TANF were especially apparent during the Great Recession (Bitler and Hoynes, 2010, 2016). In sum, the EITC, SNAP, and housing assistance play an increasingly large role in lifting families with children out of poverty (with effect sizes varying across studies), while the relative importance of TANF has fallen sharply over time.

Dealing with Measurement Error

Nearly all of the studies mentioned in this section rely on survey data to analyze the anti-poverty effects of transfer programs. While the merits of survey data lie in its accessibility and the richness of the data collected, misreporting in surveys has been found to pervade a wide range of important variables (see Bound and Krueger, 1991; Bollinger, 1998; Bound et al., 2001; Dahl and Schwabish, 2011; Abowd and Stinson, 2013; Bee and Mitchell, 2017). Meyer et al. (2015a) find significant misreporting for many government transfer programs across a number of surveys. A few studies conduct analyses using the SIPP (see Iceland et al., 2001; Scholz et al., 2009; Ben-Shalom et al., 2012), which is the survey with the most accurately reported income and transfer data. However, the vast majority of studies use the CPS Annual Social and Economic Supplement (among others, see Blank, 2002; Engelhardt and Gruber, 2006; Hoynes et al., 2006; Bitler and Hoynes, 2010; Fox et al., 2015; Tiehen et al., 2015). While the CPS ASEC does serve as the source of official government statistics, it also suffers from pronounced under-reporting. Other studies like CBO (2013) and Bitler et al. (2017) use a combination of the CPS and the IRS's administrative Statistics of Income public-use tax file.

Most of these survey-based studies do not attempt to formally adjust for misreporting, though sometimes they qualitatively discuss how estimates might be biased by measurement error in the survey. Some studies, to their credit, do attempt to correct for misreporting within the survey. For example, CBO (2013) appears to adjust survey-reported transfers by multiplying the survey amounts for a given transfer by a single fraction so that the weighted survey aggregates match the administrative totals. This, however, relies on the strong assumption that the original distribution of survey responses is correct and that misreporting is therefore uniform across all observations. Other studies like Scholz et al. (2009) and Ben-Shalom et al. (2012) use observable survey characteristics to estimate a probit model of program receipt, and assign receipt to the households with the highest predicted receipt probabilities until the number of weighted survey recipients matches administrative totals. However, by assigning receipt to the most likely recipients, this method leads to over-imputation for likely recipients and under-imputation for less likely recipients (Mittag, 2017). Moreover, the parameters used to predict true receipt probability are themselves biased because they are originally estimated using misreported data. Very few studies opt for what we consider the “gold standard” in correcting for misreporting: linking together survey and administrative data (see Nicholas and Wiseman, 2010; Fox et al., 2017; Meyer and Mittag, 2017).

4 Data and Methods

In this paper, we take a step toward addressing measurement error by simultaneously linking administrative reports for six separate transfer programs to a recent panel of a well-reported survey focusing on transfer receipt. Our main approach involves examining how poverty rates and gaps change when adding each of these programs (as well as combinations of programs) to a base measure of market income, calculating the change using a combination of administrative and survey data or survey data alone. As a result, we not only paint an accurate picture of the relative importance of each program on poverty (treating the combined measures as “truth”) but also probe the ways in which the survey reports fall short of the combined values. To the best of our knowledge, this is the first time that so many sources of administrative microdata on government transfers have been concurrently linked to a survey to examine these issues.

Data

Survey Data

Our survey data come from the 2008 panel of the Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal survey in which individuals are interviewed in four-month intervals known as interview “waves”. In each wave, the SIPP collects detailed information about different types of income and government programs received (among other topics) during each of the four months since the last interview wave. While the 2008 SIPP technically includes 16 interview waves, we use only the first 14 waves.[15] The reference months corresponding to these waves span May 2008 to March 2013.

Our unit of analysis is a family-wave. Approximately 47,000 families were first interviewed in Wave 1 of the 2008 SIPP, resulting in 490,000 family-wave observations across the 14 interview waves (with attrition). For the purposes of this study, a family is defined as either a group of two or more related individuals living together or an unrelated individual. As a result, there are more families than households. Our analysis focuses on families to align with the units used by official estimates to calculate poverty. We also follow the methodology of the official poverty estimates and exclude families residing in group quarters and unrelated individuals under age 15.[16]

Administrative Data

Our administrative records come from a variety of sources. Table 2 shows for each transfer program the source of the administrative records, the benefit unit, the disbursement frequency, and the states and years covered. OASDI and SSI administrative records come from the Social Security Administration's Payment History Update System (PHUS) and Supplemental Security Record (SSR) files, respectively. Benefits for these two programs are paid to individuals on a monthly basis. OASDI payments in the PHUS are originally split into monthly benefits paid directly (often referred to as net benefits) and medical insurance premiums withheld from the monthly disbursement. We sum these together to obtain gross OASDI benefits, which constitute our preferred measure of administrative OASDI payments.[17] SSI payments in the SSR are also originally split into monthly federal payments and monthly federally-administered state payments. We sum these together to obtain total federally-administered SSI benefits.

For Public Assistance, we have TANF administrative records from the Department of Health and Human Services (HHS), which collects them from various state agencies. States have the option to submit either sample or universe data to HHS, and 30 states submitted universe data for all years covered in the 2008 SIPP. Therefore, all results in this paper pertaining to Public Assistance are

[15] The data for waves 15 and 16 are not yet available for analysis and linkage to the administrative data.

[16] The U.S. Census Bureau defines group quarters as "a place where people live or stay, in a group living arrangement, that is owned or managed by an entity or organization providing housing and/or services for the residents". These include college dormitories, nursing centers, prisons, military barracks, etc. See https://www2.census.gov/programs-surveys/acs/tech_docs/group_definitions/2010GQ_Definitions.pdf.

[17] Note that the 1099-SSA sent to beneficiaries also uses gross benefits to calculate the taxable income.

calculated for the subsample of these 30 states.[18] These payments are disbursed at the family level on a monthly basis, although the family definition in the administrative data may differ from the definition in the SIPP. SNAP records come directly from various state agencies. In particular, we have data from 12 states that overlap with at least one calendar year of the 2008 SIPP.[19] Thus, all results pertaining to SNAP are calculated for this subsample of states and calendar years. SNAP payments are disbursed at the household level on a monthly basis.

Administrative records on housing assistance come from the Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification System (TRACS) files maintained by the Department of Housing and Urban Development (HUD). These records contain information on the bulk of public and subsidized housing assistance programs under HUD jurisdiction. A household's benefit amount is calculated as the difference between the gross rent and actual tenant payment. Past work has tended to find that gross rents closely approximate or slightly understate market rents (see ORC/Macro, 2001). While the administrative data include gross rent values for nearly all units that are part of voucher programs, they do not include rent amounts for publicly owned housing units. As a result, we impute the market rent for these units based on the average rent by five-digit zip code, household size, and year (and subsequently by five-digit zip code and year if rent is still missing).[20] We consider a household as active and receiving payments in a given month if it is within twelve months of the most recent certification date.

Finally, we calculate EITC amounts based on the Census Bureau's extracts of IRS 1040 Forms. The credit that a tax unit is eligible to receive as a refund during calendar year t is calculated based on its characteristics in tax year t - 1. We calculate the credit amount for those units the IRS believes are eligible based on their filing status, earned income, and qualifying dependents.[21] To

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[18] These states are: Alabama, Alaska, Arizona, Delaware, District of Columbia, Georgia, Hawaii, Idaho, Indiana, Iowa, Kentucky, Louisiana, Maine, Minnesota, Missouri, Montana, Nebraska, New Hampshire, New Jersey, North Dakota, Oklahoma, Oregon, Rhode Island, Tennessee, Utah, Vermont, Virginia, Washington, Wisconsin, and Wyoming.
[19] These states and calendar years are: Arizona (2009-13), Colorado (2012-13), Hawaii (2013), Idaho (2010-13), Illinois (2008-13), Indiana (2008-13), Maryland (2010-13), New Jersey (2008-13), New York (2013), Oregon (2009-13), Tennessee (2008-13), and Virginia (2009-13).
[20] Approximately 23% of all households in the administrative HUD data receive public housing and therefore do not have gross rent values in the administrative data. We only impute without using information on household size for approximately 5% of these households who need imputation. Less than 1% of public housing households lack information to allow imputation so we do not include them as recipients. Hedonic calculations by Ed Olsen suggest that our approach will overstate the gross rent in public housing by about 13% on average.
[21] The credit amounts and eligibility criteria can be found in IRS Publication 596, which is updated for every tax year: https://www.irs.gov/forms-pubs/about-publication-596.

convert the annual credit into monthly amounts, we divide the total amount by twelve and spread it evenly across all months in the calendar year.[22]

Note that the administrative values for all of these programs represent actual benefits paid with the exception of the EITC, for which we calculate the credit amount for all those the IRS believes are eligible tax units.

Alignment of Survey and Administrative Variables

The SIPP asks about receipt (yes/no) for five of the six programs for which we have administrative data (with the exception being the EITC). The SIPP asks about benefit dollar amounts for only four of the six programs for which we have administrative data (with the additional exception being housing assistance).[23] The SIPP also collects data on a number of programs for which we do not link administrative data, including unemployment insurance, veterans' benefits, and workers' compensation.

For some of the programs with both survey and administrative data, the SIPP measures receipt in a way that is not completely analogous to its administrative measure. Here, we briefly describe these cases and how we handle them. First, recall that we only have administrative data on federally-administered SSI benefits. Fortunately, the SIPP separately asks about federally- and state-administered SSI, so we compare the sum of these two survey-reported measures to the sum of administrative values for federally-administered SSI and survey reports of state-administered SSI.[24]

Moreover, the SIPP reports Public Assistance as the combination of TANF and other state and local cash welfare benefits, which covers a broader set of cash welfare programs than what is available in the administrative data (which cover only TANF). To address this, we treat all survey respondents reporting receipt that do not appear in the administrative data as true respondents, using their survey-reported amounts as truth. A similar situation exists for housing assistance, since we only have administrative data for most HUD-administered assistance while the survey asks about any type of housing assistance (including those provided by the Department of Agriculture, states,

[22] We acknowledge that this approach is not an ideal solution for assigning EITC benefits to months, especially since the annual amount is generally received at once.
[23] For a discussion on imputation methods used by the U.S. Census Bureau for housing subsidies, see Johnson et al. (2011) and Renwick and Mitchell (2015). Scholz et al. (2009) calculate housing benefits as the difference between the fair market rent in the state and reported rents paid by housing assistance recipients.
[24] The latter measure, while still potentially subject to misreporting on survey reports of state-administered SSI, is our best estimate of the true value of total SSI benefits.

and localities).[25] We once again treat survey respondents reporting receipt that do not appear in the administrative data as true respondents, but we now impute their assistance amounts using average benefits calculated from the administrative data by county, household size, and year (and by county and year if benefits are still missing). Later in this section, we discuss how these adjustments might bias our poverty reduction estimates.

Methods

Linking of Data Sources

We link the administrative data to the SIPP using individual identifiers created by the Person Identification Validation System (PVS) of the U.S. Census Bureau (Wagner and Layne, 2014). These identifiers are known as Protected Identification Keys (PIKs) and can be thought of as scrambled Social Security Numbers. Over 99 percent of most of the administrative records are linked to PIKs, and approximately 94 percent of family-waves in the SIPP contain at least one family member link to a PIK.[26] To account for incomplete linkage due to missing PIKs in the SIPP, we multiply the family-level survey weights by the inverse of the predicted probability that at least one member of a family has a PIK in a given wave (see Wooldridge, 2007). It makes sense to adjust for incomplete linkage at the family level, since most programs in the administrative data report benefits at the case level and we can match administrative cases to survey families as long as there is one common person between them. The online appendix provides further detail on this adjustment process and the construction of the predicted probabilities.

Unit of Analysis

In many instances, administrative cases (e.g., SNAP households, TANF families) do not line up exactly with survey families. In particular, an administrative case that links to the SIPP can either 1) be strictly contained within a survey family, 2) exactly correspond to a survey family (person to person), or 3) span multiple survey families. For the first two possibilities, we simply link all benefit dollars from the administrative case to the survey family. For the last possibility, we distribute

[25] Olsen (2003) states that public housing, project-based assistance from Section 236 and Section 8, and housing vouchers (which encompass 95% of all observations in our administrative data) account for approximately "70 percent of all subsidized rental units and about 50 percent of all units for low-income households that have received federal housing subsidies." Calculations in Olsen (2018) indicate that at least two million households receive assistance that is not covered by our PIC or TRACS data. However, these households tend to receive smaller subsidies than those received by the recipients in our administrative data.

[26] The administrative SNAP and TANF data have approximately 98-99% of all records matched to a PIK.

benefit dollars from the administrative case to each survey family proportionally to the number of individuals linked from that case to each family.[27] For the EITC, we link individuals in survey families only to primary and secondary filers from the administrative data.

Measuring Poverty

We define a family as being in poverty in a given wave if its average monthly income across the reference months of the wave is less than the average monthly poverty line in that wave.[28] Our base income measure is pre-tax, pre-transfer income and is calculated as the sum of earned income, asset income, distributions from pension plans, and lump-sum retirement payments (as reported in the survey). As a robustness check, we employ pre-tax cash income as an alternative measure of base income, since this is what the U.S. Census Bureau uses to calculate the official poverty rate. Finally, we use as our base price index a bias-corrected version of the CPI-U equal to the CPI-U less 0.8 percent per year. This correction roughly accounts for the biases that are known to plague the CPI-U (see Hausman, 2003; Berndt, 2006; Gordon, 2006; Meyer and Sullivan, 2012b).

Measurement Error

To motivate subsequent results, we first discuss the extent of survey error in receipt of transfer programs and benefit dollars. Table 3 compares total benefit dollars, calculated separately from survey reports and administrative values, by program and calendar year. We analyze only the four transfer programs for which we have benefit dollars in both the survey and administrative data, and we examine only calendar years 2009-12 since every month in these years is fully covered by the 2008 SIPP Panel. The first column of Table 3 reports aggregate benefit dollars calculated using survey reports over all families in the SIPP. The second column still calculates aggregate benefit dollars using survey reports but now over only those families that link to a PIK, with the survey weights adjusted for incomplete linkage to a PIK. As one should expect, the numbers in the first two columns are nearly identical.

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[27] For SNAP, TANF, and housing assistance, approximately 5% of all administrative cases that linked to the SIPP linked to multiple survey families. For the EITC, slightly less than 2.5% of all administrative case that linked to the SIPP linked to multiple survey families.

[28] In general, these averages are taken over the four reference months corresponding to a wave. However, they may be taken over fewer months if the administrative data for a given program are only available for a strict subset of months in an interview wave. For example, consider a family-wave in Colorado with reference period November 2011-February 2012. Because administrative SNAP data are only available for Colorado starting in January 2012, we would average across monthly incomes in January 2012 and February 2012 to calculate this family's poverty status for the given wave.

The third column utilizes the same sample and weighting adjustment as the second column but substitutes values from the combined data in place of survey reports to calculate benefit dollar totals. As the final column indicates, survey reports seem on average to be slightly overstated for SSI and understated for OASDI, SNAP, and Public Assistance, taking the combined values to be the truth. The understatement of OASDI receipt is small, slightly more than 8 percent in the worst year, while the understatement of SNAP and Public Assistance receipt is more noticeable at about 15 and 30 percent, respectively, in the most recent two years. The overstatement of SSI receipt varies quite a bit from year to year, from none in 2009 to 11% in 2011. These rates of reporting are similar to those previously found for these programs over a longer time period in the SIPP in Meyer et al. (2015b). While the under-reporting for OASDI, SNAP, and Public Assistance is clear, the degree of under-reporting is lower than that found previously for other programs in the SIPP (such as unemployment insurance or workers' compensation per Meyer et al., 2015b) or for these programs in other surveys (see Table 1 of Meyer et al., 2015a). The understatement of survey reports seems to have gotten marginally smaller over time for OASDI and larger over time for SNAP and Public Assistance. However, these trends are only over a short time period.

Table 4 decomposes the differences between the second and third columns in Table 1 into errors due to false positives (true non-recipients who report receipt in the survey), false negatives (true recipients who do not report receipt in the survey), and incorrect amounts reported by true recipients who report receipt in the survey. One can think about false positives and negatives as related to misreporting on the extensive margin, while measurement error among true reporting recipients is related to misreporting on the intensive margin. The average understatement of survey reports for OASDI appears to be driven by false negatives as well as mean under-reporting among true recipients who report receipt in the survey. The latter is consistent with the finding in the literature that survey responses tend to reflect OASDI benefits net of medical insurance premiums withheld from monthly payments (Huynh et al., 2002). Moreover, the slight decrease over time in average under-reporting of OASDI in the SIPP seems to be a result of increasing false positives.

For programs outside of OASDI, there does not appear to be significant misreporting in benefit amounts among true recipients who also report receipt in the survey. Instead, errors tend to be particularly concentrated in false positives and false negatives. On one hand, the average overstatement of survey reports for SSI appears to be associated with the presence of false positives. Coupled with the errors observed for OASDI, this is consistent with program confusion between

OASDI and SSI (Huynh et al., 2002; Giefer et al., 2015). On the other hand, false negatives seem to drive the average understatement of survey reports for SNAP, with both the rate of false negatives and amount of administrative benefit dollars "missed" by the survey increasing over time.

Finally, for both Public Assistance and housing assistance, we have set the false positive rates to zero, so we do not report them. In the case of Public Assistance, the understatement of survey reports seems to be entirely driven by false negatives and would be even greater if not for mean over-reporting among true recipients who report survey receipt. We also observe non-trivial false negative rates for housing assistance, although these are less than the false negative rates for SSI, SNAP, and Public Assistance.

Caveats

There are several additional caveats associated with our analysis, and here we briefly discuss how we address them. First, in analyzing only the static poverty reduction of each transfer program, our analysis does not account for behavioral responses. As a long literature has shown, these responses (e.g., changing one's labor supply, reducing savings, etc.) certainly exist – especially when considering the long-run effects of these programs. Our results therefore provide an important part of the analysis but one that is not complete, with the differences between survey and administrative estimates likely relevant to estimating such responses. Section 6 discusses in greater detail how these behavioral responses might alter the magnitudes of the anti-poverty effects of various transfer programs. However, earlier studies have found that many of these programs have behavioral responses that are unlikely to significantly change the unadjusted impacts (Danziger et al., 1981; Ben-Shalom et al., 2012).

Second, because of data limitations, we use subsets of states to calculate the poverty reduction of SNAP and Public Assistance. One may worry that differences between these states and the entire country might lead to anti-poverty effects that are not comparable between programs. In the online appendix, we run the full analysis for the SNAP and TANF states and find that the effects for OASDI, SSI, housing assistance, and EITC are comparable to what we find for the entire country. Moreover, we show that these states are generally representative of the U.S. in terms of demographic characteristics reported from the survey.

Another caveat is that the EITC amounts are not actual amounts received but rather eligible amounts calculated based on the administrative tax data. This calculation will overstate the true amount of the EITC disbursed for two reasons: 1) Not everyone whom the IRS believes is eligible for the EITC may actually be eligible for the credit, and 2) Not everyone who is eligible for the EITC will claim the credit (Scholz, 1994; Plueger, 2009; Bhargava and Manoli, 2015). We find that the actual number of EITC recipients and dollars disbursed (from publicly available totals published by the IRS) constitute approximately 75% and 90%, respectively, of the eligible EITC recipients and associated dollars that we calculate.[29] Consequently, it appears that the eligible tax units who do not take up the credit (or who are incorrectly calculated as eligible) receive relatively few EITC dollars. This comparison suggests that our estimates of receipt using eligible EITC amounts are biased upward, but not by a lot. One should note that the aggregate EITC dollar estimates from the CPS (that are incorporated in the SPM report) are biased downward by about 30 percent (Meyer, 2017).

Finally, recall that our administrative values for Public Assistance and housing assistance treat all survey respondents reporting receipt who are not in the administrative data as true recipients. On one hand, this may overestimate the effects of these programs if we erroneously treat observations that are actual false positives as true recipients.[30] Note that we are unable to disentangle actual false positives from recipients of programs asked about in the SIPP but not covered by the administrative data. Moreover, the effects of housing assistance may be overestimated since we impute benefits for state and local programs using amounts from HUD programs, despite the latter being typically more generous than the former (Olsen, 2018). However, the effects of these programs may also be underestimated given that there are false negatives associated with non-TANF Public Assistance and non-HUD housing assistance that cannot be identified.[31] In fact, the extent to which the aggregate survey dollars for Public Assistance understate the aggregate administrative dollars (constructed as described) in Table 3 falls slightly short of what Meyer et al. (2015b) find for the same time period. In sum, it is likely that our administrative estimates for Public Assistance are still somewhat understated, while the estimates for housing assistance may be a touch overstated.[32]

[29] The publicly available IRS aggregates can be found at: https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-return-form-1040-statistics.
[30] Since imputation can potentially be a reason for false positives, an alternative way of handling this is to treat only non-imputed survey respondents reporting receipt as true recipients.
[31] The false negative rates for non-TANF Public Assistance in New York in the CPS over this period were over 50% (Meyer and Mittag, 2017). Moreover, the false negative rates for the HUD programs in our data are over 15%, so similar rates might be expected to apply to non-HUD programs as well.
[32] In the online appendix, we also present estimates of the effects of these programs where we treat all survey recipients not found in the incomplete administrative data as false positives, understating the effects of the program by construction.

5 Results

This paper focuses on three measures of the poverty reduction due to each transfer program. The first is the reduction in the poverty rate associated with a given transfer – the most commonly cited statistic. Specifically, this is the percent change in the poverty rate going from no transfers to adding a single transfer.[33] The second measure is the percentage of the pre-transfer poverty gap filled by a transfer, which is often thought of as a better measure of the reduction in deprivation. The poverty gap is defined as the total dollars needed to raise all families to the poverty line and can therefore be interpreted as a measure of the "intensity" of poverty (Ravallion, 1996; Deaton, 1997). The final measure is the percentage of total program dollars going to the pre-transfer poor, capturing how much a given transfer program targets individuals in poverty.

Main Results

For each transfer program, Table 5 displays the three measures of poverty reduction, calculated separately using survey reports or combined survey and administrative values. It also calculates for each program the average number of recipients per month and the average dollar amount of the transfer for a recipient family per month. OASDI is by far the largest transfer program based on both the number of families reached as well as the average benefit paid out to recipients. In fact, the average OASDI benefit is about 2.3 times that of housing assistance, which is the second largest average transfer to recipients. Moreover, the survey data understate the number of recipients for all programs (with this difference especially noticeable for recipients of SNAP and Public Assistance), while they overstate the average transfer per recipient family for all programs other than OASDI.

As expected, OASDI also has the largest poverty reduction among all transfers, cutting the pre-transfer poverty rate of 31% by nearly a third and filling 45% of the poverty gap by itself. Despite the large poverty reduction associated with OASDI, only 65% of its dollars actually go to the pre-transfer poor. Among means-tested transfers, the EITC and SNAP have the largest effects on the poverty rate, followed by housing assistance, SSI, and Public Assistance. However, housing assistance and SSI fill more of the poverty gap than the EITC. This appears to be driven by SSI and housing assistance being far more targeted to the poor than the EITC. About 80% of all SSI and

[33] When calculating the poverty rate, we use incomes defined at the family level but count the number of people in poor families to obtain the share of the entire population in poverty. This approach follows the methodology used by the U.S. Census Bureau in calculating the official poverty measure.

housing assistance dollars go to the pre-transfer poor, while only 46% of dollars from the EITC go to the pre-transfer poor.

In general, the poverty reduction of each program calculated using the survey data are fairly similar to those obtained from the combined survey and administrative data, though there are exceptions. We will also see more exceptions when we disaggregate the analysis by family type. Using the survey data understates the reduction in the poverty rate and gap for Public Assistance by 39% and 24%, respectively, with smaller understatements for OASDI and SNAP and a slight overstatement for SSI. While the patterns for Public Assistance may be due in part to our method of constructing the combined data, they are likely also driven by survey misreporting (given the reasons outlined in Section 4). In addition, the survey data appear to overstate the extent to which OASDI, SNAP, and Public Assistance target the pre-transfer poor and understate the extent to which SSI targets the pre-transfer poor. This phenomenon is more evident for SNAP, for which the percentage of program dollars to the pre-transfer poor falls from 80% to 72% going from the survey data to the combined data. This result is an example of how the administrative and survey data are likely to produce non-trivial differences in how program dollars are disbursed across the income distribution (see Meyer and Mittag, 2017).

Deep and Near Poverty

The findings above show that, for programs outside of Public Assistance, the SIPP fairly accurately captures the number of individuals moved across the poverty line. However, we also examine how the program effects vary when using different income cutoffs. In particular, we examine changes in the number of families with incomes below 50% of the federal poverty line ("deep poverty") and families with incomes below 150% of the federal poverty line ("near poverty"). Panels A and B of Table 6 display the effects of each transfer program on deep and near poverty, respectively.

Deep Poverty

We first consider the results for deep poverty in Table 6, Panel A. Note that the pre-transfer deep poverty rate is 22%, down from 31% for the traditional poor. The percentage decrease in the deep poverty rate is higher than the decrease in the traditional poverty rate for all programs except for the EITC, indicating that these transfer programs appear to play a particularly important role in lifting families out of deep poverty. OASDI continues to have the largest effect, slashing the pre-transfer deep poverty rate and gap by 47% and 50%, respectively. Each of the means-tested transfers (with the exception of Public Assistance) leads to a reduction in the deep poverty rate of 4.5-7.6%, with housing assistance having the largest effect among them. Moreover, SNAP is actually less successful at targeting the deep poor than OASDI. However, SNAP has the largest effect on the deep poverty gap among means-tested transfers, filling it by 13%. Note that the smaller role of the EITC (relative to the other programs) stems from the deep poor receiving only 26% of its total dollars – compared to 54-71% of total dollars received by the deep poor for each of the other programs.

The survey data alone still seem to adequately measure the effects of programs on deep poverty, though there are exceptions. Most notably, the survey data understate the effect of Public Assistance on the deep poverty rate by nearly a third. The survey estimates of the reduction in the deep poverty gap are also smaller than their combined counterparts for every program, with these differences being more evident for SNAP and Public Assistance than for OASDI and SSI. As for the targeting of the program dollars to the pre-transfer deep poor, we again see the close similarity between the survey and combined estimates for all programs (except SNAP) that we observed using the traditional poverty thresholds in Table 5.

Near Poverty

Next, we examine the results for near poverty in Table 6, Panel B. The base poverty rate for the near poor is approximately 40%, up from 31% for the traditional poor. The percentage decrease in the near poverty rate is lower than the decrease in the traditional poverty rate for every program, which is the opposite of what we see for deep poverty and indicates that these transfer programs play a smaller role in lifting families out of near poverty. OASDI still has the largest effect of all programs, decreasing the near poverty rate and gap by approximately 20% and 37%, respectively. The relative effects of means-tested transfers on the near poverty rate follow a similar pattern as in Table 5, with the EITC having the largest effect, followed by SNAP, housing assistance, SSI, and Public Assistance (in that order). While the EITC still targets the pre-transfer near poor less than other programs, it now is more comparable to the other programs than it was for the deep and traditional poor. There is more homogeneity among the means-tested transfers in their effects on the near poverty gap, with SSI, SNAP, housing assistance, and the EITC each filling the gap by 4.0-5.4%. SNAP delivers the largest effect on the near poverty gap, reducing it by 5.4%.

In contrast to the measures for deep and traditional poverty, the survey and combined data now yield larger differences for the effects of programs on the near poverty rate. For SNAP and Public Assistance, the survey data yield a reduction in the near poverty rate that is about two-thirds and one-half what the combined data produce, respectively. We also observe for OASDI a reduction in the near poverty rate of 18.1% with the survey data, compared to 19.5% with the combined data. These differences between the survey and combined data for near poverty are consistent with misreporting of transfers becoming more problematic as incomes rise (Meyer and Mittag, 2017).

Effects by Family Type

The previous analyses focused on the effects of these transfer programs across all families, but it remains to be seen how the relative importance of these programs and the extent of misreporting disaggregate across family types. Doing so is critical, since many of these programs are directed toward particular types of recipients. For example, OASDI targets the elderly and disabled, SSI targets the disabled, and TANF targets single parent families. We therefore analyze eight family types: single parents (non-elderly), multiple parents (non-elderly), single individuals without children (non-elderly), multiple individuals without children (non-elderly), elderly, disabled, unemployed, and employed. Table 7 provides the number of population-weighted families of each type and their pre-transfer poverty rate and gap. Note that the first five family types are disjoint and together cover the entire sample of families.

First, we assess what programs seem to be most effective in reaching each subgroup. Using the combined data, Figure 2a illustrates for each subgroup the three transfer programs that generate the largest reductions in the poverty rate and their associated magnitudes. Because the base poverty rates vary by family type, it becomes especially important that we measure the poverty reduction as the fractional reduction in the base poverty rate. For six of the eight subgroups, OASDI is the most important transfer for poverty reduction – usually by a wide margin. This is especially striking for the elderly, for whom OASDI singlehandedly cuts the poverty rate by 75%. This is 62 times as large as the effect of the second most important program (SSI) for the elderly. For the disabled, OASDI reduces the poverty rate by a third, which is 6.5 times the effect of SSI (again the second most important program). There are similar patterns in the role of OASDI in filling the poverty gaps (see online appendix). Single parent and multiple parent families are the only subgroups for which OASDI is not the most significant poverty-reducing program.

Figure 2b follows the same structure as Figure 2a but excludes OASDI, concentrating on the three most important *means-tested* transfer programs for each subgroup. For the elderly and disabled, SSI is the most important means-tested transfer for poverty reduction. It is also the most important means-tested transfer for lifting the unemployed and multiple individuals without children out of poverty.[34] The EITC is among the three means-tested transfers yielding the largest anti-poverty effect for all subgroups except the elderly and unemployed. These latter subgroups are unlikely to have earned income and thus be eligible for the credit. For all subgroups except single childless individuals and unemployed families, SNAP is also among the three means-tested transfers that lead to the largest poverty reduction. Finally, housing assistance appears to be targeted most to single parents, single childless individuals, elderly families, and unemployed families – who tend to have substantially high pre-transfer poverty rates. Single and multiple parent families appear to particularly benefit from these means-tested transfers. For single parent families, the EITC, SNAP, and housing assistance cut poverty rates by 8.7%, 7.0%, and 5.9%, respectively. For multiple parent families, the EITC and SNAP each reduce poverty rates by 9.4%. In contrast, for no other subgroup does *any* means-tested transfer decrease poverty rates by more than 5%.

Next, we examine how the administrative data change our understanding of the poverty reduction of various programs, relative to the survey data. Figure 3a plots for every subgroup the reduction in the poverty rate due to a given program using the survey data alone as a fraction of the reduction in the combined survey and administrative data. Under-reporting in the survey is most dramatic for single parent families, for whom the poverty reduction estimates of OASDI, Public Assistance, SSI, and SNAP using the survey data are 0.34, 0.35, 0.44, and 0.91 times as large (respectively) as those obtained using the combined data. Conversely, disabled families and single individuals tend to over-report on SSI and SNAP, while the survey and combined data for programs outside of Public Assistance yield remarkably similar poverty reductions for employed families.

For every subgroup, the survey data underestimate the poverty reduction of OASDI. While this is most pronounced for single parent families, the survey data also understate the reduction in the poverty rate by 21% and 12% for multiple parent families and single individuals, respectively. This difference is least pronounced for the elderly, who also constitute the largest portion of Social Security recipients. In contrast, the survey data overestimate the poverty reduction of SSI for every

[34] Unemployed families may often be out of work precisely because they are also disabled, so it would make sense for SSI to have relatively larger effects for them. However, note that the effect of SSI for unemployed families is rather small in absolute terms, decreasing the poverty rate by only 2.3%.

subgroup except single and multiple parent families. For single childless individuals and unemployed families, the survey data overstate the poverty reduction of SSI by more than 50%. For SNAP, the poverty reduction in the survey data slightly understates that from the combined data for elderly families, multiple childless individuals, and single parents and overstates the reduction in the combined data for single childless individuals and unemployed families.[35] The effects of Public Assistance are all understated in the survey, with these differences most prominent for single parent families and single childless individuals.

Figure 3b follows the same format as Figure 3a but compares differences in the effects on the poverty gap rather than the poverty rate. The overall patterns for programs and family types in Figure 3b remain largely unchanged from Figure 3a, although the shares tend to be closer to 1. For example, the survey data yield reductions in the poverty gap for single parent families that are 0.62, 0.69, 0.78, and 0.93 times as large for SSI, OASDI, Public Assistance, and SNAP (respectively) as those produced by the combined data. The differences between the survey and combined estimates also tend to be larger for Public Assistance and SSI and smaller for OASDI and SNAP.

Multiple Program Participation

It is often the case that there are complementarities in the receipt of certain transfer programs. For example, recipients of Public Assistance are likely to also receive SNAP. Individuals who receive SSI are likely to also receive OASDI, especially if they are disabled. In this subsection, we assess the poverty reduction due to various combinations of programs and how it varies across select family types that are particularly reliant on government transfers. We also examine the total effect of the five means-tested transfers and all six programs to get a broader sense of the safety net's role in reducing poverty. Table 8 shows results calculated over those states and years for which we have both administrative SNAP and TANF data. Doing so produces a sample that is narrower than the full sample but contains administrative data for every one of the six transfer programs.

Across all families in Panel A, we see that OASDI and SSI together cut the base poverty rate by 37%, although most of this effect is driven by OASDI. SNAP and Public Assistance together decrease the poverty rate by 5%, with most of this effect driven by SNAP. The effects from the survey reports understate those from the combined data for both OASDI + SSI and SNAP + Public

[35] Note that Figure 3a omits the comparison of SNAP for unemployed families, for whom the survey and combined data yield a 0.23% and 0.02% reduction in the poverty rate, respectively. The ratio of the survey to combined estimate is therefore 11.5, which is an outlier and partly due to the small denominator.

Assistance, with the former driven by under-reporting of OASDI and the latter by under-reporting of SNAP and Public Assistance. Adding housing assistance to each of these two combinations amplifies the poverty reduction by 11% for OASDI + SSI and 71% for SNAP + Public Assistance. The five means-tested transfers in total reduce the poverty rate by approximately 16%, while all six programs (adding in OASDI) together cut the poverty rate by more than half.

For single parent families in Panel B, the combination of SNAP, Public Assistance, and housing assistance reduces the poverty rate by 17%, which exceeds the effect of the five means-tested transfers together for all families. Note that means-tested transfers play a much larger role than OASDI for single parent families, decreasing the poverty rate by 32%. After adding in OASDI, the six transfer programs together cut the poverty rate by 38%, only an additional 6 percentage points. We see similar patterns in the effects on the poverty gap, with the five means-tested transfers decreasing the poverty gap by 52% and the six programs together reducing the gap by 60%.

For elderly families in Panel C, the combination of OASDI, SSI, and housing assistance cuts the poverty rate and gap by 84% and 92%, respectively, with almost all of this driven by OASDI. The importance of OASDI is most remarkably revealed as follows: the five means-tested programs shave only 3.5% off the base poverty rate, while adding OASDI slashes the poverty rate by 85%. As a result, for the elderly, the effect of OASDI on the poverty rate is 23 times as large as that of the five means-tested transfers combined. Indeed, the total effect of these six transfer programs for elderly families is much larger than what we observe for all families and for single parent families. The effects of these programs follow a similar but less dramatic pattern for disabled families in Panel D, for whom OASDI reduces the poverty rate by twice as much as the five means-tested transfers together. The six transfer programs jointly reduce the poverty rate for disabled families by 57%, which is more in line with what we find for all families. Finally, the five means-tested transfers do a better job of targeting the pre-transfer elderly (and to a lesser extent the disabled) poor than they do the pre-transfer single parent poor. However, because OASDI plays a relatively larger role for the elderly and disabled and it is less targeted to the pre-transfer poor, the six transfer programs together target the pre-transfer single parent poor more successfully than they do the pre-transfer elderly and disabled poor.

6 Discussion

In this section, we briefly describe how the safety net functioned during the Great Recession and partial recovery period (the time frame examined in this paper), compare our poverty reduction estimates to those of prior studies, and discuss how behavioral responses might shape the anti-poverty effects of these transfer programs.

Time Period Examined

Our analysis covers the time period corresponding to the onset and aftermath of the Great Recession. During the recession, transfer programs served as an unusually important safety net for families who lost jobs or experienced other negative shocks (such as significant reductions in earnings or assets). Among the key programs we study, the EITC and SNAP saw especially large increases in spending and caseloads during the Great Recession (Ganong and Liebman, 2013; Moffitt, 2013). We also find that these two programs have the largest anti-poverty impacts among the means-tested transfers we examine. However, these expansions targeted recipients at different portions of the income distribution, with SNAP focused on households below the poverty line and the EITC on households around the poverty line (Anderson et al., 2015). Unemployment Insurance also saw expansions that tended to benefit the bottom and middle of the income distribution, with benefit durations extended to as long as 99 weeks during the Great Recession (Rothstein, 2011; Moffitt, 2013). In contrast, TANF spending and caseloads stagnated during the Recession (Bitler and Hoynes, 2010, 2016), and our findings show that Public Assistance has by far the smallest impact on reducing poverty among the six programs examined. While this time period was unusual, it is also worth examining given that we may be especially worried about the functioning of the safety net during such a time.

Comparisons to the Literature

Table 9 compares the poverty reduction estimates of our key programs, using the combined administrative and survey data, to those found in some notable studies. There are a number of differences across studies in the methods used to calculate poverty and the characteristics of the data, hampering the comparability of these estimates. These differences include the definition of base income (ranging from pre-tax measures that encompass either cash transfers or no transfers at all to post-tax, post-transfer income), reference years examined, the unit of analysis (i.e., whether the estimates are weighted to reflect the total number of individuals or families in the population), the time frame used to calculate income and poverty status (i.e., on a monthly versus annual basis), and the data used. To partly address some of these differences (which Table 9 describes in greater detail), we discuss the results here in terms of percent reductions in the base poverty rate.

First, we compare our estimates using pre-tax, pre-transfer income as the base to those in Scholz et al. (2009). This analysis compares Columns (1) and (3) in Table 9, which differ in the reference period examined, the unit of analysis employed, and the data types (combined SIPP and administrative data vs. SIPP) analyzed. Column (1) finds strictly larger anti-poverty effects for all programs except for OASDI and Public Assistance.[36] While these programs have been among the fastest-growing over the last two decades, the differences in our estimates are likely also due to under-reporting in the SIPP. This may be especially true for SNAP, as our estimate of its poverty reduction exceeds that of Scholz et al. (2009) by 219%. Our estimate for SSI exceeds that of Scholz et al. (2009) by 45%, and our estimates for housing assistance and the EITC exceed those of Scholz et al. (2009) by a more modest 26-29%. The equivalent estimate that we find for Public Assistance may be due to a combination of stagnation in program growth and under-reporting in the SIPP, although recall that our preferred measure of the anti-poverty effect of Public Assistance treats all "false positives" in the SIPP as truth.

There are more differences to keep in mind when contrasting our estimates with those using the CPS. Among other differences, the estimates using the CPS are taken over income measured annually and generally use a measure of base income incorporating some level of transfer income. To account for the latter, we use as the basis of comparison our estimates using pre-tax cash income (in Column (2) of Table 9), which includes cash transfers. Comparing our estimates in Column (2) to the SPM results in Columns (4) and (5), our study continues to yield a dramatically larger poverty reduction effect for SNAP – by 32% compared to Short (2012) and 51% compared to Fox (2017). Our estimate for the poverty reduction of SNAP also exceeds that of Tiehen et al. (2013) by 41%. This pattern is consistent with existing evidence showing that the CPS markedly understates SNAP receipt (see Meyer et al., 2015b; Meyer et al., 2017). Our estimate of the poverty reduction of housing assistance also exceeds those of Short (2012) and Fox (2017) by 63% and 32%, respectively. While we may overestimate the effect of housing assistance, it is unlikely that this gap

[36] However, note that Scholz et al. (2009) separately calculate the effects of OASI and DI, so we report their estimate for OASDI in Table 9 as the sum of the percent reductions in poverty of OASDI and DI.

is entirely due to this difference. This pattern is once again consistent with evidence showing that the CPS understates housing assistance benefits (Meyer and Mittag, 2017).

Our estimate of the poverty reduction of OASDI in Column (2) is smaller than those of Short (2012) and Fox (2017), while our estimate of the poverty reduction of SSI exceeds that of Short (2012) but is less than that of Fox (2017). These patterns are consistent with the general increase in OASDI and SSI spending in recent years as well as evidence showing that surveys often over-report receipt of these programs (Davies and Fisher, 2009; Giefer et al., 2015). Our estimate for Public Assistance in Column (2) falls short of those in Short (2012) and Fox (2017), which is noteworthy since Public Assistance spending has declined in recent years and Meyer et al. (2015b) find that Public Assistance is even less well-reported in the CPS than in the SIPP. Consequently, this result suggests that past estimates of the anti-poverty effect of Public Assistance may be on the high side due to measurement issues or differences in the base income measure. Finally, our anti-poverty estimate for the EITC is also below those of Short (2012) and Fox (2017), though the EITC in these two studies cannot be disentangled from other refundable tax credits like the child tax credit. Our estimate for the EITC is also lower than that of Hoynes et al. (2006), who examine an earlier time period, use a post-tax measure of base income, and focus on non-elderly individuals (who tend to be most targeted by the EITC).

Behavioral Responses

Behavioral responses to program receipt can further augment or diminish the anti-poverty effects of transfer programs. The specific magnitudes of these adjustments generally depend on the incentives and structure of each program. In this subsection, we broadly discuss what the existing literature has concluded on the behavioral incentives of each of this paper's six transfer programs, focusing on adjustments in labor supply.

Consider first Social Security (OASDI). It makes sense here to separately discuss OASI and DI, given that they are structured differently and target distinct groups. Theoretically, there is an ambiguous effect of OASI on labor supply, since it may induce some individuals to retire through a "wealth effect" and other individuals to remain employed given that benefits, up to a certain point, are increasing in retirement age (Krueger and Meyer, 2002). While there is little agreement on the magnitude of the effects, well-identified studies tend to find a modest reduction in employment (see Lumsdaine and Mitchell, 1999; Krueger and Meyer, 2002). On the other hand, DI theoretically disincentivizes work through an income effect and through benefit receipt being tied to the inability to engage in any "substantial gainful activity" (Bound and Burkhauser, 1999). While a number of studies have empirically analyzed the labor supply effects of DI, there is once again little consensus on the magnitude of the work disincentive. A survey of some of these studies (which cover different populations and empirical strategies) shows that DI reduces the employment of recipients by 20 percentage points to 35 percentage points (see Bound, 1989; Chen and van der Klaauw, 2008; Maestas et al., 2013; French and Song, 2014).

There are fewer studies that have empirically analyzed the labor supply effects of SSI, for which it once again make sense to separate the effects for the elderly and disabled. For the elderly, SSI largely shares the characteristics of a standard means-tested cash transfer by guaranteeing income for poor elderly individuals and taxing away the benefit with additional work (Ben-Shalom et al., 2012). In this case, the theoretical effect on labor supply should be clearly negative, and Kaushal (2010) finds evidence of this for elderly immigrants.[37] For the disabled, the labor supply effects of SSI should once again be negative but are likely smaller than those of DI. This is partly because disabled recipients of SSI are far less likely than DI recipients to have been employed prior to applying for benefits (Daly and Burkhauser, 2003).

A relatively large literature has arisen around the behavioral effects of TANF when it was previously known as AFDC (i.e., prior to 1996). These studies generally find that AFDC reduces employment, although there is substantial variation in the magnitudes of these effects (see Danziger et al., 1981; Moffitt, 1992; Hoynes, 1997). However, in its current form, TANF incorporates work requirements and time limits on lifetime receipt that may provide incentives for work. Several papers using observational analyses find positive effects of employment associated with TANF (versus AFDC), although some of these studies suffer from weak identification strategies and/or are unable to precisely disentangle the effects of TANF from simultaneous policy reforms (see Ziliak, 2015). More recent studies use structural models to simulate the effects of TANF rules, finding positive labor supply effects of work requirements and time limits despite differing in their estimates on the relative magnitudes of each (Keane and Wolpin, 2010; Chan, 2013). Nevertheless, few – if any – studies have estimated causal impacts of the current TANF program on labor supply using robust identification strategies.

[37] Neumark and Powers (2000) also find evidence that SSI receipt reduces pre-retirement labor supply.

Earlier studies examining the work disincentives of SNAP tend to find effects that are small or statistically insignificant (see Currie, 2003). Theoretically, for a single earner, SNAP receipt should unambiguously decrease labor supply through both an income effect and substitution effect (since the benefit amount is decreasing in earnings). However, the labor supply disincentives may be smaller when there are multiple earners within a family.[38] These predictions treat SNAP benefits as equivalent to cash, which is plausible since the benefit amounts are typically below the pre-receipt food consumption levels of recipient families (Ben-Shalom et al., 2012). More recent studies exploiting quasi-experimental variation in policy changes at the state level find no significant average labor supply effects but labor supply reductions for families headed by single females (Hoynes and Schanzenbach, 2012; East, 2017). Stacy et al. (2016), in contrast, find a positive effect of SNAP receipt on employment for "Able-Bodied Adults without Dependents", who are generally subject to work requirements to qualify for benefits. However, the magnitude of the effects in Stacy et al. (2016) and East (2017) are rather small, at around 5 percentage points on the extensive margin.

Housing assistance should also theoretically decrease labor supply through income and substitution effects (since tenant payment is increasing in earnings). Susin (2005) uses a selection-on-observables design to conclude that public housing reduces earnings by 19%, with Olsen et al. (2005) finding negative effects on earnings of 30-35% associated with public housing or voucher receipt. Jacob and Ludwig (2012) use experimental evidence from voucher lotteries to find that voucher receipt decreases employment and quarterly earnings by 6% and 10%, respectively – although Jacob et al. (2015) show that these effects fade out in the longer run.

On the other hand, receipt of the EITC – unlike most of the other programs analyzed – should theoretically yield positive labor supply effects, at least for labor supply at the extensive margin by single parents. However, for a single parent who is already working, the impact of the EITC on labor supply at the intensive margin depends on where their earnings place them on the EITC schedule. For married parents, the theoretical labor supply effects are ambiguous and may vary between the primary and secondary earner. Indeed, a number of empirical studies find positive effects of the EITC on employment rates that are pronounced for single mothers but small for married women and men (see the reviews in Hotz and Scholz, 2003; Eissa and Hoynes, 2006; Meyer, 2017). Nonetheless, it remains unclear to what extent the behavioral effects of the EITC affect its anti-

[38] Ben-Shalom et al. (2012) also attribute the small effects found in the empirical literature to the small size of the benefit relative to family income and the possibility that families do not actually perceive the in-kind transfer as equivalent to cash.

poverty impact. Ben-Shalom et al. (2012) argue that these effects are likely too small to make any significant difference, while Hoynes and Patel (2015) contend that omitting these behavioral responses understates the poverty reduction of the EITC by up to 50%.

In sum, given these labor supply responses, the anti-poverty effects of the EITC are likely understated while those of non-EITC programs are likely overstated. While the adjustments for many of these programs are potentially small on average, they may be more prominent for certain family types (e.g., single mothers for SNAP and the EITC). Moreover, certain aspects of these programs (e.g., the presence of work requirements associated with SNAP and TANF) may temper some of the labor supply effects otherwise expected to be associated with their receipt. Finally, it is worth noting that labor supply is just one margin on which behavioral responses might occur, with other margins including changes in time spent at home and changes in saving behavior.

7 Conclusions

A long literature has documented the extent to which government transfers mitigate poverty. Nearly all of these studies base their results on survey reports of incomes and government transfers, despite previous work showing that these variables are often substantially misreported in surveys. While a small number of studies have linked administrative data to surveys to overcome this misreporting, they generally do so for a small set of programs and/or a narrow set of states and years. This paper contributes to the literature by linking administrative data for six separate transfer programs (including the largest social insurance program and four largest means-tested transfers) to survey data. In particular, we concurrently link more administrative sources of transfer program data than any previous study. By using the most recent completed panel of the SIPP before its redesign, we examine the advantages of administrative data added to perhaps the most accurate survey data on transfers likely to be available in the near future. We also update past research by using recent data. While a significant step in the use of administrative data, this paper is a first step in a larger project to link administrative income data to household surveys.

Using the combined administrative and survey data, the results in this paper show that OASDI has the largest impact on cutting the poverty rate, while the EITC and SNAP have the largest anti-poverty effects (even though they are omitted from the official poverty measure) among means-tested transfers. These notable effects persist despite OASDI and the EITC being the least targeted to the pre-transfer poor of this study's key programs. Among means-tested transfers, SNAP, housing assistance, and SSI are most important at filling the poverty gap. The relative importance of these programs also varies considerably across subgroups, with the elderly benefiting predominantly from OASDI, the disabled from OASDI and SSI, and single parent families from the EITC and SNAP. In analyzing other income thresholds, we find that the EITC is more important at reducing near poverty while the other means-tested transfers have a larger impact on deep poverty. On average, the survey and combined data yield similar estimates of the effects of each program on the poverty rate and gap. There are, however, some significant exceptions. Specifically, the survey data understate Public Assistance's reduction in poverty and deep poverty, SNAP and Public Assistance's reduction in near poverty, and the poverty reduction of most transfers to single parent families.

Comparing our estimates to those found in the literature can be difficult, owing to differences across studies in the methods used to calculate poverty and the data used. However, compared to analyses that use earlier versions of the SIPP, we find larger anti-poverty effects for all programs except Public Assistance. Compared to analyses using the CPS, we find larger estimated poverty reductions for SNAP and housing assistance. It is also important to keep in mind that our administrative estimates for Public Assistance and housing assistance treat all survey respondents not in the administrative data as true recipients. We make this assumption since the administrative data are incomplete, and one expects there to be under-reporting for the missing sub-programs (as there is substantial under-reporting of the sub-programs that are included). As a result, our estimates for these programs could understate or overstate the true poverty reduction. We do overestimate the effect of the EITC since we predict eligible amounts based on the administrative tax data, though the error is likely on the order of 10 percent. In the longer run, behavioral responses to program receipt, particularly on labor supply, can further augment or diminish the anti-poverty effects of these programs. The effects of programs outside of the EITC are likely to be overstated, while the effect of the EITC is likely to be understated.

This paper shows that the 2008 SIPP Panel does well for most programs in producing accurate estimates of the anti-poverty effects of various transfer programs for the entire population. However, comparing only survey and combined survey and administrative estimates across all families and for traditional poverty thresholds misses important patterns in how misreporting is distributed across income thresholds and family types. For single parent families, we find a very large survey underestimate of poverty reduction for all programs and near poverty reduction for SNAP and Public Assistance that echoes the findings in Meyer and Mittag (2017). This result points to limitations in simple misreporting corrections to survey data that do not reflect differences in misreporting by income and family type. Such corrections are likely to go wrong if one hopes to conduct more granular analyses by subgroup. While the SIPP has weaknesses, it is the most accurate survey for examining issues related transfer programs and poverty. However, the recent redesign of the SIPP in 2014 produced a number of changes (including interviewing annually as opposed to every four months) that make its post-redesign accuracy uncertain.

As mentioned earlier, this paper is one of the first steps of the larger Comprehensive Income Dataset project that seeks to improve income measurement through the linkage of administrative data to household surveys. While this paper incorporates more administrative data in a household survey than any past work, we hope to expand the administrative data used in the future. We also hope to link these administrative data to additional surveys as well as over time in order to examine trends in income and poverty reduction.

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Tables and Figures

Table 1. Transfer Programs Studied in the Literature

Program	Hoynes et al. (2006)	Scholz et al. (2009)	CBO (2013)	SPM (various years)
Means-Tested				
Supplemental Security Income	Yes	Yes	Yes	Yes
Public Assistance	Yes	Yes	Yes	Yes
SNAP	Yes	Yes	Yes	Yes
Child Tax Credit	No	Yes	Yes	Yes
EITC	Yes	Yes	Yes	Yes
Foster Child Payments	No	Yes	No	No
Housing Assistance	Yes	Yes	Yes	Yes
WIC	No	Yes	Yes	Yes
Medicaid	Yes	Yes	Yes	No
School Lunch	Yes	No	Yes	Yes
LIHEAP	No	No	Yes	Yes
Non Means-Tested				
Social Security	Yes	Yes	Yes	Yes
Unemployment Insurance	Yes	Yes	Yes	Yes
Workers' Compensation	Yes	Yes	No*	Yes
Veterans' Benefits	Yes	Yes	Yes	No
Medicare	No	Yes	Yes	No
Populations Emphasized	Non-Elderly Persons	All Families	All Persons	All Persons

*CBO (2013) only includes Black Lung Payments and no other type of workers' compensation.

Notes: This table displays the transfer programs examined by each of four key studies on the distributional and poverty-reduction effects of assistance programs. Among the SPM reports specifically analyzed are Short (2012) and Fox (2017), which focus on reference years 2011 and 2016, respectively.

Table 2. Administrative Data Sources

Program	Administrative Source	Benefit Unit	Benefit Frequency	States Covered	Years Covered
OASDI	PHUS (SSA)	Individual	Monthly	All	All
SSI	SSR (SSA)	Individual	Monthly	All	All
TANF	HHS	Family	Monthly	30 States	All
EITC	Form 1040 (IRS)	Tax Unit	Annual	All	All
SNAP	State Agencies	Household	Monthly	12 States	Various Years
Housing Assistance	PIC & TRACS (HUD)	Household	Monthly	All	All

Notes: This table shows – for each transfer program in the administrative data – the source of the data, the unit at which the dollar amounts are reported, the frequency at which the benefit dollars are reported, and the states/years covered. Note that all of the administrative data, with the exception of SNAP and TANF, cover the universe of recipients in the United States. Within the reference period for the 2008 SIPP Panel, the states and years for which we have administrative SNAP data are Arizona (2009-13), Colorado (2012-13), Hawaii (2013), Idaho (2010-13), Illinois (2008-13), Indiana (2008-13), Maryland (2010-13), New Jersey (2008-13), New York (2013), Oregon (2009-13), Tennessee (2008-13), and Virginia (2009-13). The states for which we have administrative TANF data are Alabama, Alaska, Arizona, Delaware, District of Columbia, Georgia, Hawaii, Idaho, Indiana, Iowa, Kentucky, Louisiana, Maine, Minnesota, Missouri, Montana, Nebraska, New Hampshire, New Jersey, North Dakota, Oklahoma, Oregon, Rhode Island, Tennessee, Utah, Vermont, Virginia, Washington, Wisconsin, and Wyoming.

Table 3. Total Benefit Dollars in Survey and Administrative Sources
(in millions, 2008 dollars)

Program	Year	(1) Survey Values (Full Sample)	(2) Survey Values (Linked Sample)	(3) Admin Values (Linked Sample)	(4) Survey as % of Admin (Linked Sample)
OASDI	2009	573,695	574,225	625,196	91.85%
	2010	590,574	591,257	643,550	91.87%
	2011	599,982	600,692	631,076	95.19%
	2012	629,806	630,721	657,594	95.91%
SSI	2009	47,547	47,928	47,986	99.88%
	2010	50,752	51,098	48,205	106.00%
	2011	53,790	54,070	48,778	110.85%
	2012	56,310	56,635	52,429	108.02%
SNAP*	2009	44,755	44,844	49,436	90.71%
	2010	52,071	52,259	59,531	87.78%
	2011	55,466	55,686	64,945	85.74%
	2012	54,021	54,258	64,121	84.62%
PA**	2009	5,799	5,738	7,608	75.41%
	2010	5,541	5,603	7,654	73.21%
	2011	4,573	4,629	6,587	70.28%
	2012	4,136	4,296	5,897	72.86%

*These estimates are for the 12 states and years for which we have administrative SNAP data.
**These estimates are for the 30 states for which we have administrative TANF data.

Notes: This table shows aggregate dollar amounts (in millions) of various programs by calendar year in the 2008 SIPP Panel, Waves 1-14. The numbers are shown for 3 samples - one using survey reports in the entire SIPP sample, one using survey reports in the linked sample (which is just the PIKed subsample with weights adjusted for incomplete PIKs in the SIPP), and one using administrative numbers in the linked sample. Dollar amounts are in 2008 dollars, using an adjusted CPI-U (where the annual percent growth rate is adjusted downward by 0.8 percentage points to account for bias in the CPI-U). An observation is a family for a reference month. For SNAP and PA, the numbers are scaled to be representative of the entire U.S. Specifically, the original amounts from each subsample are multiplied by the ratio of the total number of families in the full sample to the number of families in that subsample by year. The administrative values for SSI combine administrative federally-administered amounts and survey-reported state-administered amounts. The administrative values for PA combine administrative TANF amounts and survey-reported amounts for survey respondents reporting receipt that do not appear in the administrative data.

Table 4. Sources of Errors in Aggregate Reported Dollars for OASDI and Means-Tested Transfers

Program	Year	False Positives		False Negatives		True Reporting Recipients	Overall
		%	% Bias in Aggregate Dollars	%	% Bias in Aggregate Dollars	% Bias in Aggregate Dollars	% Bias in Aggregate Dollars
OASDI	2009	1.73	2.91	7.43	-5.76	-5.30	-8.15
	2010	2.03	3.29	8.51	-6.74	-4.67	-8.13
	2011	3.25	5.44	8.46	-6.50	-3.76	-4.81
	2012	3.25	5.26	8.66	-6.87	-2.48	-4.09
SSI	2009	1.19	26.51	26.72	-26.49	-0.15	-0.12
	2010	1.45	31.74	28.93	-27.61	1.88	6.00
	2011	1.60	34.22	28.68	-27.07	3.71	10.85
	2012	1.66	33.23	29.48	-27.90	2.69	8.02
SNAP*	2009	1.64	11.99	22.74	-20.58	-0.69	-9.29
	2010	1.63	10.79	25.05	-22.34	-0.67	-12.21
	2011	1.66	9.07	25.04	-23.59	0.26	-14.26
	2012	1.53	8.55	25.11	-22.89	-1.05	-15.38
PA**	2009			30.71	-25.71	1.12	-24.59
	2010			30.84	-27.95	1.16	-26.79
	2011			30.35	-31.26	1.54	-29.72
	2012			30.95	-27.88	0.74	-27.14
Housing	2009			16.54			
	2010			17.64			
	2011			16.63			
	2012			15.94			

*These estimates are for the 12 states and years for which we have administrative SNAP data.
**These estimates are for the 30 states for which we have administrative TANF data.

Notes: This table shows, by program and year, the rate of false positives (fraction of true non-recipient families that report survey receipt), the rate of false negatives (fraction of true recipient families that do not report survey receipt), the percentage bias in aggregate dollars (as a share of the admin. dollars in the third column of Table 3) due to false positives and negatives, the percentage bias in aggregate dollars due to measurement error among true recipients who report receipt, and the overall percentage bias in aggregate dollars. Survey weights are adjusted by multiplying the inverse of the predicted probability that a family has a member with a PIK. The false positive rates for PA and housing assistance are set to zero and not reported.

Table 5. Poverty Reduction of OASDI and Means-Tested Transfers

Program	Average Monthly Recipient Families (mil.)		Average Monthly Transfer per Recipient Family ($)		% Decrease in Poverty Rate with Transfer		% of Poverty Gap Filled by Transfer		% of Dollars Going to Pre-Transfer Poor	
	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin
OASDI	36.77	37.75	1,334	1,386	30.60	31.94	44.42	45.02	66.48	65.17
SSI	6.58	6.79	645	595	2.45	2.39	6.73	6.59	79.35	81.02
SNAP*	14.87	18.19	284	266	4.15	4.21	7.55	7.89	79.95	72.41
PA**	1.44	2.15	290	266	0.20	0.33	0.77	1.01	83.59	80.06
Housing		7.49		605		2.55		7.40		79.56
EITC		32.55		156		4.58		4.75		45.58

	Base Poverty Rates and Gaps	
	Poverty Rate	Poverty Gap (mil.)
Full Sample	30.96%	$44,401
SNAP States	29.43%	$41,964
TANF States	30.13%	$44,106

*These estimates are for the 12 states and years for which we have administrative SNAP data.
**These estimates are for the 30 states for which we have administrative TANF data.

Notes: For OASDI, SSI, housing assistance, and the EITC, calculations are over all families and unrelated individuals from waves 1-14 of the 2008 SIPP Panel, excluding group quarters and unrelated individuals under age 15. For SNAP and PA, calculations are for the states and years for which we have administrative SNAP and TANF data, respectively. The administrative amounts for OASDI, SSI, SNAP, PA, and housing assistance represent actual amounts received, while the administrative amounts for the EITC represent eligible EITC benefits calculated from 1040 tax returns. The administrative values for SSI combine administrative federally-administered amounts and survey-reported state-administered amounts. The administrative values for PA and housing assistance combine administrative amounts and survey-reported (for PA) and imputed (for housing) amounts for survey respondents reporting receipt that do not appear in the administrative data. Poverty rates are weighted by family size. Dollar amounts are in 2008 dollars, using an adjusted CPI-U. For SNAP and PA, the numbers are scaled to be representative of the full sample.

Table 6. Deep and Near Poverty Reduction of OASDI and Means-Tested Transfers

Program	% Decrease in Deep/Near Poverty Rate with Transfer		% of Deep/Near Poverty Gap Filled by Transfer		% of Dollars Going to Pre-Transfer Deep/Near Poor	
	Survey	Admin	Survey	Admin	Survey	Admin
			A. Deep Poverty (≤ 50% of Poverty Line)			
OASDI	46.55	46.97	49.20	49.57	58.08	56.80
SSI	7.15	7.06	9.70	9.74	70.55	71.31
SNAP*	5.98	5.95	12.24	12.99	60.17	54.10
PA**	0.43	0.63	1.39	1.79	71.94	67.78
Housing		7.60		11.29		67.65
EITC		4.56		5.92		26.12
			B. Near Poverty (≤ 150% of Poverty Line)			
OASDI	18.08	19.51	36.40	37.44	72.70	71.50
SSI	1.01	1.01	4.55	4.44	85.19	87.16
SNAP*	1.12	1.68	5.11	5.43	89.09	83.03
PA**	0.07	0.13	0.49	0.65	88.32	86.01
Housing		1.08		4.97		87.24
EITC		2.84		4.06		63.62

Base Poverty Rates and Gaps

	Deep Pov. Rate	Deep Pov. Gap (mil.)	Near Pov. Rate	Near Pov. Gap (mil.)
Full Sample	22.37%	$19,970	39.71%	$75,738
SNAP States	21.23%	$18,369	37.72%	$72,185
TANF States	22.08%	$20,365	38.73%	$74,559

*These estimates are for the 12 states and years for which we have administrative SNAP data.
**These estimates are for the 30 states for which we have administrative TANF data.

Notes: Deep and near poverty are defined as having incomes less than 50% and 150% of the federal poverty line, respectively. For OASDI, SSI, housing assistance, and the EITC, calculations are over all families and unrelated individuals from waves 1-14 of the 2008 SIPP Panel, excluding group quarters and unrelated individuals under age 15. For SNAP and PA, calculations are for the states and years for which we have administrative SNAP and TANF data, respectively. The administrative amounts for OASDI, SSI, SNAP, PA, and housing assistance represent actual amounts received, while the administrative amounts for EITC represent eligible EITC benefits calculated from 1040 tax returns. The administrative values for SSI combine administrative federally-administered amounts and survey-reported state-administered amounts. The administrative values for PA and housing assistance combine administrative amounts and survey-reported (for PA) and imputed (for housing) amounts for survey respondents reporting receipt that do not appear in the administrative data. Near and deep poverty rates are weighted by family size. Dollar amounts are in 2008 dollars, using an adjusted CPI-U. SNAP and PA numbers are scaled to be representative of the full sample.

Table 7. Family Types: Sizes and Poverty Status

Family Type	Number of Families (weighted, mil.)	Pre-Transfer Poverty (All)		Pre-Transfer Poverty (SNAP States)		Pre-Transfer Poverty (TANF States)	
		Rate (%)	Gap/Poor Fam ($)	Rate (%)	Gap/Poor Fam ($)	Rate (%)	Gap/Poor Fam ($)
Single Parents*	9.42	55.03	1,028	55.79	1,015	53.97	1,015
Multiple Parents*	29.45	19.93	1,078	18.46	1,064	17.89	1,126
Single Individual, No Children*	37.87	35.40	809	34.50	803	34.89	795
Multiple Individuals, No Children*	27.95	16.47	1,149	15.89	1,041	16.32	1,341
Elderly	26.65	66.45	938	65.04	941	66.83	923
Disabled	23.29	50.71	1,183	48.63	1,183	49.81	1,166
Unemployed*	11.65	96.63	995	96.48	992	96.55	992
Employed	67.46	44.44	1,258	41.75	1,275	44.51	1,264

* Non-Elderly Families

Notes: This table displays the weighted number of families of each type, averaged across interview waves, as well as the pre-transfer poverty rate for each family and the pre-transfer poverty gap per poor recipient family. Calculations are over all families and unrelated individuals from waves 1-14 of the 2008 SIPP Panel, excluding group quarters and unrelated individuals under age 15. Poverty rates are weighted by family size. Elderly families are defined as having a family reference person who is 65 years of age or older. Disabled families are defined as having at least one individual who has a work-limiting physical or mental disability. Unemployed (non-elderly) families are defined as having no individuals employed, while employed families are defined as having at least one individual employed.

Table 8. Poverty Reduction Due to Multiple Transfer Programs

Program	% Decrease in Poverty Rate with Transfer		% of Poverty Gap Filled by Transfer		% of Dollars Going to Pre-Transfer Poor	
	Survey	Admin	Survey	Admin	Survey	Admin
			A. All Families			
OASDI	34.32	35.51	46.64	47.25	66.23	64.81
OASDI + SSI	36.53	37.38	50.76	51.58	66.80	65.50
SNAP + PA	4.66	4.89	8.43	8.86	81.42	75.47
OASDI + SSI + Housing		41.42		55.77		66.44
SNAP + PA + Housing		8.36		14.86		77.76
All Means-Tested		16.38		22.16		68.90
All		53.48		65.98		65.76
			B. Single Parent (Non-Elderly) Families			
SNAP + PA + Housing		16.81		39.79		85.27
All Means-Tested		31.54		52.40		78.22
All		37.94		60.17		77.13
			C. Elderly Families			
OASDI	79.01	80.08	90.17	89.51	69.47	68.69
OASDI + SSI + Housing		83.83		92.05		69.44
All Means-Tested		3.53		8.13		87.71
All		85.43		93.10		69.53
			D. Disabled Families			
OASDI	33.70	35.88	49.37	51.06	68.10	66.70
OASDI + SSI + Housing		45.58		66.39		69.56
All Means-Tested		16.98		31.32		78.55
All		56.68		75.68		69.95

Notes: Calculations are over all families and unrelated individuals from waves 1-14 of the 2008 SIPP Panel for those states and years for which we have both administrative SNAP and TANF data, excluding group quarters and unrelated individuals under age 15. They are not scaled to be representative of the full sample. The administrative amounts for OASDI, SSI, SNAP, PA, and housing assistance represent actual amounts received, while the administrative amounts for EITC represent eligible EITC benefits calculated from 1040 tax returns. "All Means-Tested" programs refer to SSI, SNAP, PA, housing assistance, and EITC, while "All" programs refer to the five aforementioned means-tested transfers plus OASDI. The administrative values for SSI combine administrative federally-administered amounts and survey-reported state-administered amounts. The administrative values for PA and housing assistance combine administrative amounts and survey-reported (for PA) and imputed (for housing) amounts for survey respondents reporting receipt that do not appear in the administrative data. Poverty rates are weighted by family size. Dollar amounts are in 2008 dollars, using an adjusted CPI-U. Numbers are scaled to be representative of the full sample. The pre-transfer poverty rate and gap (in $ millions) are 29.43% and $43,572 for all families, 57.04% and $5,583 for single-parent families, 66.22% and $16,431 for elderly families, and 49.93% and 13,644 for disabled families.

Table 9. Comparison of Estimates to Effects in the Literature (Percent Reductions in Poverty Rate)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Program	**This Paper**		**Scholz et al. (2009)**	**Short (2012)**	**Fox (2017)**	**Tiehen et al. (2013)**	**Hoynes et al. (2006)**
OASDI	31.94	30.07	33.00*	34.02	36.84		
SSI	2.39	6.63	1.65	6.40	6.99		
SNAP	4.21	11.24	1.32	8.52	7.42	8.00	
PA	0.33	1.03	0.33	1.83	1.34		
Housing	2.55	8.63	1.98	5.29	6.56		
EITC	4.58	9.12	3.63	14.81**	15.38**		12.23
Base Income	Pre-Tax, Pre-Transfer	Pre-Tax Cash	Pre-Tax, Pre-Transfer	Post-Tax, Post-Transfer	Post-Tax, Post-Transfer	Pre-Tax Cash	Post-Tax Cash, Except EITC
Reference Years	2008-13	2008-13	2008	2011	2016	2011	2003
Unit of Analysis	Individual	Individual	Family	Individual	Individual	Individual	Individual
Income Time Frame	Month	Month	Month	Year	Year	Year	Year
Data Used	Admin-SIPP	Admin-SIPP	SIPP	CPS	CPS	CPS	CPS

*This estimate sums the separate percent reductions in poverty of OASI and DI, since these are calculated separately in Scholz et al. (2009).
**These estimates are for all refundable tax credits (including the child tax credit).

Notes: This paper compares the percent reductions in the poverty rate calculated in this paper (using both pre-tax, pre-transfer and pre-tax cash measures of base income) with those found in other notable studies. The numbers for Column (1) come from Table 5, and the numbers for Column (2) come from the online appendix. For this paper, the estimates for SNAP are for the 12 states and years for which we have administrative SNAP data and the estimates for PA are for the 30 states for which we have administrative TANF data. This table also describes for each study the base income measure used, reference years, unit of analysis (i.e., whether the effects are weighted to reflect the number of individuals or families in the population), time frame used to measure income, and survey analyzed. Note that Tiehen et al. (2013) also calculate the poverty reduction of SNAP over a longer time period (1988-2011) and characterize base income in several ways, but we list only the effect for 2011 using pre-tax cash base income for comparability with the other studies and our study. The EITC estimate reported from Hoynes et al. (2006) is only over non-elderly persons. Finally, Scholz et al. (2009) use a version of the SIPP where they adjust survey responses for underreporting.

Figure 1a. Expenditures on Social Insurance Benefits in 2008 ($ billions)

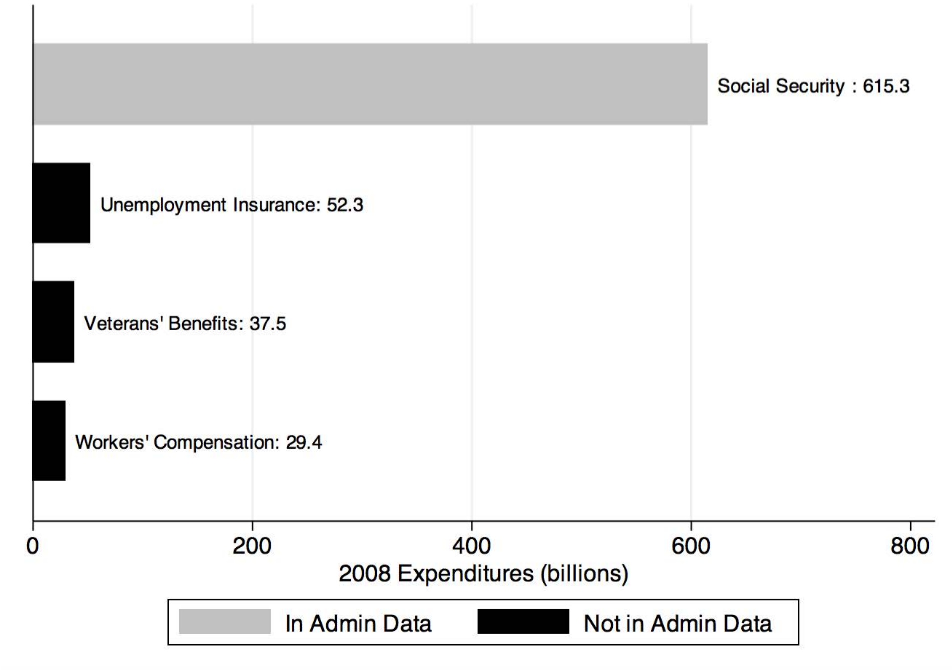
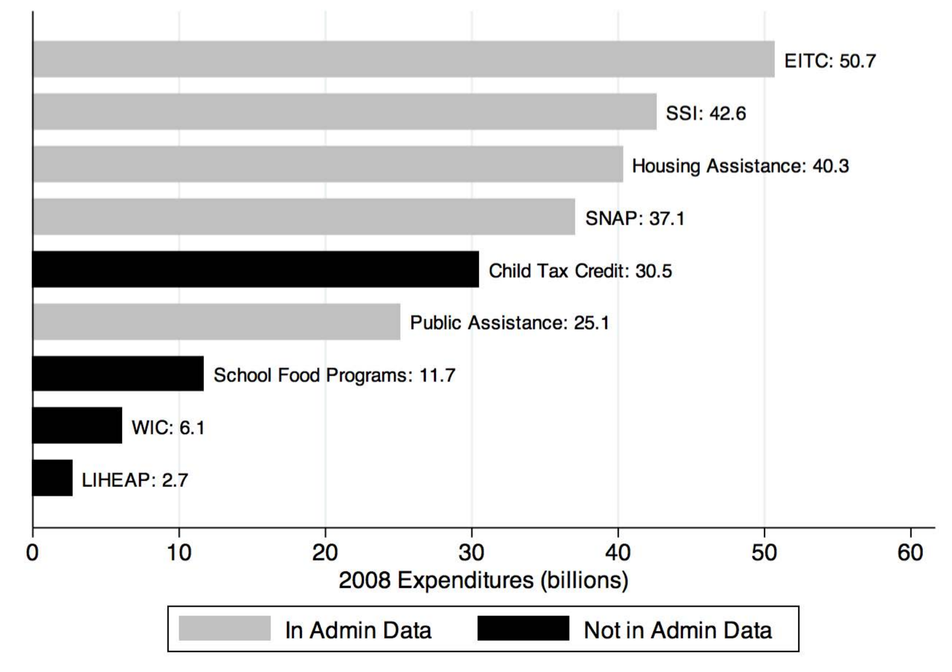


Figure 1b. Expenditures on Means-Tested Transfers in 2008 ($ billions)



Notes: These figures display the total expenditures on social insurance programs and on means-tested transfers in 2008, respectively. Gray bars reflect programs in our administrative microdata, and black bars reflect programs not in our administrative microdata. The key programs analyzed in this study capture 84% of all social insurance programs (excluding Medicare) and 79% of all means-tested transfers (excluding Medicaid). In total, this study's six programs capture 83% of all transfers (excluding Medicaid and Medicare). See online appendix for a list of sources.

Figure 2a. Largest Poverty-Reducing Transfers (by Family Type)

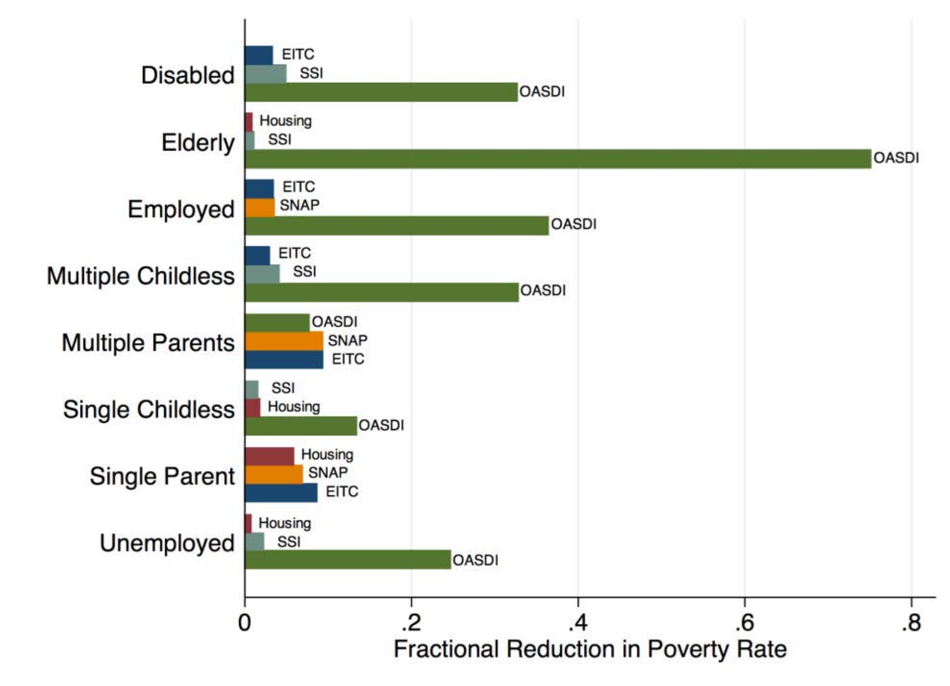
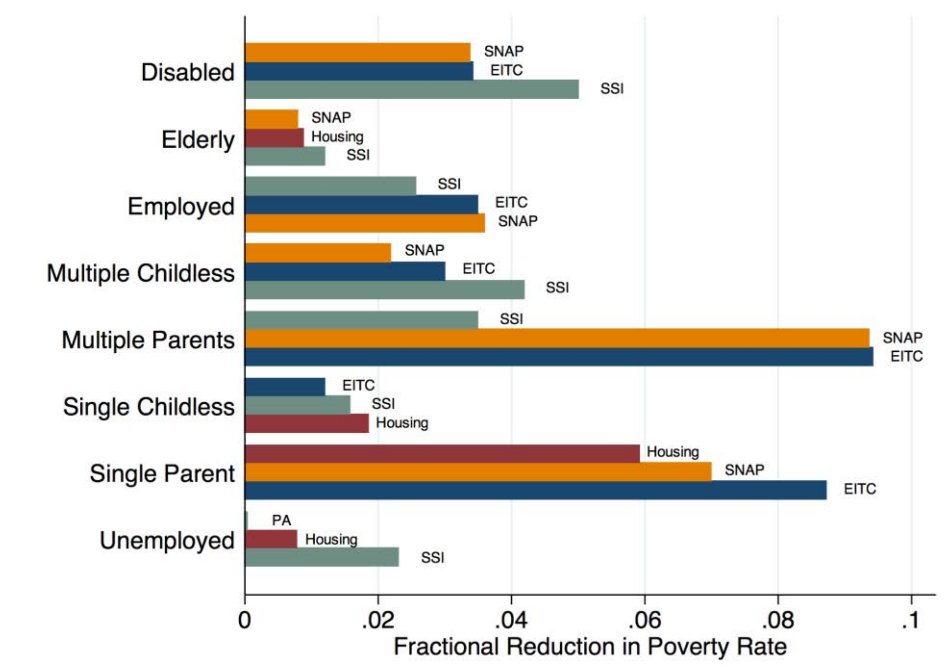


Figure 2b. Largest Poverty-Reducing Means-Tested Transfers (by Family Type)



Notes: These figures show, for each family type, the three largest transfer programs (over all six transfers and over the five means-tested transfers) ranked by the fractional reduction in the base poverty rate. See Table 7 for a list of base poverty rates for each family type).

Figure 3a. Comparison of Poverty Rate Reduction from Administrative and Survey Data

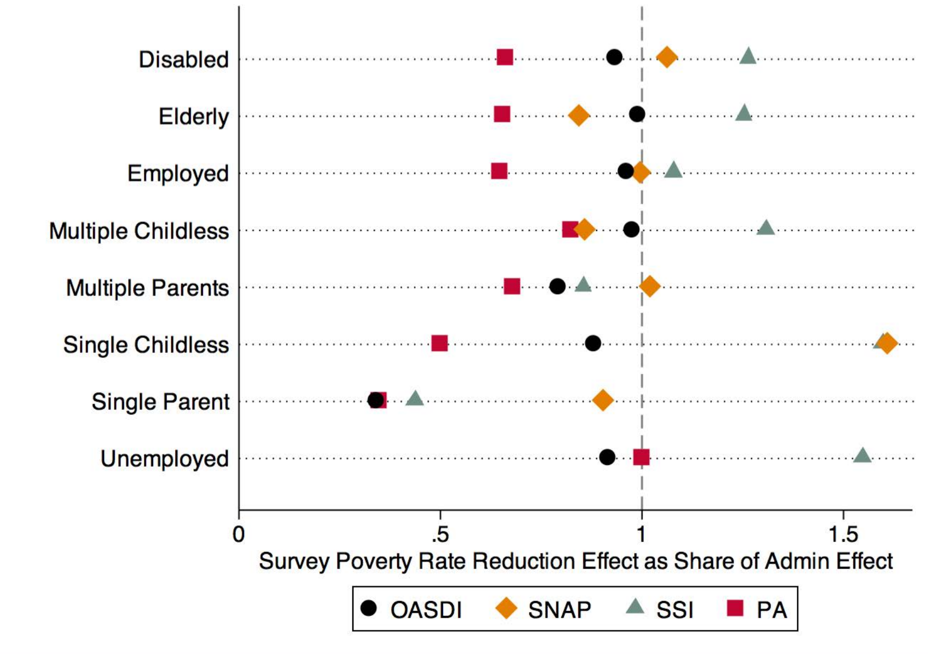
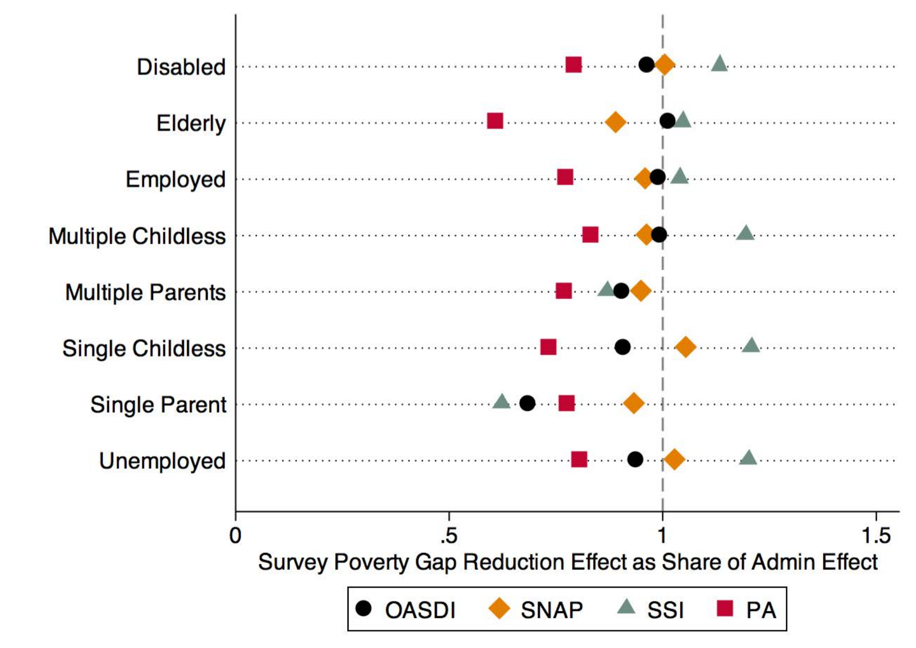


Figure 3b. Comparison of Poverty Gap Reduction from Administrative and Survey Data



Notes: These figures show for each family type the reduction in the poverty rate and gap from each program calculated from the survey data as a share of the effect calculated from the administrative data. For OASDI and SSI, calculations are over all families and unrelated individuals from waves 1-14 of the 2008 SIPP Panel, excluding group quarters and unrelated individuals under age 15. For SNAP and PA, calculations are over the states and years for which we have administrative SNAP and TANF data, respectively. Poverty rates are weighted by family size. We exclude the comparison of SNAP for unemployed families in Figure 3a, since the ratio of the survey to administrative estimate is an outlier at 11.5 given the small denominator of a 0.02% poverty reduction in the administrative data.