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Means-tested transfers in the U.S.: Facts and parametric estimates [☆]

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ABSTRACT

How large and important are means-tested transfers to working-age households in the United States? Using microdata from the Survey of Income and Program Participation, we document that a substantial share of households, more than one-third of them, receive transfers in a given year. Conditional on receipt, transfers average about $17,000 in 2016 dollars, exceeding one-fifth of mean household income. For households with no income, total conditional transfers amount to $26,500, nearly one-third of the mean household income. Transfers decline sharply with income but remain surprisingly widespread even in the middle and upper portions of the distribution. The system substantially compresses inequality, and its redistributive role has grown over time, driven largely by the expansion of Medicaid. Non-medical transfers are strongly countercyclical, and benefit reduction rates (the implicit tax rates on the first dollar earned) are significant. We provide parametric estimates of effective transfer functions by program, household type, and income level, ready for use in quantitative work in macroeconomics and public finance.

1. Introduction

How substantial are means-tested government transfers in the United States for households headed by working-age adults? How do these transfers change by household income and demographic characteristics? How do they affect income inequality? This paper addresses these questions. First, we document the scope of the main means-tested programs that target the non-retired population, presenting key facts about their generosity and coverage and how these features vary by households' income and demographic characteristics. We also document how the size and coverage of transfer programs have evolved over time, and their cyclical properties. Second, we examine the impact of these programs on the distribution of household income. Finally, we provide parametric estimates of effective transfer functions that can be readily used in applied research.

Several key observations motivate our work. First, the transfer system to households of working age in the United States reaches a substantial portion of the population and redistributes significant resources. We document that between 2013 and 2016, about 35%

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of working-age households received some transfers in a given year, and, conditional on receipt, the transferred amount exceeded one-fifth of the average household income, about $17,000.[1] Second, the U.S. welfare system encompasses multiple programs that combine cash and in-kind transfers. As these programs differ in scope and magnitude, the significance of the system is sometimes obscured or poorly understood. In addition, the transfer system has grown significantly in recent years, both in coverage and in the amounts transferred. We contribute by providing a systematic, big-picture characterization of the system's generosity and coverage, and of its evolution over time. Finally, a large and growing body of research in modern macroeconomics and public finance that incorporates household heterogeneity requires a description of effective transfers to households at different income levels. We fill this void by providing a ready-to-use set of parametric estimates. We estimate transfers and coverage as functions of household income to capture the system's nonlinear nature in practice.

We use data from different waves of the Survey of Income and Program Participation (SIPP) from 1998 to 2016 (U. S. Census Bureau 2014), covering the period after the 1996 Welfare Reform. Our benchmark analysis pertains to the last waves from 2013 to 2016. We subsequently use previous waves to document time trends. We consider four major transfer programs for which we have direct measurements of the monetary value of transfers received: Temporary Assistance for Needy Families (TANF), Supplemental Nutrition Assistance Program (SNAP), Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), and Supplemental Security Income (SSI). Two other programs, Housing Assistance and Medicaid, require imputations to calculate their monetary values. For the analysis, we differentiate between non-medical and total transfers. We report the average amounts received (both unconditional and conditional upon receipt) and coverage at different percentiles of the income distribution. We measure coverage along the extensive margin (the fraction of households that receive any assistance in a given year) and the intensive margin (the fraction of months in which a household receives some assistance in a given year). We also document how these magnitudes depend on the household head's marital status and the number and ages of children in the household. All of the programs we study are income-tested. While some, such as SSI, have asset testing, others, such as WIC and housing assistance, do not. For the other programs, TANF, SNAP, and Medicaid, asset testing became less important over time.

The transfers received by households decline rapidly as household income increases. On average, households without any pre-transfer income, who constitute about 6.5% of all households, receive about $7,500 from non-medical transfers and $13,700 from Medicaid. The sum, about $21,000, amounts to 26% of the mean household income in the U.S. The transfers decline for households with positive but very low pre-transfer incomes and then increase again, creating a hump-shaped pattern with respect to household pre-transfer income. At the bottom 10% of the income distribution, households receive $4,000 and $14,000 in non-medical and total transfers, respectively. These transfers decline to $600 and $3,800 at the 5th decile and to $170 and $1,200 at the top decile. The decline in transfers with household income reflects reduced coverage, as transfers conditional on receipt remain constant beyond the bottom 10% of the income distribution.

The transfer system has extensive coverage. Almost 82% of U.S. households with no pre-transfer income receive some transfers in a given year. The share is 70% for the 1st decile and declines to less than 30% at the 5th decile. Surprisingly, the share of households receiving transfers remains significant even at the top of the income distribution. About 5% of households in the top 10% of the income distribution receive some non-medical transfers during a year. The data suggest that the presence of a disabled or elderly household member is a key driver of transfer receipt among relatively high-income households. While non-medical transfers and their coverage are significant, Medicaid, as a single program, dominates other programs.

We next show the extent to which transfers reduce household income inequality. For the benchmark sample between 2013 and 2016, the Gini coefficient declines from 0.48 for the pre-transfer to 0.42 for the post-transfer income distribution. Changes in these magnitudes are significant and, surprisingly, often overlooked in analyses of income inequality. Even without large Medicaid transfers, non-medical transfers have a significant impact at the bottom of the income distribution.

Transfers to households, as a fraction of mean household income, quadrupled from the start to the end of our sample, from 1998 to 1999 to 2013–2016. Average transfers were about 2% of mean household income (about $1,500) in 1998–1999; in 2013–2016, they amounted to about 7.3% of mean household income (about $6,000). Transfers, conditional on receipt, also increased from about $12,000 to $17,000. The increase in transfers was mainly due to the expansion of Medicaid, partly reflecting the Affordable Care Act's creation of a large, income-based Medicaid pathway for non-elderly adults. While average non-medical transfers increased from $1,000 in 1998–1999 to about $1,500 in 2013–2016, total transfers more than tripled, from $1,700 to $6,000.

Transfer programs also reach a larger share of households. At the start of our sample, in 1998–1999, 19% of households received at least one transfer during the year. In 2013–2016, about 35% of households did. The increase in participation was not solely due to the expansion of Medicaid; the share of households receiving non-medical transfers also increased from 16% to 24%. During this period, the share of total transfers received by households in the bottom 10% of pre-transfer income declined, while transfers accruing to households in the second and third deciles increased.

Transfers significantly moderate the increase in income inequality in recent decades. Between 1998–1999 and 2013–2016, the pre-transfer income Gini increased from 0.40 to 0.48. The increase in post-transfer income Gini was more muted, from 0.38 to 0.42. Given their means-tested nature, non-medical transfers are countercyclical. At quarterly frequency, the correlation between their deviations from a Hodrick-Prescott (HP) filter trend and GDP is -0.32 for transfers and -0.44 for the fraction of households that receive at least one transfer in a quarter. On the other hand, fluctuations in total transfers, which include Medicaid, are much less cyclical.

[1] All monetary values reported are in 2016 dollars.

Finally, we focus on estimating the relationship between transfers received and household incomes. Specifically, we estimate a flexible function that captures the non-linear nature of transfers across income levels. Our parametrization allows us to estimate effective transfers received at zero income and the relationship between transfers and household income as income increases. We estimate functions for each major transfer program, the non-medical program, and total transfers. We also provide estimates for married and unmarried households, as well as by the number of children in the household. The estimated transfer functions allow us to compute the reduction in transfers associated with increases in pre-transfer income. The implicit benefit reduction rates we calculate are large: the first dollar of pre-transfer income reduces non-medical and total transfers by about $5,000 and $12,000, respectively. We also estimate an extended version of our effective transfer function, which maps an aggregate of household income and wealth into transfers received.

We note that there also are important means-tested supports in the U.S. that operate through the federal tax system, most notably the Earned Income Tax Credit (EITC) and the Child Tax Credit (CTC), which are not included in our estimates. These programs can be viewed as negative taxes rather than traditional transfers, and eligibility depends only on household income. In contrast, the welfare programs we study vary substantially across states and are administered by different federal and state agencies. Estimating effective transfer functions for these programs, therefore, provides a unified way to summarize a highly fragmented and heterogeneous system.

Related literature. This paper connects to a substantial body of research documenting the U.S. transfer system, its evolution, and its impact on inequality and poverty. Key works, such as those by Currie (2006), Moffitt (2007, 2016) describe the structure of the U.S. transfer system and the changes it underwent following the 1996 reforms. Within this literature, Ben-Shalom et al. (2012), Scholz et al. (2009) estimate the effects of transfers on poverty, while Hardy et al. (2018) examine how macroeconomic conditions, policy changes, and demographic shifts have driven increased program participation since the 1980s. Our contribution provides a comprehensive overview and time trends for all major means-tested programs, with a focus on ready-to-use, effective transfer functions for applied research.

Our paper is also closely related to papers that provide parametric representations of effective taxes paid or transfers received as a function of pre-tax-and-transfer income. Gouveia and Strauss (1994) is an early contribution that estimates effective tax functions for the U.S. for the 1980s. Benabou (2002) put forward a two-parameter tax function that posits a log-linear relation between post- and pre-tax income, which was first estimated for the U.S. and used to study optimal progressivity by Heathcote et al. (2017).[2] Guner et al. (2014) estimate effective taxes as functions of income using different functional forms with microdata from the Internal Revenue Service. Using a Benabou tax function, Borella et al. (2023) estimate changes in the progressivity of taxes in the U.S. since the 1980s, while Qiu and Russo (2026) provide estimates for a large set of countries. Some of these papers, such as Guner et al. (2014), focus explicitly on taxes paid, while others, such as Heathcote et al. (2017), combine taxes paid and transfers received, resulting in a higher estimated progressivity of the tax function. Finally, Fleck et al. (2021) provide estimates of the log-linear tax function at the state level to evaluate the progressivity of different tax and transfer provisions at the state level.

We differ from these papers by focusing on providing estimates of effective means-tested transfers, separately from the U.S. tax system. To introduce transfers succinctly for applied work, Hubbard et al. (1995) model them as a consumption floor, which is reduced one-to-one by households' resources (income plus assets). This functional form has since been adopted in quantitative macroeconomic models, particularly to model medical transfers, as in De Nardi et al. (2010). More recently, and in closer alignment with our analysis, Guner et al. (2023) estimated a transfer function that assumes transfers decline linearly with household income, while Ferriere et al. (2023) propose a non-linear transfer function where transfers decline non-monotonically as household income rises. Other papers focus on particular programs and model them in greater detail to capture eligibility and generosity. Low et al. (2018), Wellschmied (2021), Hosseini et al. (2026), Ortigueira and Siassi (2023), Agostinelli et al. (2024), Zhang (2025) are recent examples.

Finally, the current analysis contributes to papers documenting how income inequality has evolved in the U.S. in recent decades and the potential role of taxes and transfers. Fisher et al. (2022), Heathcote (2010), Kuhn and Ríos-Rull (2016), Heathcote (2023) are examples in this literature. The role of transfers in moderating income inequality in the U.S. has recently been emphasized by Gramm et al. (2022).

The paper is organized as follows. Section 2 presents a brief overview of the transfer programs we study. Section 3 describes the data used in our analysis. Section 4 discusses our basic findings regarding transfer amounts, coverage, and concentration. Section 5 presents the implications of our data for pre- and post-transfer income inequality. Section 6 presents and discusses trends over time and the changing impact of transfers on household income inequality. Section 7 contains our parametric estimates of transfer functions. Finally, Section 8 concludes.

2. Overview of U.S. transfer programs

This section provides a brief summary of the major U.S. transfer programs aimed at assisting low-income families and individuals included in our analysis. In Online Appendix A, we provide a more extensive description of each program.[3] These programs differ in how they condition participation on income and wealth. WIC and housing programs rely solely on income, while SSI has strict asset testing. On the other hand, the importance of assets for eligibility in TANF, SNAP, and Medicaid has been declining over time.

[2] This log-linear tax function has been widely used in quantitative macro models in recent years. See, among others, Guner et al. (2016), Holter et al. (2019), Imrohoroğlu et al. (2023).

[3] Online Appendix A provides program-by-program descriptions covering eligibility rules, benefit levels, asset tests, and recent caseload and spending figures, along with the references for statistics.

Temporary assistance for needy families (TANF). This program is the main U.S. cash-assistance program for low-income families with children, created by the 1996 welfare reform that replaced Aid to Families with Dependent Children (AFDC). TANF operates as a federal block grant: states receive a fixed $16.5 billion per year in federal funding, unchanged since 1996 and worth about 49 percent less in real terms by 2024. States must also contribute their own resources through a Maintenance of Effort (MOE) requirement, which in the 2023 fiscal year amounted to $17.4 billion out of total TANF-related spending of $33.9 billion. TANF funds can be used to pursue four broad statutory goals-including promoting work, reducing non-marital childbearing, and supporting two-parent families-and, consequently, to finance a wide range of activities, from cash assistance and wage supplements to child care, tax credits, and child welfare services. Only about one quarter of TANF spending ($8.3 billion in the 2023 fiscal year) is devoted to basic cash assistance. There is a 5-year lifetime limit on TANF receipt.

Despite its breadth, TANF cash assistance now reaches a small share of poor families. In September 2024, about 861,000 families received TANF cash benefits, far below historical levels, and most recipients were children. States have wide discretion over eligibility, benefit levels, work requirements, sanctions, and time limits, subject to a federal five-year lifetime limit on federally funded aid for adults. Eligibility is also tightly restricted by income and asset tests. While federal law imposes no asset limit, states may set their own. In recent years, many states have relaxed or eliminated asset tests to reduce barriers to saving and participation (Pirog and Edwin Gerrish, 2017).

Supplemental nutrition assistance program (SNAP). This program, formerly known as Food Stamps, is the United States' primary nutrition assistance program for low-income households. It is fully federally funded and administered by the states under uniform national rules. Households are generally eligible if gross income is below 130 percent of the federal poverty line and net income (after deductions) is below 100 percent of the poverty line, with greater flexibility for households containing elderly or disabled members. SNAP also uses categorical eligibility, most notably through broad-based categorical eligibility (BBCE), which allows households receiving certain non-cash TANF benefits to qualify under higher income and asset limits (Pirog and Edwin Gerrish, 2017). As a result, SNAP reaches many working poor families in addition to the very poorest. In fiscal year 2024, SNAP served an average of 41.7 million people per month at a total federal cost of $99.8 billion, making it the largest means-tested nutrition program in the United States, with an average benefit of about $187 per person per month (roughly $6.20 per day).

SNAP combines income targeting with asset tests and work-related rules. Federal law sets asset limits of $3,000 for households without an elderly or disabled member and $4,500 for those with one, but most states exempt vehicles and, through BBCE, have largely relaxed or eliminated asset tests for much of the caseload. Benefits are calculated using the USDA's Thrifty Food Plan, which determines the maximum benefit for each household size; in the 2026 fiscal year, the maximum monthly benefit for a three-person household is $785. Households are expected to spend 30 percent of their net income on food, so benefits decline with income, with net income calculated after deductions for work expenses, child care, housing, medical costs, and child support. Most households can receive SNAP without a time limit.

Special supplemental nutrition program for women, infants, and children (WIC). This program is a federally funded nutrition program that supports low-income pregnant and postpartum women, infants, and young children up to age five who are certified as being at nutritional risk. In addition to providing targeted food packages, WIC offers nutrition education, breastfeeding promotion and support, and referrals to health and social services. Eligibility requires income at or below 185 percent of the federal poverty line or participation in SNAP, Medicaid, or TANF, and applicants must also be assessed by health professionals as nutritionally at risk. Unlike TANF and SNAP, WIC does not impose any asset test, making eligibility depend solely on income, categorical status, and nutritional need.

Supplemental security income (SSI). SSI provides federally financed cash assistance to aged, blind, and disabled individuals with very low income and assets, and has evolved from a program largely supplementing Social Security for the elderly into a core antipoverty program for people with disabilities of all ages. Administered by the Social Security Administration and financed from general revenues, SSI served an average of 7.3 million recipients per month in 2024 at a federal cost of $63.1 billion, with optional state supplements in many states. Eligibility is determined by categorical status and strict means tests: in 2025, the federal benefit rate was $967 per month for an individual and $1,450 for a couple. Benefits phase out with earnings and other income, and countable assets are limited to $2,000 for individuals and $3,000 for couples. Consistent with its modern role, the vast majority of SSI recipients qualify on the basis of disability rather than age, including a substantial number of working-age adults and children.

Medicaid. is the United States' primary public health insurance program for low-income Americans, providing comprehensive coverage to children, pregnant people, parents, low-income adults, seniors, and people with disabilities. It is jointly financed by the federal government and the states, but administered at the state level under broad federal rules, resulting in substantial cross-state variation in eligibility thresholds, covered services, and provider payment rates. Medicaid is also the nation's largest payer of long-term care, accounting for more than half of all spending on nursing home care and community-based long-term services and supports. As of June 2025, Medicaid covered over 70 million people, and together with the Children's Health Insurance Program, it insured about one in five U.S. residents, including roughly two in five children, one in six non-elderly adults, and a large share of seniors and people with disabilities.

The Affordable Care Act (ACA) fundamentally reshaped Medicaid by creating a new eligibility pathway for nearly all non-elderly adults with incomes up to 138 percent of the federal poverty level, including adults without dependent children who were previously excluded. Although the Supreme Court made this expansion optional, 40 states and the District of Columbia had adopted it by mid-2025, covering more than 20 million low-income adults under enhanced federal financing that pays 90 percent of expansion costs. Eligibility rules now differ by pathway: most children, parents, pregnant people, and ACA expansion adults qualify based on income alone under the Modified Adjusted Gross Income (MAGI) system with no asset test, while seniors and people with disabilities face

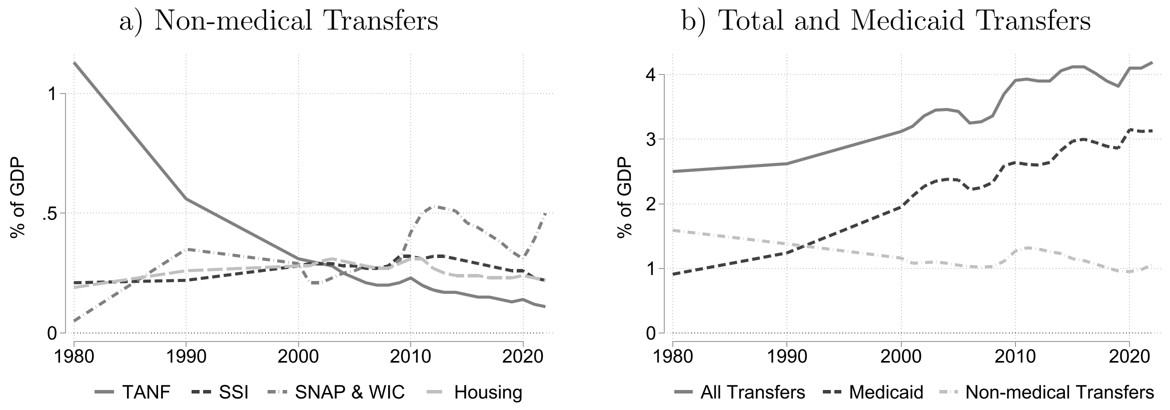

Fig. 1. Aggregate spending over the years.

Notes: Expenditure on TANF until 2012 is based on Ziliak (2015), Figure 4.2, and TANF Financial Data from the U.S. Department of Health and Human Services, Administration for Children and Families, for later years. For SNAP and WIC, USDA spending on food and nutrition assistance, fiscal years 1970–2023, available at https://www.ers.usda.gov/topics/food-nutrition-assistance/food-assistance-data-collaborative-research-programs/charts/expenditures/ is used. Spending on housing is from White House Historical Tables, Table 8.7 - Outlays for Discretionary Spending Programs: 1962 - 2029. Spending on Medicaid is taken from the National Health Expenditure Tables provided by the Centers for Medicare and Medicaid Services, Table 03 National Health Expenditures, by Source of Funds, https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/nhe-fact-sheet.

stricter non-MAGI rules that include both income and asset limits. As a result, Medicaid has become a central pillar of health coverage for low-income working-age adults and families (Altman, 2025).

Housing programs. Federal housing assistance in the United States is delivered primarily through three programs: Housing Choice Vouchers, Project-Based Rental Assistance, and Public Housing, which together subsidize roughly five million low-income households. These programs provide in-kind housing support by capping tenants' rent payments at about 30 percent of adjusted household income and covering the remaining cost up to administratively set limits. Eligibility is means-tested using Area Median Income (AMI) rather than the federal poverty line, with priority given to households with incomes below 30 percent of AMI. There are no binding asset tests, so savings and vehicles do not affect eligibility. Because funding is capped, only about one in four income-eligible renters receives assistance, making housing subsidies a large but rationed income-based transfer in the U.S. safety net. The total number of participants in the three programs was 5 million households in 2024, about 3.8% of all U.S. households (Freemark and Hermans, 2025).

2.1. Aggregate spending

We provide in Fig. 1 an overview of the evolution of aggregate expenditures allocated to the different programs as a share of U.S. GDP since 1980. Panel A documents trends in different non-medical transfers, while Panel B shows non-medical transfers, Medicaid, and the total. The spending on TANF decreased significantly during this period, from above 1% of GDP to about 0.1% in 2022, a decline that had already begun before the Welfare Reform of 1996.[4] Expenditures on SSI and housing assistance have stayed fairly constant, around a quarter percentage point of GDP each. Expenditures on SNAP and WIC are countercyclical with a general upward trend and substantial increases during the Great Recession and the COVID pandemic, reaching up to half a percentage point of GDP.[5] The total transfers have increased from 2.5% of GDP in 1980 to more than 4% in 2022 (Panel B). This increase is driven by Medicaid spending, which rose from less than 1% in 1980 to more than 3% in 2022. In contrast, the expenditure on non-medical transfers declined from 1.6% to about 1% of GDP.

3. Data

We use five panels of the *Survey of Income and Program Participation* (SIPP), the most comprehensive source of information on means-tested transfers in the U.S. (Meyer et al., 2015). Each SIPP panel consists of waves that follow households for up to 4 years and provides detailed information on household pre-transfer income, participation in various social insurance programs, transfer payments received, and other socioeconomic variables. Our main analysis relies on the 2014 SIPP panel, which spans 2013-2016. We then incorporate the 1996, 2001, 2004, and 2008 panels to document trends over the 1998-2016 period. Because the SIPP underwent a

[4] Parolin (2021) estimates that declining participation accounts for about 52% of the decline in spending between 1993 and 2016.
[5] On the growing importance of SNAP, see Bartfeld et al. (2015).

significant redesign after 2016, key information-particularly transfer amounts-is no longer consistently reported, with many programs recording only participation. This break in measurement makes comparisons across pre- and post-2016 panels unreliable, and we therefore exclude later panels from the analysis. We use the household weights, making the SIPP a representative sample of the non-institutionalized civilian U.S. population. Every four months, interviews are conducted with all members above the age of 15 of participating households, asking them about their income and transfers received retrospectively for the preceding four months.

Payments from TANF, SSI, and SNAP are recorded at the household level. The WIC payments, on the other hand, are recorded for each child under age 15, and we sum all payments for each child to obtain the household total. For housing benefits, we only know whether a household was enrolled in the program. To compute the monetary value of Medicaid and housing transfers, we follow Scholz et al. (2009), Ben-Shalom et al. (2012). For housing, we first obtain the Fair Market Rent (FMR) for each state from the Department of Housing and Urban Development.[6] From SIPP, we also know the rents paid for all households, including those enrolled in housing programs. The monetary value of in-kind housing benefits is then calculated as the difference between the FMR in the state and the rent paid.[7]

For Medicaid, we know the enrollment of each household member. To impute a monetary value, we use the cost of a typical Health Maintenance Organization (HMO) policy in the household's region.[8] If a household contains one individual covered by Medicaid, then we assign the costs of a single HMO policy. On the other hand, if a household contains more than one individual covered by Medicaid, we use the cost of the equivalent number of single policies or the cost of one family policy, depending on which is cheaper.[9]

Sample inclusion criteria. In our analysis, we restrict the sample to the 2014 panel (years 2013 to 2016) and include households in which the head is between 25 and 54 years old. The entire sample of monthly observations within this age group consists of 460,500 observations.[10] The unit of observation is a household-year cell, so if a household is observed, for example, over two full years, it provides two observations. We restrict the sample to households in which the household head's marital status does not change during a given calendar year. Finally, we exclude households headed by self-employed individuals (about 7% of households) and those with negative annual total pre-transfer income (about 0.1% of households). Pre-transfer household income is defined as the sum of labor and asset income from all sources for all household members. Hence, below, whenever we refer to income or household income, unless otherwise stated, we mean pre-transfer, pre-tax total household income. These sample restrictions leave us with 18,612 households and 38,375 household-year observations. Among households in the final sample, 43% are observed for only one year, 25% for two years, 15% for three years, and 17% for four years. Married, single women, and single men households constitute 50%, 29%, and 21% of household-year observations in the sample, respectively. Although some programs impose asset tests, most transfer programs are increasingly income-tested, which is why income is the primary state variable in our empirical analysis.

We provide additional details on the benchmark sample and the measurement issues associated with the SIPP in Online Appendix B. We report therein summary statistics for the full sample and for transfer recipients, document heterogeneity by marital status and by the presence of elderly or disabled household members, and we describe additional means-tested programs observed in the SIPP that are not included in our baseline transfer measure. We also compare the SIPP income distribution with comparable Current Population Survey and Survey of Consumer Finances samples in Online Appendix B, report basic wealth statistics used later in the analysis, and discuss the main caveats of the SIPP-seam bias, attrition, and misreporting.

4. Transfers to households

We present key findings from our data, starting with transfer amounts received by various demographic groups across income levels, followed by an analysis of transfer coverage. Transfer coverage includes both the percentage of households receiving transfers in a given year and the proportion of months within that year during which households receive transfers. Tables showing transfers by income levels indicate the average annual amount households in each income percentile receive from major means-tested programs, expressed in 2016 U.S. dollars. Income percentiles are calculated excluding households with zero income. Therefore, for instance, the 0-10 percentile range corresponds to the bottom decile of the positive-income distribution. Normalized, these amounts are also expressed as percentages of the average annual household income (in 2016, $82,060). Income percentiles are based on all household-year observations in the sample. To enable across-group comparisons and facilitate interpretation, overall percentiles are applied rather than recalculated for each subgroup when presenting results for specific groups (e.g., married individuals, single men, single women).

[6] An API is available at https://www.huduser.gov/portal/dataset/fmr-api.html.

[7] For 2.7% of the sample, this difference is negative, for whom we assign a value of zero. The state FMRs are population-weighted averages by county (or major metropolitan area). For 0.08% of the sample whose state of residence is unknown, we use the national average FMR value. In assigning FMR values, we assume that childless individuals or couples live in a one-bedroom dwelling and families with one or two children live in two-bedroom dwellings. An extra bedroom is added for each child over two.

[8] When the region of the household is not available (0.08% of the 2014 survey panel), we take the national average. Regions are the Northeast, the Midwest, the South, and the West.

[9] The value of a single policy for elderly or disabled individuals is multiplied by a factor of 2.5. For households with elderly or disabled individuals, a family policy is also multiplied by a factor of 2.5 to account for the greater medical needs of these groups. The cost of an HMO policy by region is taken from the "Kaiser Family Foundation Employer Health Benefits" (Kaiser Family Foundation 2016) annual survey (1999–2016).
We classify a household member as disabled if the answer to the question "Does …have a physical, mental or other health condition that limits the kind or amount of work he/she can do?" is affirmative.

[10] We exclude household heads aged under 25 so that most college graduates have completed their education. The sample ends at age 54 to exclude those entering into (early) retirement.

Table 1
Transfers received by income quantile.

Quantile	TANF	SNAP	WIC	SSI	Housing	Medicaid	Transfers Non-med.	Transfers All	Income
Panel A: $ Amounts									
No income	379	1977	69.9	3062	2106	13744	7594	21338	0.00
0-1%	85.5	897	26.5	1182	744	6720	2934	9654	194
1–5%	197	1982	86.9	1160	1457	11041	4883	15924	5451
5–10%	179	1806	84.0	716	970	9856	3756	13611	14353
0–10%	177	1786	79.4	940	1142	10016	4124	14141	9376
10–20%	77.1	1057	90.5	595	454	8107	2274	10382	24282
20–30%	39.2	518	71.7	348	189	5711	1166	6876	35861
30–40%	49.4	327	54.9	211	124	4345	766	5112	47322
40–50%	31.7	247	39.9	218	65.9	3189	602	3792	59248
50–60%	14.9	162	30.1	143	75.1	2581	425	3006	72795
60–70%	11.8	111	13.4	104	17.9	1844	258	2103	88922
70–80%	12.6	75.8	10.0	102	21.6	1477	222	1699	110568
80–90%	3.94	58.3	8.32	111	10.7	1221	192	1413	146106
90–100%	1.40	60.3	4.88	96.9	5.77	1031	169	1200	278570
Mean	63.5	537	42.0	466	332	4567	1440	6007	82060
Panel B: Percentage of Mean Household Income									
No income	0.46	2.41	0.09	3.73	2.57	16.7	9.25	26.0	0.00
0-1%	0.10	1.09	0.03	1.44	0.91	8.19	3.58	11.8	0.24
1–5%	0.24	2.42	0.11	1.41	1.78	13.5	5.95	19.4	6.64
5–10%	0.22	2.20	0.10	0.87	1.18	12.0	4.58	16.6	17.5
0–10%	0.22	2.18	0.10	1.15	1.39	12.2	5.03	17.2	11.4
10–20%	0.09	1.29	0.11	0.73	0.55	9.88	2.77	12.7	29.6
20–30%	0.05	0.63	0.09	0.42	0.23	6.96	1.42	8.38	43.7
30–40%	0.06	0.40	0.07	0.26	0.15	5.30	0.93	6.23	57.7
40–50%	0.04	0.30	0.05	0.27	0.08	3.89	0.73	4.62	72.2
50–60%	0.02	0.20	0.04	0.17	0.09	3.15	0.52	3.66	88.7
60–70%	0.01	0.14	0.02	0.13	0.02	2.25	0.31	2.56	108
70–80%	0.02	0.09	0.01	0.12	0.03	1.80	0.27	2.07	135
80–90%	0.00	0.07	0.01	0.13	0.01	1.49	0.23	1.72	178
90–100%	0.00	0.07	0.01	0.12	0.01	1.26	0.21	1.46	339
Mean	0.08	0.65	0.05	0.57	0.41	5.57	1.76	7.32	100

Notes: This table shows transfers accruing to households at different quantiles of the income distribution. Panel A presents the value of transfers received in dollars for 2016. Panel B presents the information after normalizing by the mean household income in 2016.

4.1. *Transfer amounts*

Table 1 summarizes the level of transfers to working-age households in the United States. The table shows average transfers across income percentiles for different programs, along with the average income at each corresponding percentile. Panel A presents absolute amounts, while Panel B presents amounts normalized by the mean household income.

Households without pre-transfer income receive significant support, with total transfers averaging $21,000 in 2016 dollars, or 26% of the mean U.S. household income.[11] Of this, about one-third ($7,500) is non-medical, while the remaining $13,700 comes from Medicaid. Among the lowest-income households, transfers initially drop sharply, then increase slightly as household income rises. Households in the bottom 1% receive approximately $10,000, about $11,000 less than those with no income, and $6,000 less than those in the 1–5% income range. Beyond the bottom 5%, transfers decline rapidly. By the bottom 10%, households receive roughly $4,000 in non-medical transfers and a total of $14,000. Transfers decrease further to $600 and $3,700 at the 5th decile and to $170 and $1,200 in the top 10%.

While non-medical transfers are substantial, averaging $1,400 for all households and $4,000 for those in the bottom decile, Medicaid's importance stands out. Moreover, Medicaid's proportion of total transfers grows with income. For households with no income, total transfers are less than three times non-medical transfers, whereas for those in the 50–60% income percentile, this ratio exceeds six.

The role of marital status. We present in Table 2 transfer distributions by marital status and household income level, underscoring the significant role marital status plays in transfer allocation. Households headed by single women with no income receive non-medical transfers amounting to about 12% of average household income (approximately $9,800), and total transfers are nearly a third of average income (around $25,500). Married households receive roughly 27% of the average household income (about $22,000), while single men receive significantly less at 17.9% (about $14,700). Surprisingly, at higher income levels, married households receive

[11] Throughout the tables, we follow the convention of reporting rounded values for values above 100, one decimal for values between 10 and 100, and two decimals for values smaller than 10.

Table 2
Transfers by marital status (% of mean household income).

Quantile	Non-medical Transfers				All Transfers			
	Married	Single Women	Single Men	All	Married	Single Women	Single Men	All
No income	7.13	12.0	5.97	9.25	27.0	31.3	17.9	26.0
0-1%	1.66	5.24	2.37	3.58	10.4	14.7	8.60	11.8
1–5%	4.19	8.23	2.82	5.95	19.1	24.4	9.98	19.4
5–10%	4.69	5.72	2.24	4.58	19.1	19.4	8.74	16.6
0–10%	4.26	6.73	2.49	5.03	18.3	21.0	9.22	17.2
10–20%	2.95	3.43	1.38	2.77	16.2	13.8	6.17	12.7
20–30%	1.83	1.62	0.58	1.42	12.2	7.81	3.68	8.38
30–40%	1.14	1.07	0.40	0.93	8.27	5.97	2.82	6.23
40–50%	0.77	0.85	0.54	0.73	5.26	4.76	3.16	4.62
50–60%	0.50	0.79	0.35	0.52	4.01	4.08	2.41	3.66
60–70%	0.26	0.56	0.26	0.31	2.30	3.52	2.50	2.56
70–80%	0.18	0.63	0.35	0.27	1.61	3.89	2.58	2.07
80–90%	0.20	0.40	0.30	0.23	1.38	3.27	2.43	1.72
90–100%	0.19	0.48	0.15	0.21	1.30	2.82	1.86	1.46
Mean	0.91	3.71	1.34	1.76	5.39	12.5	5.49	7.32

Notes: This table shows transfers accruing to households at different quantiles of the income distribution when households are divided between married and single. The information is presented for values normalized by the mean household income in 2016.

more in total transfers than single women do, though not in non-medical transfers. This pattern emphasizes the relative impact of Medicaid within the overall transfer system.

In Tables C1 and C2 in Online Appendix C, we expand the information presented in Table 2 by considering the amounts received by the number and age of children. Transfers increase with the number of children in a household. For households in the first income decile, for instance, a married household without children receives approximately 1.7% (about $1,400) of average household income as non-medical transfers and 9.0% (about $7,400) of average household income in total transfers. Among married households with one child, non-medical transfers rise to 2.6% of average household income and total transfers to 12.4%. For married households with two or more children, the corresponding figures are 5.3% and 22.2%, respectively. Thus, for married households in this income decile, non-medical transfers increase by about 60% with the first child and more than triple with two or more children, while total transfers increase by about 40% and by roughly a factor of 2.5, respectively. The increase in transfers is even more pronounced for single-woman households. Those in the same income decile without children receive around 1.7% (about $1,400) and 6.7% (about $5,500) of average household income in non-medical and total transfers, respectively. Non-medical transfers rise by about a factor of 2.5 with one child and by nearly a factor of 5 with two or more children; total transfers also increase substantially, although by a smaller factor. Transfers decline with children's age, except in households with no income. However, the impact of children's age is significantly smaller than the number of children in the household.

4.2. Coverage

Tables 3 and 4 present data on transfer coverage, detailing the likelihood of transfer receipt at various income levels. Panel A in both tables shows the probability of receiving a specific transfer in at least one month of the year, reflecting the extensive margin-the fraction of households receiving transfers. Panel B reports the probability of receiving a transfer in a randomly chosen month, representing the intensive margin-the average fraction of months households receive transfers annually.[12]

The transfer system reaches a substantial portion of households at the lower end of the income distribution, as shown in Panel A of Table 3. Among households with no income, approximately 82% receive some form of transfer, which decreases to about 75% when medical transfers are excluded. As income rises, the share of households receiving transfers initially increases, then declines. About 51% of households in the bottom 1% of the income distribution receive some transfers, compared with 70% of households in the lowest decile. The coverage then drops to 29% by the fifth decile. Notably, even at the highest income decile, approximately 5% of households receive non-medical transfers, which doubles to 11% when Medicaid is included. At the lowest income levels, Medicaid and SNAP are the most common forms of assistance, followed by SSI and housing benefits.

Panel B of Table 3 illustrates the proportion of months households receive transfers. As with the extensive margin, at the lowest income levels, the welfare system not only reaches a significant share of households but also provides support for most of the year. Households with zero income receive transfers in over 80% of months. For households with positive income, this proportion

[12] Let there be Y years and N households in the sample. Let T_{iy} be the total transfers of household i in year y. Panel A shows $\frac{\sum_1^Y \sum_1^N \mathbb{1}_{\{T_{iy}>0\}}}{N\times Y}$. Let T_{iym} be transfers of household i in month m of year y. Panel B shows $\frac{\sum_1^Y \sum_1^{12} \sum_1^N \mathbb{1}_{\{T_{iym}>0\}}}{N\times Y\times M}$, where $M = 12$. By dividing the share of months that receive transfers by the share of households that receive transfers, one can calculate the share of months conditional on receipt.

Table 3
Transfer coverage by income quantiles.

							Transfers	
Quantile	TANF	SNAP	WIC	SSI	Housing	Medicaid	Non-med.	All
Panel A: Percentage of Households Receiving								
No income	11.0	66.6	9.56	34.0	24.4	71.7	75.1	81.6
0-1%	3.47	31.7	4.85	14.5	9.56	40.4	37.7	51.2
1–5%	8.04	54.5	13.6	14.2	15.6	65.3	61.0	73.0
5–10%	6.06	51.0	14.5	9.12	11.4	63.3	58.0	70.5
0–10%	6.59	50.5	13.2	11.7	12.9	61.8	57.1	69.6
10–20%	3.38	34.2	14.6	7.64	5.66	53.1	43.6	58.6
20–30%	1.62	19.1	11.7	4.56	2.41	39.1	28.2	44.7
30–40%	1.46	12.3	9.37	3.59	1.54	32.3	20.9	36.4
40–50%	0.92	8.38	6.45	3.18	0.99	24.3	15.4	28.5
50–60%	0.42	6.49	5.24	2.77	1.04	20.8	12.4	24.3
60–70%	0.59	5.21	2.80	1.98	0.53	15.7	8.88	18.5
70–80%	0.53	3.42	1.79	1.66	0.46	12.3	6.35	14.5
80–90%	0.11	2.51	1.66	1.81	0.25	10.0	5.02	12.2
90–100%	0.04	2.46	0.93	1.77	0.16	9.05	4.80	10.9
Mean	1.61	17.7	6.92	6.00	3.99	30.6	24.0	34.9
Panel B: Percentage of Months Received								
No income	6.37	63.0	8.67	32.7	24.4	69.8	72.8	80.1
0-1%	1.79	28.2	4.17	13.6	9.56	38.8	35.4	47.7
1–5%	4.17	48.9	11.0	13.0	15.6	62.1	56.2	69.9
5–10%	3.51	45.1	11.6	8.31	11.3	59.9	53.2	66.9
0–10%	3.60	44.9	10.6	10.7	12.9	58.6	52.6	66.2
10–20%	2.04	28.7	12.0	7.04	5.66	50.4	38.8	55.4
20–30%	0.97	15.1	9.69	4.13	2.41	35.7	24.5	40.7
30–40%	1.11	9.46	7.51	3.24	1.52	29.3	17.7	33.1
40–50%	0.57	6.45	5.20	2.73	0.97	21.6	12.9	25.5
50–60%	0.28	5.01	4.19	2.33	1.04	18.0	10.6	21.0
60–70%	0.29	3.69	2.06	1.61	0.49	13.5	7.01	16.0
70–80%	0.32	2.56	1.41	1.49	0.40	10.8	5.70	12.7
80–90%	0.04	1.86	1.11	1.53	0.25	8.90	4.10	10.6
90–100%	0.03	1.97	0.75	1.44	0.16	7.97	4.42	9.68
Mean	1.27	15.2	5.64	5.51	3.97	28.2	21.3	32.3

Notes: This table shows facts related to transfer coverage. The data are presented in percentages. Panel A presents the percentage of households at each income level that received various forms of assistance. Panel B presents the percentage of months in a given year that transfers are received at different income levels.

initially rises and then gradually decreases. At the first and fifth income deciles, the share of months with transfer receipt drops to approximately 66% and 26%, respectively. Medicaid emerges as the most significant transfer program, followed by SNAP.

Transfer coverage by marital status is documented in Table 4. Additional coverage results by the number and age of children are reported in Tables C6-C9 in Online Appendix C. At very low-income levels (below the first decile), single-women households have the highest coverage on both the extensive and intensive margins, followed by married households and single men. Among single women with no income, 88% receive some form of transfer (83.6% for non-medical transfers). For married and single-man households, these figures are 78% and 74%, respectively. As income rises, married households take the lead in transfer coverage. For instance, in the fifth decile, 33% of married households receive transfers compared to 28% of single women. This pattern is mirrored in the fraction of months in which transfers are received. Notably, single men show substantial coverage even at higher income levels. Around the median income, nearly one in five single-man households receive transfers, and at the 80-90th income percentile, more than one in six still receive support.

4.3. Transfers conditional on receipt

Table 5 summarizes transfers, conditional upon receipt, across income levels. Panel A provides raw amounts in 2016 dollars, while Panel B presents these values as percentages of mean household income. The gap between unconditional amounts in Table 1 and conditional amounts reflects the extent of coverage at different income levels documented in Table 3.

At the bottom of the income distribution, conditional transfers are close to unconditional transfers since a large fraction of households participate in the transfer system. For households with no income, total conditional transfers average $26,500, over 32% of the national mean household income, while unconditional transfers were about $21,000, 26% of the mean household income. At higher income percentiles, conditional transfers are markedly higher than unconditional averages, underscoring their impact on recipient households. Households in the lowest decile receive about $21,000, or 26% of the mean income, compared to $14,000 in unconditional transfers. After the first three income deciles, conditional transfer levels stabilize, remaining above 15% of mean household income for total transfers, as shown in Panel B. Finally, the medical-to-non-medical transfer ratio is substantially lower for

Table 4
Transfer coverage by income quantiles and marital status.

Quantile	Non-medical Transfers				All Transfers			
	Married	Single Women	Single Men	All	Married	Single Women	Single Men	All
Panel A: Percentage of Households Receiving								
No income	65.5	83.6	66.1	75.1	77.7	87.9	73.9	81.6
0-1%	25.0	44.0	36.3	37.7	46.2	55.3	48.5	51.2
1–5%	53.7	72.7	43.7	61.0	70.0	82.6	56.7	73.0
5–10%	55.5	68.7	39.5	58.0	73.3	78.2	52.7	70.5
0–10%	52.3	68.1	40.8	57.1	69.8	77.9	53.8	69.6
10–20%	51.2	48.7	25.1	43.6	69.5	63.6	36.3	58.6
20–30%	38.3	27.8	14.4	28.2	59.2	44.3	24.6	44.7
30–40%	26.1	21.1	11.1	20.9	46.2	35.4	19.8	36.4
40–50%	17.4	16.4	10.1	15.4	33.2	27.4	20.0	28.5
50–60%	11.7	16.0	11.3	12.4	24.8	28.8	19.3	24.3
60–70%	7.71	12.0	9.72	8.88	17.0	21.9	20.1	18.5
70–80%	5.06	12.3	7.04	6.35	11.9	22.5	19.2	14.5
80–90%	4.24	8.07	7.14	5.02	10.3	19.3	17.5	12.2
90–100%	4.11	10.9	6.24	4.80	9.44	19.9	17.0	10.9
Mean	16.9	39.6	21.7	24.0	27.9	51.0	31.5	34.9
Panel B: Percentage of Months Received								
No income	63.3	81.5	63.7	72.8	75.9	86.6	72.0	80.1
0-1%	27.6	40.3	32.9	35.4	44.7	51.6	44.1	47.7
1–5%	47.3	68.7	38.3	56.2	67.2	80.3	51.8	69.9
5–10%	51.1	63.1	36.0	53.2	70.2	74.7	48.5	66.9
0–10%	47.8	63.4	36.5	52.6	67.0	74.9	49.3	66.2
10–20%	45.0	44.5	21.1	38.8	66.6	60.8	32.0	55.4
20–30%	34.0	23.3	12.6	24.5	54.7	40.1	21.7	40.7
30–40%	22.3	17.6	9.34	17.7	42.9	31.4	17.3	33.1
40–50%	14.6	13.9	8.46	12.9	29.9	24.7	17.4	25.5
50–60%	10.4	13.1	9.26	10.6	22.3	23.4	15.6	21.0
60–70%	6.27	10.4	6.18	7.01	14.5	19.9	17.0	16.0
70–80%	4.70	10.8	5.84	5.70	10.5	20.4	15.9	12.7
80–90%	3.58	6.64	5.09	4.10	9.02	17.2	14.6	10.6
90–100%	3.92	9.43	5.08	4.42	8.25	18.3	15.7	9.68
Mean	14.5	36.2	18.9	21.3	25.6	48.1	28.4	32.3

Notes: This table shows facts related to transfer coverage in relation to marital status. The data are presented in percentages. Panel A presents the percentage of households at each income level that received all transfers and non-medical transfers by marital status. Panel B presents the percentage of months in a given year that all transfers and non-medical transfers are received at different income levels by marital status.

conditional transfers than for unconditional transfers, with a ratio of approximately 3.2 at the 40–50% income percentile, compared to 6.3 unconditionally. This variation highlights significant differences in medical and non-medical transfer receipts at similar income levels.

We present in Tables C3, C4, and C5 in Online Appendix C the conditional transfers by marital status and by the number and age of children, distinguishing between married and single households. Conditional transfers also increase with the number of children, but the rise is not as steep as for unconditional transfers, reflecting the importance of children for eligibility in different programs.

4.4. *Concentration*

How concentrated are transfers across different income levels? Table 6 answers this question by documenting the share of total transfers in percentage points received by households at different income percentiles. In the table, the numbers in each column sum to 100, as transfers received at different income levels add up to the total spending for each program.

Given the means-tested nature of these transfers, it is unsurprising that most benefits are concentrated among low-income households. Approximately 23% of all transfers go to households with no income, while households in the bottom decile receive about 22% of total transfers. Nearly 90% of transfer spending is directed to households below the sixth income decile. The concentration is particularly pronounced for some non-medical transfer programs, such as TANF, SSI, and housing assistance. In contrast, Medicaid transfers are more evenly distributed across income levels. These findings, along with the magnitude of the transfers involved, suggest that the post-transfer income distribution can differ significantly from the pre-transfer distribution.

Table 5
Transfers conditional on receipt by income quantile.

							Transfers	
Quantile	TANF	SNAP	WIC	SSI	Housing	Medicaid	Non-med.	All
Panel A: $ Amounts								
No income	5954	3137	806	9360	8645	19683	10425	26644
0-1%	4778	3181	636	8695	7788	17299	8297	20222
1–5%	4726	4056	790	8914	9323	17789	8692	22776
5–10%	5087	4005	722	8624	8571	16467	7060	20334
0–10%	4905	3976	747	8774	8878	17082	7840	21358
10–20%	3785	3690	755	8457	8026	16095	5860	18727
20–30%	4061	3432	740	8437	7845	15988	4766	16895
30–40%	4470	3455	730	6518	8176	14808	4337	15449
40–50%	5551	3823	767	8003	6771	14736	4658	14849
50–60%	5312	3228	719	6156	7191	14367	3994	14306
60–70%	4059	3011	649	6468	3681	13643	3683	13166
70–80%	3890	2963	709	6856	5404	13669	3892	13368
80–90%	9097	3126	748	7230	4351	13715	4679	13334
90–100%	4355	3062	651	6747	3655	12936	3830	12404
Mean	2930	3025	608	7763	8328	14941	6071	17200
Panel B: Percentage of Mean Household Income								
No income	7.26	3.82	0.98	11.4	10.5	24.0	12.7	32.5
0-1%	5.82	3.88	0.78	10.6	9.49	21.1	10.1	24.6
1–5%	5.76	4.94	0.96	10.9	11.4	21.7	10.6	27.8
5–10%	6.20	4.88	0.88	10.5	10.4	20.1	8.60	24.8
0–10%	5.98	4.84	0.91	10.7	10.8	20.8	9.55	26.0
10–20%	4.61	4.50	0.92	10.3	9.78	19.6	7.14	22.8
20–30%	4.95	4.18	0.90	10.3	9.56	19.5	5.81	20.6
30–40%	5.45	4.21	0.89	7.94	9.96	18.0	5.29	18.8
40–50%	6.76	4.66	0.93	9.75	8.25	18.0	5.68	18.1
50–60%	6.47	3.93	0.88	7.50	8.76	17.5	4.87	17.4
60–70%	4.95	3.67	0.79	7.88	4.49	16.6	4.49	16.0
70–80%	4.74	3.61	0.86	8.35	6.59	16.7	4.74	16.3
80–90%	11.1	3.81	0.91	8.81	5.30	16.7	5.70	16.2
90–100%	5.31	3.73	0.79	8.22	4.45	15.8	4.67	15.1
Mean	3.57	3.69	0.74	9.46	10.1	18.2	7.40	21.0

Note: This table presents the amounts received by households conditional on receiving transfers at different quantiles of household income. Panel A presents the raw values in 2016 dollars. Panel B presents the corresponding results normalized by the average household income.

4.5. *Transfers at top incomes*

A key feature of the data is that, although transfers fall sharply with income, high-income households still receive sizable transfers. As we showed earlier, the top income quintile captures about 4 percent of total transfers. Conditional on receipt, households in this quintile receive transfers equal to roughly 15-16 percent of mean household income (Table 5). This pattern appears to be strongly associated with the presence of disabled and elderly household members, a mechanism detailed in Online Appendix E.

Households with disabled children or adults may qualify for Medicaid and related programs even at relatively high income levels. In particular, children with disabilities can be eligible at incomes well above the poverty line, and in some states, parents can receive Medicaid payments as caregivers. As shown in Figure E1 in Online Appendix E, around two-thirds of households with no pre-transfer income include a disabled member. This share declines steeply with income but remains non-negligible, close to 5 to 10%, even in the upper part of the income distribution.

A second channel is the presence of elderly household members. Even though our sample is restricted to households headed by individuals aged 25-54, some households include elderly adults who may qualify for Medicaid-often jointly with Medicare-when medical expenses are high relative to income (see De Nardi et al., 2012). Importantly, Figure E1 also shows that the presence of elderly household members is largely flat across the income distribution in our benchmark period (2013–2016), with around 3% of households including an elderly household member.

These mechanisms are reflected clearly in Table 7. Panel A shows that high-income households with a disabled or elderly member receive substantially larger transfers-especially Medicaid-than those without such members. Panel B shows that they also receive transfers in a larger fraction of months. Together, these patterns help explain why a non-trivial share of transfers accrues to the top of the income distribution despite strong means-testing. Figures E2 and E3 in Online Appendix E show that households with disabled or elderly members are more likely to receive transfers. In particular, having a disabled or elderly household member is associated with substantially higher Medicaid participation for high-income households.

Table 6
Concentration of transfers by income group.

Quantile	TANF	SNAP	WIC	SSI	Housing	Medicaid	Transfers		Sample
							Non-med.	All	share
No income	39.0	24.0	10.9	42.9	41.3	19.6	34.4	23.2	5.97
0-1%	1.24	1.55	0.58	2.38	2.07	1.39	1.90	1.51	0.86
1–5%	11.9	13.9	7.84	9.48	16.4	9.04	12.8	9.94	3.41
5–10%	12.6	15.4	9.05	6.93	13.6	9.94	11.9	10.4	4.27
0–10%	25.7	30.9	17.5	18.8	32.0	20.4	26.6	21.9	8.55
10–20%	11.4	18.3	20.4	11.9	12.5	16.5	14.6	16.1	8.55
20–30%	5.78	8.86	15.9	6.88	5.29	11.6	7.47	10.6	8.55
30–40%	7.17	5.73	12.0	4.43	3.36	8.91	5.01	7.98	8.54
40–50%	4.47	4.21	8.83	4.15	1.84	6.41	3.79	5.78	8.55
50–60%	2.17	2.88	6.45	2.83	2.09	5.22	2.75	4.63	8.55
60–70%	1.72	1.76	3.00	1.97	0.51	3.66	1.57	3.16	8.55
70–80%	1.83	1.31	2.18	2.09	0.58	3.07	1.44	2.68	8.55
80–90%	0.57	1.00	1.86	2.13	0.30	2.47	1.21	2.17	8.55
90–100%	0.20	1.03	1.04	1.95	0.16	2.07	1.09	1.84	8.55

Notes: This table shows the concentration of various transfers and benefits across income groups, measured as a percentage of the category's total transfers. The 'Sample share' column indicates the proportion of the sample population represented by each income group.

5. Post-transfer income inequality

We now report on how transfers affect inequality by comparing pre-tax and pre-transfer income inequality measures with post-transfer measures. Table 8 highlights the impact of various transfers on inequality measures, both individually and collectively. The results show that transfers substantially reduce inequality across all standard metrics. For example, the Gini coefficient decreases by six points when all transfers are included, dropping from 0.48 to 0.42. With non-medical transfers alone, the reduction is more modest, from 0.48 to 0.46. Similar trends are observed with alternative measures: the variance of log income declines by nearly 36% (47 log points) with all transfers and by approximately 20% with non-medical transfers. The impact is particularly pronounced at the lower end of the income distribution. The 50-10 income ratio, which is 10.2 for the pre-transfer distribution, falls to 3 when all transfers are included. Even excluding Medicaid, the ratio is nearly halved, declining to 5.6. Overall, these reductions in inequality driven by the transfer system are substantial. They also reflect the importance of Medicaid to working-age households.

Pre- and post-transfer income. Another way to illustrate the impact of transfers on inequality is to focus on the relation between post- and pre-transfer income. This is shown in Fig. 2, where both measures are reported as multiples of average pre-transfer household income. The figure shows that transfers exceed twice the total income of households with pre-transfer incomes around 10% of the average. While the effect declines after that, even for households with 20% of the average pre-transfer income, it remains substantial: their post-transfer income is approximately 35% of the average pre-transfer income. The figure also highlights Medicaid's considerable role in shaping post-transfer income. When Medicaid is excluded, the impact of transfers is small beyond households with pre-transfer income below 10% of the average.

Fig. 3 focuses on income from different sources for households in the bottom quintile of the pre-transfer income distribution. For the poorest households (below the 10th percentile), non-transfer income (wages plus asset income) accounts for less than 50% of total household income, with Medicaid transfers making up the largest share of the transfer component. As pre-transfer income rises, the role of transfers diminishes, and the contribution of non-medical transfers declines as well. At the top of the bottom quintile, transfers still account for a significant share, amounting to slightly more than 20% of total household income.

5.1. Summary

At the big-picture level, the following key facts stand out from our findings.

1. Transfers reach a significant share of U.S. households and provide substantial support for those who receive them. Over one-third of working-age households receive means-tested transfers annually, averaging $17,000 per recipient household. Close to 83% of all households without any pre-transfer income, 6.5% of households in the sample, received some transfers, and conditional on receipt, total transfers to these households are $26,500.
2. The amount of unconditional total transfers decreases as household income rises, from $21,000 for households with no income to $1,200 for those in the top decile. Non-medical transfers decline more sharply, from $7,500 to nearly zero for top-decile households.
3. While transfers per recipient household decrease gradually with income, they remain substantial at top incomes, amounting to over 15% of average household income for households at the top 10% of the income distribution. Hence, the decline in unconditional transfers is mainly due to reduced program coverage at higher income levels.
4. Medicaid is the largest transfer program, reaching 31% of households with an average benefit of $15,000 per recipient. SNAP, the next largest program in terms of coverage, reaches 18% of households with smaller average benefits of about $3,000.

Table 7
Transfer amounts and coverage by income quantile and elderly/disabled household-member status.

	Elderly						Disabled					
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	Transfers						Transfers					
	Medicaid		Non-med.		All		Medicaid		Non-med.		All	
Panel A: Percentage of Mean Household Income												
No income	16.5	24.7	9.26	9.22	25.8	33.9	9.73	20.1	7.63	10.0	17.4	30.1
0-1%	7.71	24.3	3.50	6.02	11.2	30.4	4.88	11.6	2.54	4.64	7.42	16.2
1–5%	13.3	18.2	5.99	4.99	19.3	23.2	9.08	20.4	5.13	7.25	14.2	27.6
5–10%	11.8	16.3	4.56	5.04	16.4	21.4	9.22	20.1	4.18	5.72	13.4	25.8
0–10%	12.0	17.8	5.02	5.10	17.0	22.9	8.84	19.0	4.40	6.27	13.2	25.2
10–20%	9.57	17.9	2.73	3.83	12.3	21.8	7.88	19.2	2.33	4.82	10.2	24.1
20–30%	6.64	15.5	1.38	2.42	8.03	18.0	5.57	14.6	1.15	2.91	6.72	17.5
30–40%	5.12	10.1	0.88	2.47	6.00	12.5	4.40	10.9	0.70	2.35	5.10	13.2
40–50%	3.68	10.0	0.70	1.66	4.39	11.7	2.95	10.8	0.48	2.60	3.43	13.4
50–60%	2.85	10.8	0.47	1.86	3.32	12.7	2.55	7.77	0.36	1.73	2.91	9.50
60–70%	2.02	10.0	0.29	1.28	2.30	11.3	1.58	7.91	0.19	1.40	1.76	9.31
70–80%	1.61	7.89	0.24	1.27	1.85	9.17	1.32	6.90	0.19	1.08	1.52	7.97
80–90%	1.22	9.11	0.17	2.09	1.39	11.2	0.90	7.76	0.10	1.62	1.01	9.38
90–100%	0.91	9.94	0.16	1.45	1.07	11.4	0.81	7.73	0.12	1.42	0.93	9.15
Mean	5.36	12.7	1.74	2.72	7.10	15.4	3.63	15.0	1.07	5.11	4.70	20.1
Panel B: Percentage of Months Received												
No income	69.6	79.0	72.7	78.4	79.9	85.6	58.6	75.2	58.4	79.7	67.0	86.3
0-1%	37.7	76.2	34.9	50.5	46.7	83.2	32.6	45.3	24.8	46.3	37.5	58.3
1–5%	61.5	77.1	56.4	48.9	69.5	80.5	55.7	72.1	48.9	67.7	63.2	80.5
5–10%	59.8	60.7	53.0	58.4	66.5	77.7	56.1	70.8	49.2	64.9	62.4	80.0
0–10%	58.3	68.6	52.6	53.9	65.7	79.3	54.1	67.6	47.2	63.4	60.8	77.0
10–20%	49.7	68.4	38.2	53.9	54.8	71.5	47.6	63.4	35.1	56.3	52.3	70.3
20–30%	35.1	51.5	23.9	39.6	39.9	61.4	33.0	50.7	21.8	39.3	37.5	58.1
30–40%	28.9	42.2	17.0	37.1	32.4	52.9	27.1	43.3	14.6	36.6	30.2	50.8
40–50%	20.9	43.0	12.3	30.6	24.7	50.0	19.0	41.0	10.6	30.4	22.6	46.9
50–60%	17.1	40.5	9.83	31.8	20.0	46.6	16.2	31.7	8.48	27.4	18.8	37.9
60–70%	12.7	41.2	6.53	23.3	15.0	49.8	11.2	33.0	5.26	21.7	13.4	37.6
70–80%	9.93	38.3	5.10	24.5	11.7	44.1	9.18	28.1	4.40	19.5	10.9	32.5
80–90%	7.91	37.2	3.39	24.4	9.21	50.1	6.88	30.6	2.74	18.7	8.20	36.3
90–100%	6.72	39.5	3.59	25.3	8.24	46.1	6.15	34.2	2.85	27.1	7.49	41.2
Mean	27.7	48.9	20.9	37.0	31.6	56.9	22.8	55.3	15.3	50.8	25.9	63.5

Notes: The table reports transfer amounts and coverage by pre-tax, pre-transfer household income group and by the presence of elderly or disabled household members. The no-income group is shown separately; income quantiles are computed among households with positive pre-transfer income. Panel A reports average annual transfers as a percentage of mean household income. Panel B reports the percentage of household-months in which a positive transfer is received. The first six columns split households by whether at least one member is age 65 or older. The last six columns split households by whether at least one member is disabled. These two splits are shown separately and are not mutually exclusive.

Table 8
Pre- and post-transfer income inequality.

	Pre-transfer	Post-transfer income							
Measure	income	TANF	SNAP	WIC	SSI	Housing	Medicaid	Non-med.	All
90/10	28.0	26.5	21.5	27.6	22.9	22.5	10.3	15.2	7.87
50/10	10.2	9.66	7.86	10.0	8.38	8.19	3.88	5.61	3.01
90/50	2.75	2.75	2.74	2.75	2.74	2.74	2.64	2.72	2.61
Mean/median	1.42	1.64	1.64	1.64	1.64	1.64	1.63	1.64	1.63
Gini	0.48	0.48	0.47	0.48	0.47	0.48	0.44	0.46	0.42
Variance of log	1.31	1.29	1.14	1.30	1.23	1.23	0.92	1.05	0.84
Variance of (log + 1)	8.54	7.82	4.07	7.97	6.18	6.83	3.15	3.19	2.37

Notes: This table presents summary measures of household income inequality. The first column presents the household income before any transfer. Columns 2–7 show the effect of each transfer program in isolation. Column 8 shows the combined effect of all non-medical transfers, while column 9 shows the combined effect of all transfers, including Medicaid. All measures are pre-tax. See text for details.

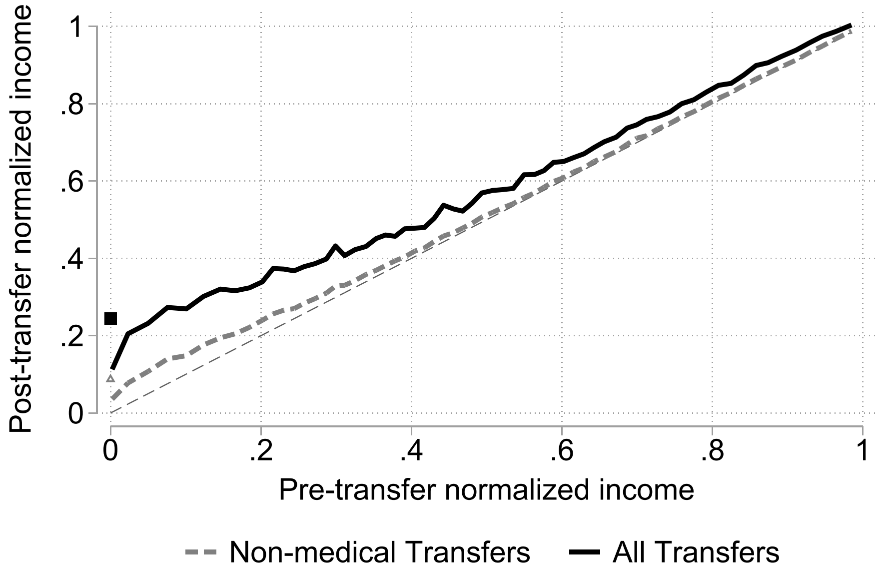

Fig. 2. Relation between pre- and post-transfer income.

Notes: The figure displays the relationship between pre-transfer (horizontal axis) and post-transfer income (vertical axis) in terms of shares of mean household income. The solid line applies to all transfers, while the other excludes Medicaid. See text for details.

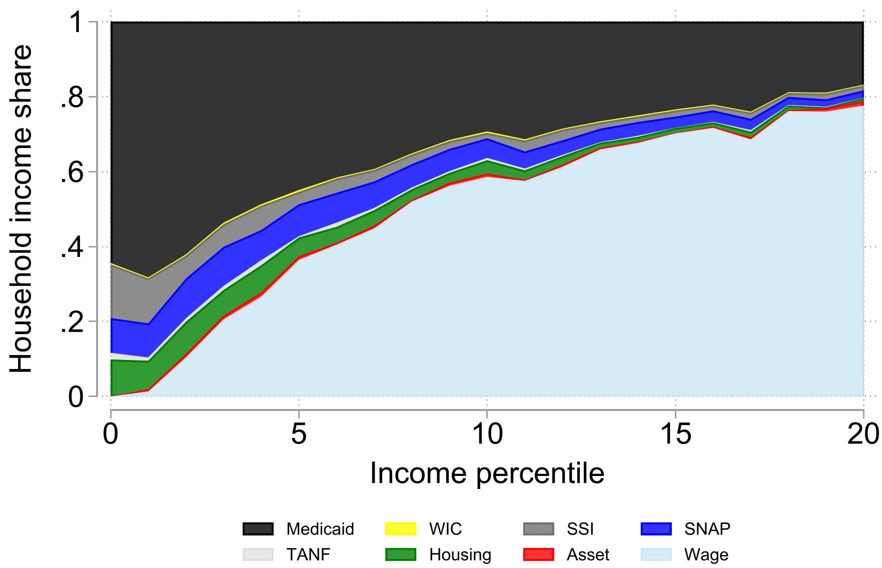

Fig. 3. Impact of transfers, bottom quintile.

Notes: The figure presents the composition of post-transfer income as income changes. The vertical axis shows the sources of total post-transfer household income as a function of pre-transfer income percentile. The percentiles are computed based on pre-transfer income.

5. Transfers substantially reduce income inequality, particularly at the lower end of the income distribution. For instance, the pre-transfer 50-10 income ratio drops from 10 to 3 when transfers are included. The Gini coefficient for household income distribution declines from 0.48 to 0.42 with transfers.

6. Trends

We next investigate how transfers (their generosity and coverage) changed over time and how they affected the evolution of income inequality in the U.S. To this end, we use data from the previous waves of SIPP, covering the period from 1998-1999 to the benchmark sample for 2013–2016.

Fig. 4 shows changes in the magnitude of transfers and their coverage. Transfers (both unconditional and conditional on receipt) increased sharply over time. Unconditional transfers rose from about 1.9% of the mean household income in 1998-99 (about $1,535) to about 7.3% (about $6,000) in 2013-16, nearly a fourfold increase. There is also a significant increase in coverage, with the fraction of households receiving some transfers rising from about 20% to about 35%.

The increase in transfer magnitudes is driven by the expansion of Medicaid. Non-medical transfers as a share of mean household income increased little, from about 1.2% in 199-1999 (about $998) to about 1.8% in 2013–2016. The coverage of non-medical transfers also increased from 16% to 24% of households. The net result was a decline in non-medical transfers, conditional on receipt: they declined from 9.4% of average household income in 1998-1999 ($7,676) to 7.4% of average household income ($6,071) in 2013–2016.

These patterns are also highlighted in Fig. 5, which shows generosity and coverage in three periods (1998-99, 2004–6, and 2013-16) at different income levels. Since real incomes and transfers vary over time, we present data normalized to the mean household income in each period.[13] The figure shows that when all transfers are considered (the right panels), transfer levels increase significantly over the years at all levels of income. There is essentially a parallel shift between 1998-99 and 2013-16, and the level of transfers increased by more than five percentage points of mean income. We observe similar patterns for the fraction of households receiving transfers and the fraction of months in a year. The left columns in Fig. 5 show the corresponding outcomes for non-medical transfers. While coverage increased between 1998-1999 and 2013–2016, the magnitude of non-medical transfers declined significantly for lower-income households. In 1998-1999, households with incomes equal to 10% of the average household income received about 6.4% of the mean household income. The same household received only 5% of the mean household income in 2013–2016.

Fig. 6 shows the evolution of the concentration of transfers over time. The x-axis displays the pre-transfer income bins, starting at zero income, along with the ten deciles of positive income. The y-axis shows the concentration of total transfers per household, indicating how much an average household receives in transfers when the total transfer distributed is set to $100 (total transfers allocated to each segment divided by the population size in that segment). The left panel shows non-medical transfers, and the right panel reports the total. From $100 distributed, a household without pre-transfer income received about $9 in 1998-1999. This amount declined significantly over the years and was about $4 in the recent panel in 2013–2016. Similarly, the relative share of transfers for households at the bottom declined by almost half. In contrast, the share for all other deciles, particularly the second, third, and fourth, increased.

Post-transfer income inequality. We now examine how transfers affected income inequality over time. Table 9 shows summary measures of inequality over time. Panel A shows the changes in the pre-tax income distribution, while Panels B and C show the post-transfer income distribution resulting from non-medical and total transfers, respectively.

The pre-transfer inequality has risen substantially, with the Gini coefficient increasing by eight points, from 0.40 in 1998-1999 to 0.48 in 2013-2016. The post-transfer inequality, however, shows a more moderate rise when all transfers are included: the Gini increases by only four points, from 0.38 to 0.42. Transfers have had a particularly strong impact at the lower end of the income distribution. While the 50-10 income ratio doubled for pre-transfer income over this period, it remained stable at around 3 for post-transfer income. Excluding Medicaid, the effect of transfers is less pronounced: the Gini coefficient rises by seven points, from 0.39 to 0.46.

Cyclicality. Finally, we study the cyclicality of transfers using a quarterly panel of average non-medical and total transfers for 1998-2016. We extract cyclical components with an HP filter and compare them to cyclical GDP per capita in Fig. 7.[14] Both transfer series are far more volatile than GDP, with standard deviations about five times larger. Non-medical transfers are strongly countercyclical, with a correlation of -0.32 with cyclical GDP per capita, and the share of households receiving them is even more countercyclical (-0.44). In contrast, total transfers-which include medical transfers-are slightly procyclical (0.19), and the fraction of households receiving any transfers is essentially acyclical (-0.07). This difference arises because medical transfers respond much less to the business cycle than non-medical programs.

7. Parametric estimates

In this section, we present parametric estimates of effective transfer functions designed for use in applied research. These functions map pre-transfer household income to transfers received, enabling researchers to model transfers without needing the full administrative details of the programs. We estimate individual transfer programs, total transfers, and total non-medical transfers. Additional estimates for transfers received by marital status and number of children, as well as estimates for conditional transfers and transfer coverage, are presented in Online Appendix C.

[13] Mean household income in real terms grew in our sample by about 8.6% between 1998-99 and 2013–16.

[14] The series reports real GDP per capita in chained 2017 dollars, at a quarterly frequency and seasonally adjusted annual rate. The data were obtained from the Federal Reserve Bank of St. Louis's FRED database, available at https://fred.stlouisfed.org (Federal Reserve Bank of St. Louis 2025).

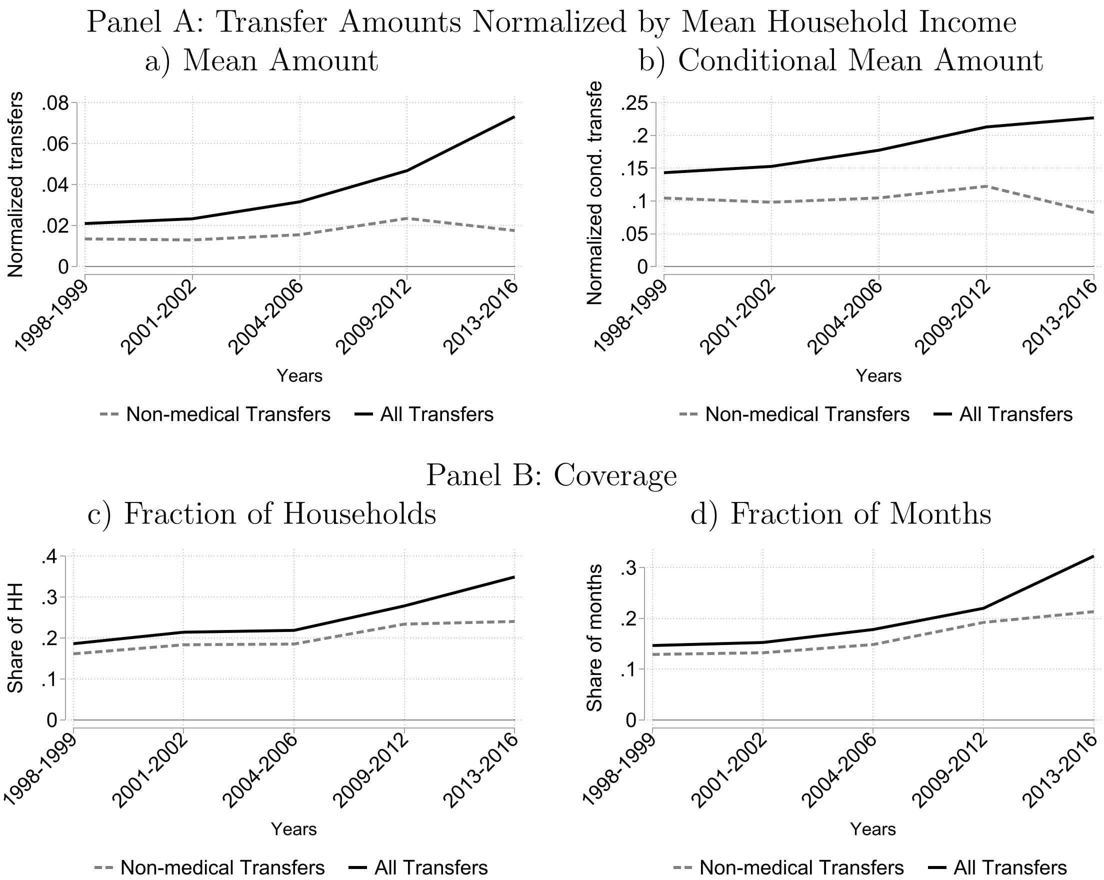

Fig. 4. Trends in transfer magnitudes and coverage.

Notes: This figure shows transfer amounts and coverage over time. The horizontal axis shows SIPP panel years. Panel A reports transfers normalized by mean household income in each period: unconditional mean transfers in panel (a) and conditional mean transfers in panel (b). Panel B reports coverage: the share of households receiving transfers in panel (c) and the share of months in which households receive transfers in panel (d).

Our functional form is informed by earlier findings. Transfers are strictly positive at zero income. For low positive income levels, transfers initially increase, then decline, and eventually taper to zero. This behavior requires a flexible function that accommodates a discontinuity at zero income and captures subsequent non-linearities. To ensure that our estimates are unit-free, we model transfers as a function of household income normalized by the mean household income. The resulting effective transfer functions are therefore invariant to the units used to measure income and transfers, which facilitates their use in applied and quantitative work.

Fig. 8 illustrates the data used for these estimates, showing transfer amounts at various normalized income levels. The tight confidence intervals around average transfer amounts, both with and without Medicaid, indicate that a fitted line will closely approximate observed transfer patterns.

Let I denote household income relative to the mean household income and $T(I)$ denote transfers received, again relative to the mean income. We estimate the following function:

$$T(I) = \begin{cases} e^{\alpha} e^{\beta_0 I} I^{\beta_1} & \text{if } I > 0, \\ \gamma & \text{if } I = 0. \end{cases} \tag{1}$$

The function, defined for cases where income I is positive and for $I = 0$, is flexible enough for our data. It has four parameters; α, β_0, β_1, when I is positive, and a parameter γ for when I equals zero. We estimate α, β_0, β_1 for positive household income by regressing normalized transfers on household income using non-linear least-squares.[15] In Table 10, we list the estimated parameters for the received transfer amounts for each transfer considered and for all transfers, both unconditional and conditional on receipt. [16]

[15] The functional form for positive incomes is based on Ricker (1954), and was used first to model the expected number of fish in the next generation as a function of their number in the previous generation.

[16] Since transfer receipt is the highest and most likely at the bottom of the income distribution, we restrict the sample to positive household incomes below half of the mean household income for the probability of receipt and conditional amounts. Since unconditional amounts taper off

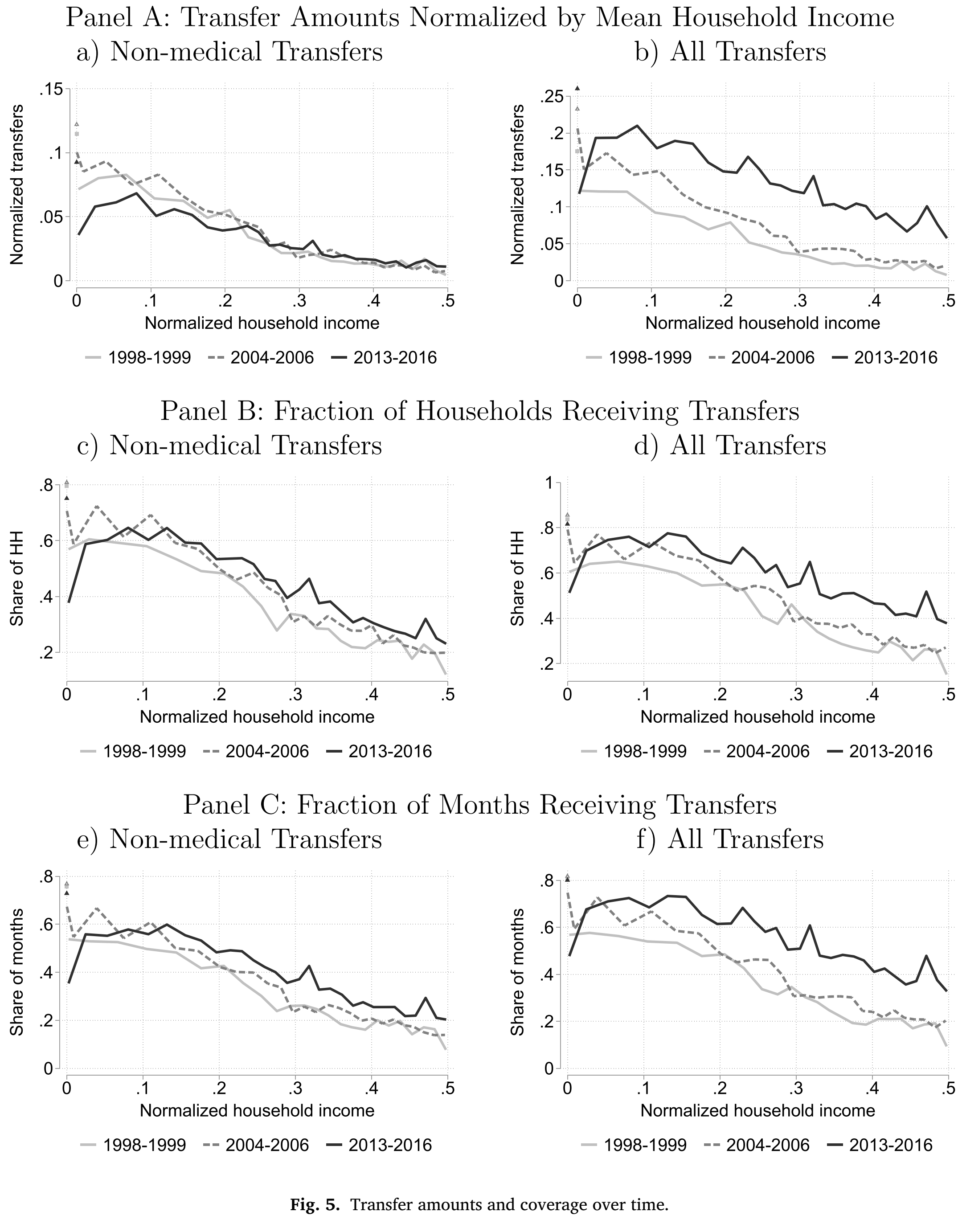

Fig. 5. Transfer amounts and coverage over time.

Notes: This figure shows the magnitude of transfers and coverage for different income levels over the years. The horizontal axis shows normalized household income. Household income is normalized to the mean income for each period (1998-1999, 2004–2006, 2013–2016). The vertical axis shows normalized transfers in Panel A, the fraction of households receiving transfers in Panel B, and the fraction of months households receive transfers in Panel C. The left panels exclude Medicaid and refer to non-medical transfers, while the right panels include Medicaid and refer to all transfers.

more slowly, we restrict the sample to households with incomes below the mean household income for estimating unconditional transfer amounts. We average normalized transfers T and incomes I across income percentiles p so the specification becomes $T_p = e^{\alpha} e^{\beta_0 I_p} I_p^{\beta_1} + \varepsilon$. Online Appendix Table C10 contains the estimates by marital status, Table C11 by number of children, Tables C12-C14 by number of children and marital status, and Table C15 for the probability of receipt and the fraction of months receiving transfers.

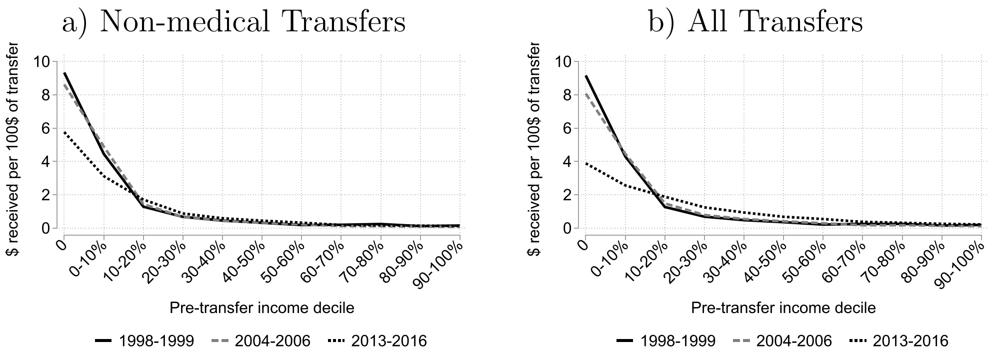

Fig. 6. Concentration of transfers over time.

Notes: The y-axis reports each income group's share of transfers, divided by its population share. Equivalently, if total spending in the relevant transfer category were $100 and the population were normalized to 100 households, the value would represent the average dollars received by a household in that income group. Panel A refers to non-medical transfers; Panel B refers to all transfers, including Medicaid.

Table 9
Post-transfer income inequality over time.

SIPP panel years	1998-1999	2001-2002	2004-2006	2009-2012	2013-2016
Panel A: Pre-Transfer Household Income					
50/10	4.19	4.35	4.81	8.39	10.2
90/10	9.11	9.78	11.1	21.3	28.0
90/50	2.17	2.25	2.32	2.54	2.75
Gini	0.40	0.41	0.42	0.45	0.48
Mean/median	1.21	1.22	1.25	1.32	1.42
Variance of (log+1)	5.05	4.71	5.41	7.11	8.54
Variance of log	1.15	1.39	1.64	2.01	1.31
Panel B: Household Income After Non-medical Transfers					
50/10	3.31	3.61	3.68	4.39	5.61
90/10	7.16	8.08	8.51	11.1	15.2
90/50	2.16	2.24	2.31	2.53	2.72
Gini	0.39	0.40	0.41	0.43	0.46
Mean/median	1.19	1.22	1.24	1.33	1.64
Variance of (log+1)	1.76	1.71	1.80	2.45	3.19
Variance of log	0.80	0.92	0.94	1.20	1.05
Panel C: Household Income After All Transfers					
50/10	3.04	3.22	3.09	3.23	3.01
90/10	6.56	7.17	7.11	8.08	7.87
90/50	2.16	2.23	2.30	2.50	2.61
Gini	0.38	0.39	0.39	0.41	0.42
Mean/median	1.19	1.23	1.25	1.34	1.63
Variance of (log+1)	1.47	1.43	1.42	1.92	2.37
Variance of log	0.74	0.82	0.80	1.05	0.84

Notes: This table shows summary measures of income inequality over time, before and after transfers. Panel A shows pre-tax, pre-transfer household income. Panel B shows household income after non-medical transfers. Panel C shows household income after all transfers, including medicaid.

Fig. 9 shows transfers received for different levels of income relative to the mean income. In Panel A, the figure shows the effective transfers estimated for different programs, along with the data (in blue). Panel B shows the estimated functions for non-medical and total transfers. Our parameter estimates imply that, in all cases, transfers are high at zero, and as income becomes positive, the transfer function first increases, reaches a maximum, and then declines at varying rates.

For all transfers, the estimated amounts remain positive at around the mean income, but for non-medical transfers, they become negligible. Finally, Fig. 10 shows fitted transfers by marital status, separately for non-medical and total transfers. At very low income levels, estimated transfers are highest for single-female households, exceeding those received by both married couples and single males. However, transfers to single females decline rapidly with income, whereas transfers to married couples fall much more gradually. As a result, at moderate and higher income levels, married-couple households receive higher total transfers than single-female

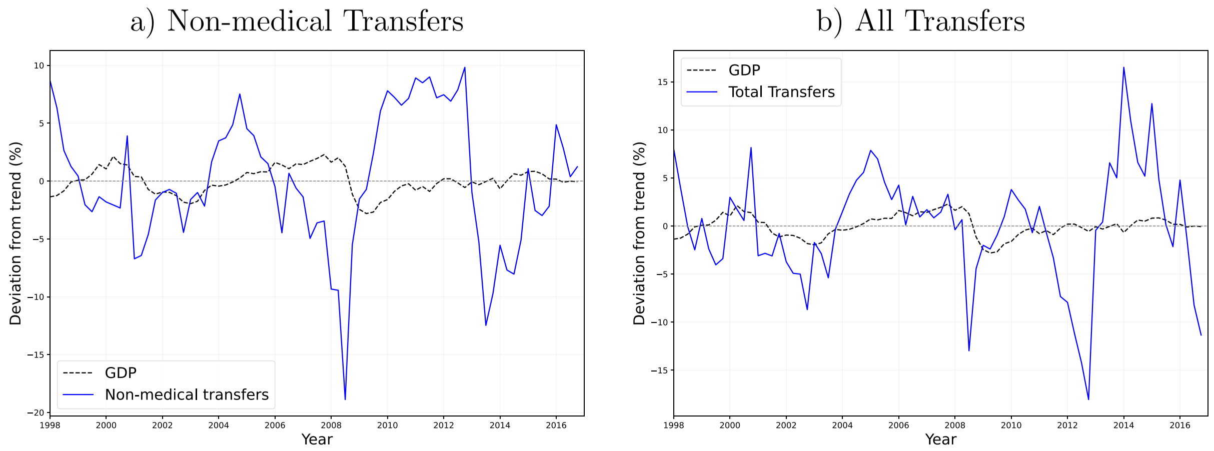

Fig. 7. Cyclicality of transfers.

Notes: The figure plots the cyclical components of real GDP per capita (dashed line) and mean transfers for 1998Q1-2016Q4 (solid line). Panel (a) compares GDP with non-medical transfers, and panel (b) compares GDP with all transfers. Cyclical components are computed using an HP filter with a smoothing parameter of 1600.

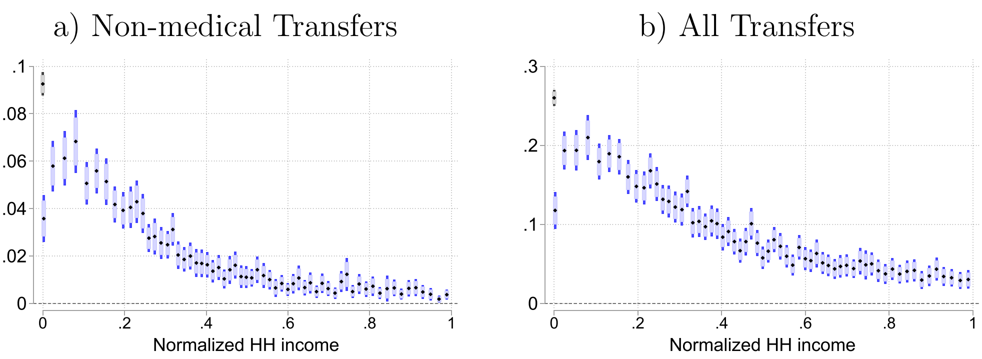

Fig. 8. Total unconditional transfers (as a fraction of mean income).

Notes: Each dot in the figures represents the mean transfers of an income percentile. The thin bars indicate the 99% and the thick bars the 95% confidence intervals.

households. Single males receive substantially lower transfers throughout the income distribution. The corresponding parameter estimates are reported in Online Appendix C.

Implicit penalties. We now use the estimated functions to quantify the effects of additional pre-transfer income on transfers received. As additional income may reduce transfers, we refer to this as an implicit *penalty*. This sheds light on the much-discussed disincentives embedded within the transfer system and large effective taxes on the labor supply of poorer households.

We show in Fig. 11 the benefit reductions for households with zero income for alternative increases in their pre-transfer income. We consider the cases of $1, $1,000, $5,000, and $10,000. The left panel shows the decline in non-medical transfers, and the right panel shows the case for all transfers. The implicit penalties are large. A $1 increase in pre-transfer income reduces total transfers by more than $11,000. More realistically, an increase in pre-transfer income of $10,000 reduces benefits by more than $5,000, an implicit tax penalty of more than 50%. The corresponding figures for non-medical transfers are smaller but still significant, more than $4,500 and $3,300, respectively. The upshot of these findings is that implicit taxes can be substantial and therefore non-trivially affect behavior in economic models.

Discussion. The functional form in Eq. (1) has two key advantages. First, it allows for a discontinuity at zero income, capturing the high implicit tax rate on the first dollar of pre-transfer income due to means-tested programs. Second, it allows transfers (or taxes) to rise at low incomes and then decline as income increases.

A common functional form in the literature maps pre-tax income to after-tax income as $\hat{I} = I - T(I) = \lambda I^{1-\tau}$, where λ governs the average tax level and τ its progressivity ($\tau = 0$ implies proportional taxes, $\tau > 0$ progressive). When this form is estimated using both taxes and transfers, as in Heathcote et al. (2017), where $\hat{I}$ denotes the after-tax and transfer income, it can match transfer receipt at

Table 10
Estimates for amount of transfers (% of mean household income).

	TANF	SNAP	WIC	SSI	Housing	Medicaid	Transfers Non-med.	Transfers All
Panel A: Unconditional on Receipt								
γ	0.001	0.037	0.024	0.005	0.026	0.167	0.093	0.260
α	−5.665	−3.851	−2.145	−3.980	−2.498	−1.224	−1.634	−0.783
	(0.250)	(0.206)	(0.120)	(0.626)	(0.203)	(0.101)	(0.113)	(0.094)
β_0	−2.356	−3.632	−5.840	−7.876	−7.659	−2.915	−5.502	−3.496
	(0.467)	(0.563)	(0.288)	(1.627)	(0.599)	(0.227)	(0.295)	(0.218)
β_1	0.396	0.066	0.404	0.506	0.360	0.206	0.283	0.219
	(0.087)	(0.050)	(0.036)	(0.183)	(0.055)	(0.030)	(0.031)	(0.027)
Panel B: Conditional on Receipt								
γ	0.010	0.114	0.038	0.073	0.105	0.240	0.127	0.325
α	−4.567	−2.234	−2.715	−2.743	−2.154	−1.553	−2.037	−1.131
	(0.067)	(0.199)	(0.058)	(0.446)	(0.214)	(0.044)	(0.081)	(0.047)
β_0	−0.241	−0.078	−0.920	−0.359	−0.370	−0.236	−1.866	−1.000
	(0.138)	(0.422)	(0.122)	(0.951)	(0.457)	(0.095)	(0.193)	(0.103)
β_1	0.043	0.000	0.084	0.020	0.022	−0.004	0.039	0.039
	(0.019)	(0.055)	(0.017)	(0.124)	(0.060)	(0.012)	(0.021)	(0.013)

Notes: This table presents the estimated coefficients of equation (1), across the different types of government assistance programs. Values are averaged by income percentile before estimation. The standard errors for the NLS coefficients reflect cross-percentile variation and are shown in parentheses.

low incomes. While such an approach can capture the transfer receipts of poor households and implies that transfers decline with household income, it also yields a high estimate of τ, leading to much higher marginal tax rates for high-income households.[17]

Blundell et al. (2016) extend this to $\hat{I} = \lambda(b + I)^{1-\tau}$, where b is a universal transfer that allows $\hat{I} > I$ at low incomes and transfers that decline with income. Ferriere et al. (2023), as we do here, model transfers directly as $T(I) = m\frac{2e^{-\xi I}}{1+e^{-\xi I}}$, where m controls generosity and ξ governs how fast transfers fall with income. However, none of these functional forms can capture the nonlinearities in the data that our formulation is designed to match.

7.1. Including wealth

We now aim, in a parsimonious way, to explicitly account for net worth in our parametric estimates. A data challenge is that the SIPP is not designed primarily to collect wealth information. It only provides measures of household net worth through topical modules on assets and liabilities, fielded in specific waves of each panel. In these modules, households report the value of major asset categories, such as housing equity, other real estate, vehicles, financial accounts (including checking, savings, retirement accounts, stocks, bonds, and mutual funds), business ownership, and cash-value life insurance, as well as liabilities, including mortgages, vehicle loans, credit card debt, and other personal loans. Household net worth is then constructed as the sum of reported assets minus the sum of reported debts. The wealth data are collected only in designated topical modules, so net worth is available for 12 years, from 2002 to 2016.[18] In any case, the SIPP combines detailed income and program participation data with information on wealth, even though net worth measures rely on self-reports and are subject to underreporting, particularly at the tails of the wealth distribution (Czajka et al., 2003).

For the wealth subsample, we include all years from 2002 to 2016. Even with these sample inclusion criteria, we end up with only 100,223 household-year observations. After dropping those with negative net worth, 16.9% of the sample, this number declines to 83,271 observations.[19]

In Panel A of Fig. 12, we show how, in (a), the amount of transfers received, and in (b) the average share of months households receive transfers, relate to household wealth normalized by mean household income. Again, we see an exponential decay. In Fig. 13, we provide heatmaps showing that benefits are generally highest for households with neither income nor wealth and tend to decline as either resource increases. The amount of transfers received is lowest and least likely when both income and wealth are large. These heatmaps also show that high-income households with low wealth can receive transfers, complementing the discussion in Section 4.5

[17] Heathcote et al. (2017) estimate of τ for tax and transfer function is 0.18, while others, such as Guner et al. (2014), Borella et al. (2023), find lower estimates, between 0.05 and 0.1, using after-tax income.

[18] The years are 2002–2006, 2009–2011, and 2013–2016.

[19] Households with negative net worth tend to have a negative correlation between wealth and income (-0.06) as well as an *increasing* relationship between wealth and transfers. Both of these relationships are, as expected, reversed for those with non-negative net worth. For households with positive wealth, the correlation between income and wealth is 0.18. Including the negative-net-worth group would therefore conflate distinct dynamics that are not directly comparable to the broader population of interest, while dropping them yields internally consistent patterns between resources and transfer dependence.

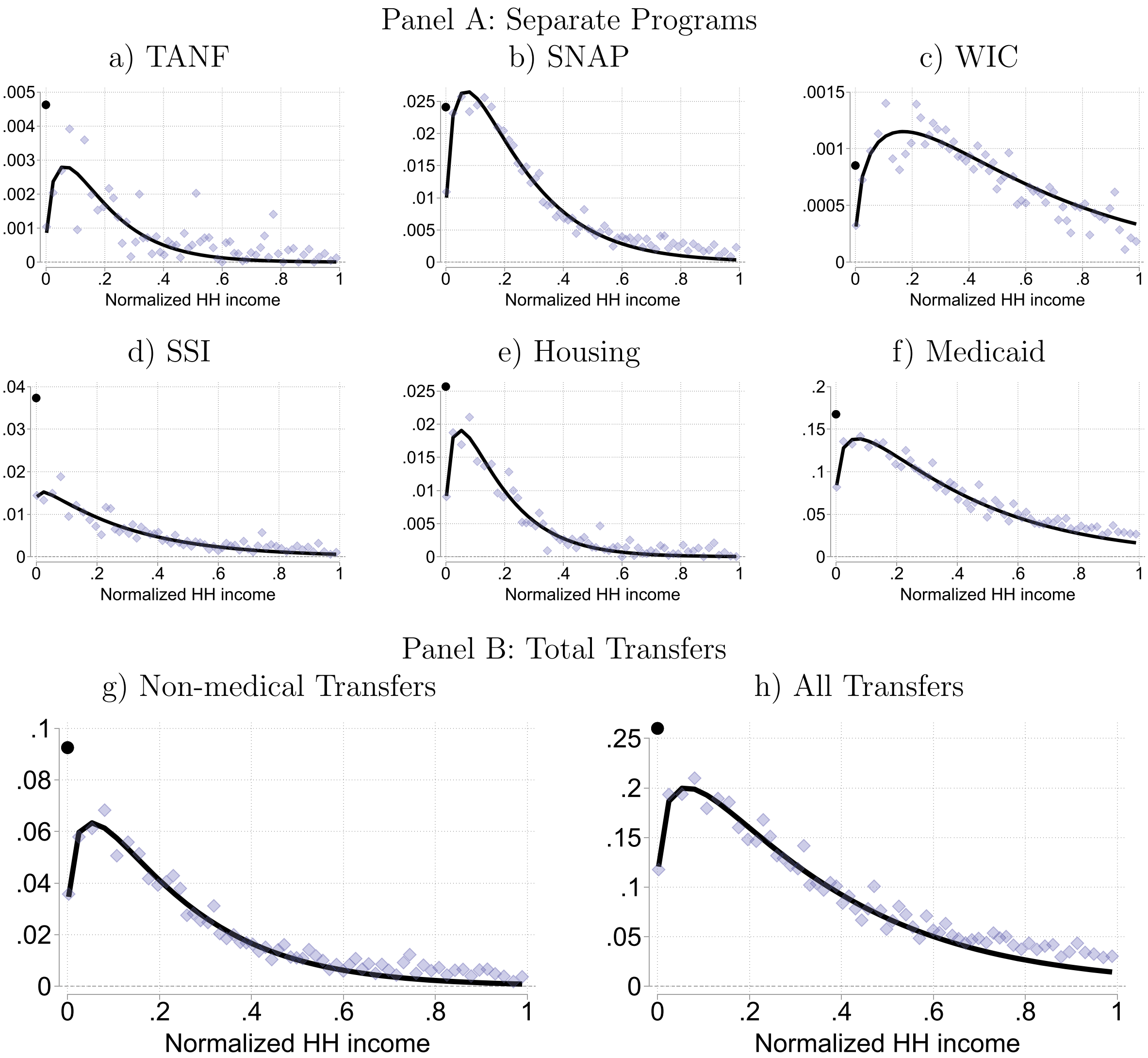

Fig. 9. Unconditional transfers.

Notes: The horizontal axis shows normalized household income (relative to mean income). The vertical axis shows normalized transfers received (relative to mean income). The source of transfers is indicated in the figure headings. The blue diamonds indicate data points, and the black line is the fitted model.

on transfers received by high-income households. For instance, Panel (d) in Fig. 13 shows that households with above-median income but no assets received transfers (non-medical plus Medicaid) in almost 31% of months in a given year.

A parametric specification. In order to approximate the transfer function in relation to both wealth and income, let I and W denote income and wealth of a household, and define an income and wealth composite, $\tilde{I}$, as $\tilde{I} = I^{\theta} W^{(1-\theta)}$. Hence, when $\theta = 1$, we recover the estimates where wealth does not play any role.

Given this income-wealth composite, let $\tilde{I}$ be the composite relative to the mean household income. Let $T(\tilde{I})$ denote the mean transfers relative to the mean income. For a given θ, we then estimate the following function:

$$T(\tilde{I}) = \begin{cases} e^{\tilde{\alpha}} e^{\tilde{\beta}_0 \tilde{I}} \tilde{I}^{\tilde{\beta}_1} & \textit{if } \tilde{I} > 0 \\ \gamma & \textit{if } \tilde{I} = 0 \end{cases} \tag{2}$$

We choose θ so that the sum of the R^2 of the two models explaining the amount of normalized non-medical and total transfers is maximized. The resulting value is $\theta = 0.37$ with an R^2 just above 0.997, and the evolution of the R^2 is presented in Online Appendix Figure D1. While R^2 tends to be relatively lower for small values of θ (e.g., $R^2 = 0.99$ when $\theta = 0.01$), it is high for high values of θ (e.g., $R^2 = 0.995$ when $\theta = 0.99$), indicating that little predictive power is lost by limiting the model to income in our benchmark

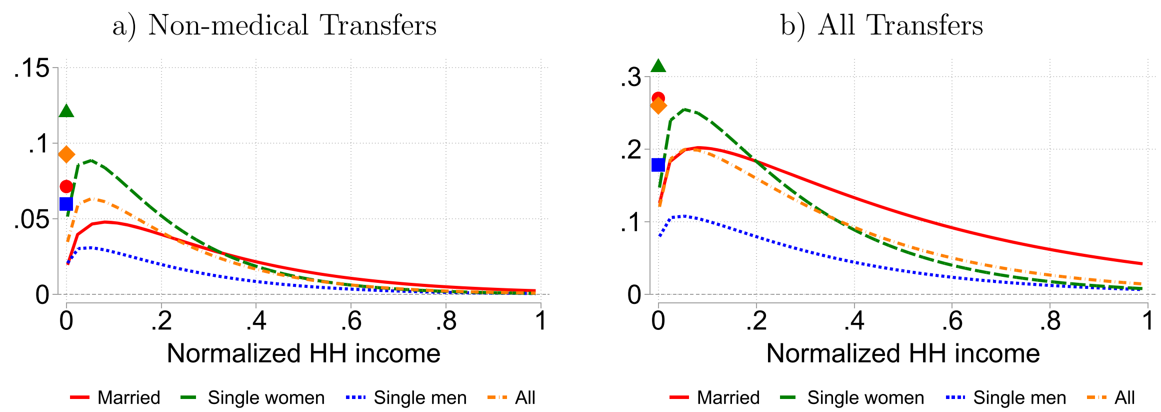

Fig. 10. Unconditional transfers by marital status.

Notes: The horizontal axis shows normalized household income (relative to mean income). The vertical axis shows normalized transfers received (relative to mean income). The lines indicate the fitted model.

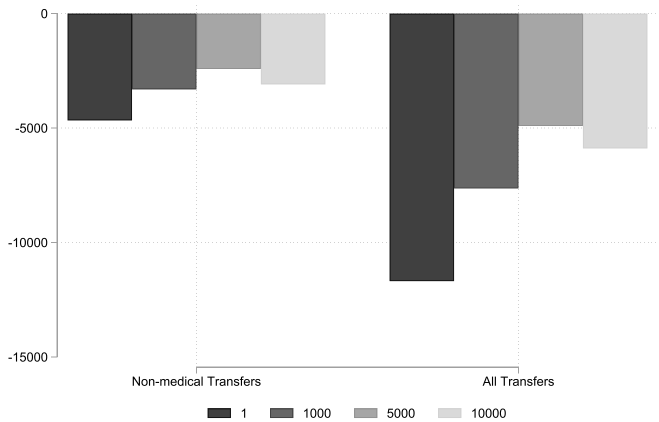

Fig. 11. Implied reduction in transfers from additional pre-transfer income (Penalty).

Notes: The figure shows the reduction in transfers associated with increasing pre-tax, pre-transfer household income from zero by the amount shown on the horizontal axis. The left bar reports the reduction in non-medical transfers, while the right bar reports the reduction in all transfers, including Medicaid. Values are expressed in 2016 dollars.

analysis. In Panel B of Fig. 12, we present the close fit of the estimated models using the income-wealth composite in (c) for the amount of transfers received and in (d) for the average share of months a household receives transfers. In Table 11 we present the resulting coefficients.

7.2. *Use of transfer functions*

How can the estimated transfer functions be used in applied work? To this end, consider a standard life-cycle consumption savings decision with idiosyncratic risk. Denote the individual's state by her/his age j and the pair $x = (a, \Omega)$, where a denotes current asset holdings and Ω is a generic representation for idiosyncratic shocks. Let $e(\Omega, j)$ denote his/her labor-efficiency units. Let w be the wage rate and r be the interest rate, which are potentially determined in a general equilibrium.

Consequently, optimal decision rules for an age-j individual are functions for consumption $c(x, j)$, labor $l(x, j)$, and next period asset holdings $a(x, j)$ that solve the following dynamic programming problem:

$$V(x, j; \bar{I}) = \max_{\{c,a',l\}} u(c, l) + \beta E[V(a', \Omega, j + 1; \bar{I})|x] \tag{3}$$

subject to

$$c + a' \leq a(1 + r) + we(\Omega, j)l + \bar{I}T(I) - \tau(I)I\bar{I},$$

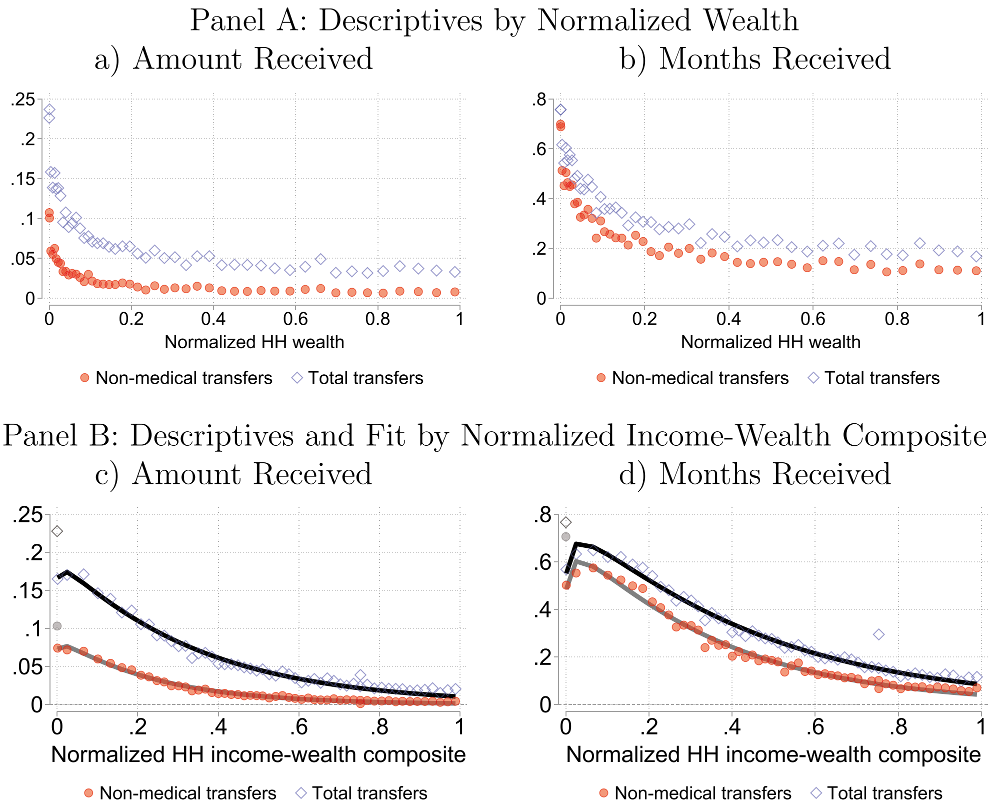

Fig. 12. Unconditional transfers and months received depending on wealth.

Notes: In Panel A, the horizontal axis shows normalized household wealth (relative to mean household income). The vertical axis in (a) shows normalized transfers received (relative to mean household income), and in (b) the share of months in which transfers are received. In Panel B, the horizontal axis shows the normalized household income-wealth composite. The vertical axis in (c) shows normalized transfers received (relative to mean household income), and in (d) the share of months in which transfers are received. The red dots (non-medical transfers) and blue diamonds (total transfers) indicate the data points, and the lines are the fitted models.

Table 11
Estimates for transfers using income-wealth composite.

	Amount		Cond. Amount		Fraction HH		Fraction Months	
Transfers	No med.	All	No med.	All	No med.	All	No med.	All
γ	0.103	0.228	0.146	0.297	0.748	0.809	0.706	0.766
α	−2.288	−1.536	0.015	0.050	−0.090	−0.023	−2.402	−1.646
	(0.038)	(0.033)	(0.034)	(0.025)	(0.038)	(0.026)	(0.051)	(0.039)
β_0	−4.355	−3.055	−2.829	−2.210	−3.117	−2.455	−0.696	−0.285
	(0.111)	(0.076)	(0.070)	(0.047)	(0.083)	(0.051)	(0.086)	(0.062)
β_1	0.047	0.037	0.096	0.083	0.092	0.083	−0.079	−0.068
	(0.008)	(0.008)	(0.009)	(0.007)	(0.010)	(0.007)	(0.012)	(0.010)

Notes: This table presents the estimated coefficients of Eq. (2) with $\theta = 0.37$. Standard errors of the coefficients estimated via NLS are provided in parentheses beneath the coefficients.

with

$$I \equiv \frac{we(\Omega, j)l + ra}{\bar{I}}.$$

In this formulation, $T(I)$ is the estimated function in Eq. (1) that maps income I, as a fraction of mean household income ($\bar{I}$), into transfers received, again a fraction of mean income. For completeness, the function $\tau(I)$ represents a parametric function that maps the household income, relative to the mean income, into an average effective tax rate. Since the functions $T(I)$ and $\tau(I)$ depend on the average household income in the economy, one can start from a guess for average household income ($\bar{I}$), solve the model, i.e.,

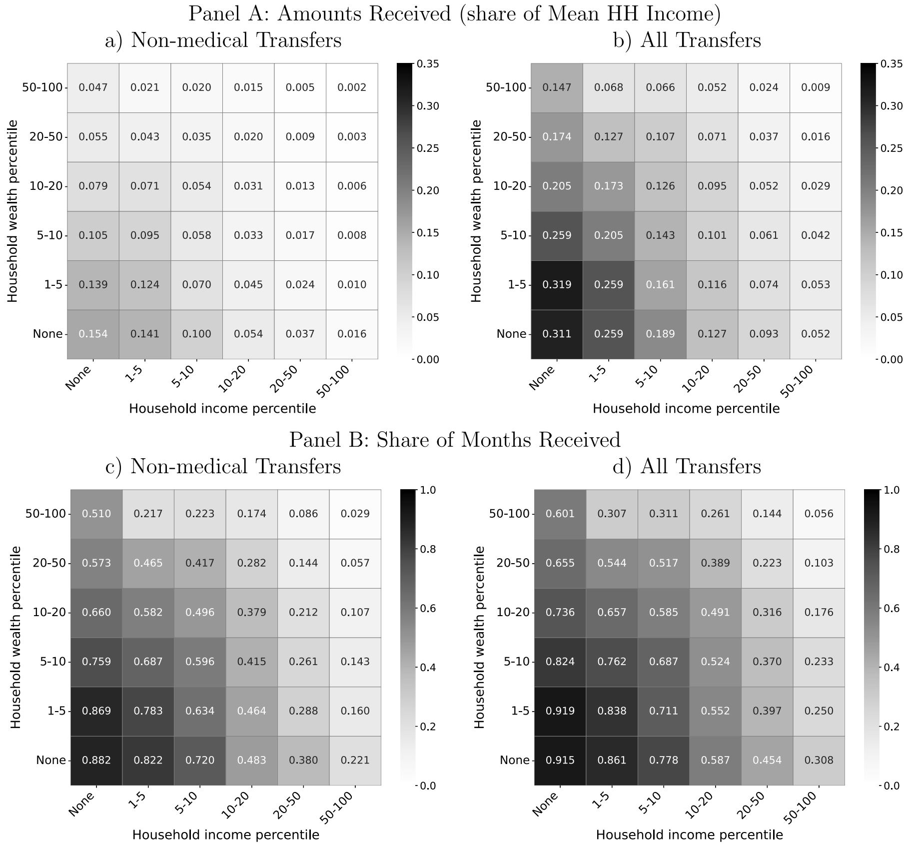

Fig. 13. Unconditional transfers and months received by income and wealth.

Notes: The heatmaps show the amounts received (Panel A) and the share of months households receive transfers (Panel B), depending on their level of income (x-axis) and wealth (y-axis). The darker the cell's shade, the higher the value, as indicated by the legends on the right. "None" denotes households with zero income or zero wealth, respectively. Percentile bins are computed among households with positive income or positive wealth. Entries report group averages.

solve the value functions and equilibrium objects, and iterate on $\overline{I}$. Alternatively, $T(I)$ can be replaced by $T(\tilde{I})$, using wealth-income composite as an input, given estimates of Eq. (2).

The $T(I)$ function can be integrated into standard heterogeneous-agent models of the Aiyagari-Bewley-Huggett class to study, for example, optimal transfer policies as in Rauh and Santos (2022), Ferriere et al. (2023). This approach is analogous to using parametric tax schedules to analyze optimal income-tax progressivity, as in Heathcote et al. (2017), or to the role of income-tax progressivity in shaping aggregate tax revenues, as in Guner et al. (2016).

8. Concluding remarks

We use data from the Survey of Income and Program Participation to document properties of means-tested transfers to households in the United States headed by working-age individuals. We document the transfer amounts and coverage across programs by household income, marital status, and number of children. Our findings highlight the substantial role that programs such as SNAP, WIC, TANF, SSI, Medicaid, and housing assistance play in transferring resources to low-income households.

We show the extent to which these transfers are concentrated among poorer households and contribute to their available resources. We find that, conditional on receipt, transfers are present and relatively constant over a wide range of income levels. We find that Medicaid is the largest of these transfers. Our results also show that the transfer system plays a substantial role in reducing income inequality in our sample, with Medicaid as the most important contributor to this reduction.

Our analysis also reveals that, over the study period from 1998 to 2016, the scope and magnitude of these transfers increased markedly, and that they significantly moderated the rise in inequality during this period. The data show a fourfold increase in the magnitude of per-household transfers relative to mean household income. This increase is primarily driven by the expansion of Medicaid, including increased coverage and higher amounts transferred, conditional on receipt.

Our parametric estimates of transfer functions provide a useful tool for applied researchers. Our specification is flexible enough to capture the large transfers accruing to households with zero income while also capturing the non-linear patterns we observe in the data. These estimates are portable and can be used in a variety of contexts.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Nezih Guner reports financial support was provided by Spanish State Research Agency. Christopher Rauh reports financial support was provided by Spanish State Research Agency. Gustavo Ventura declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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