STANFORD CENTER ON POVERTY & INEQUALITY

The California Poverty Measure

2012 Technical Appendices

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Sarah Bohn, Caroline Danielson, Sara Kimberlin, Marybeth Mattingly, Christopher Wimer

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Abbreviations

CPM	California Poverty Measure
CalFresh	California name for SNAP
CalWORKs	California Work Opportunity and Responsibility to Kids (California TANF program name)
CFAP	California Food Assistance Program
EITC	Earned Income Tax Credit
GA/GR	General Assistance/General Relief
LIHEAP	Low Income Home Energy Assistance Program
MEDS	Medi-Cal Eligibility Determination System
MOOP	Medical Out-of-Pocket Expenses
OPM	Official Poverty Measure
SNAP	Supplemental Nutrition Assistance Program (formerly Food Stamps)
SPM	Supplemental Poverty Measure
SSI	Supplemental Security Income
TANF	Temporary Assistance for Needy Families
WIC	Special Supplemental Nutrition Program for Women, Infants, and Children

Introduction and Changes in Methodology from CPM 2011 to CPM 2012

The goal of these technical appendices is to provide detailed information on the methods, assumptions, and validation exercises we have undertaken in creating the California Poverty Measure (CPM). The key motivation for developing the CPM is to provide an arguably more accurate and comprehensive picture of poverty. This is no simple task, because the resources, expenses, and standards of living of California families must all be individually measured using a variety of data sources and methods. Indeed, this work is the product of a joint collaboration between the Stanford Center on Poverty and Inequality and the Public Policy Institute of California.

Appendix A provides some background on poverty measurement and then describes the main tasks and data source used to create the CPM. The appendix then describes the procedures implemented to create CPM poverty units (e.g., those included in the same family) and the procedures implemented to flag unauthorized immigrants. Appendices B through D describe the methodology for determining poverty thresholds, poverty unit resources, and poverty unit thresholds. Appendix E provides supplemental tables with more estimates and additional detail not included in the main report.

Methodology Changes from CPM 2011 to CPM 2012

In general, the methodology used to construct CPM 2012 was very similar to that used to construct CPM 2011.[1] However, we made a few minor corrections and improvements to the methods for the 2012 poverty measure.

Housing Subsidies. For CPM 2012, we slightly modified our approach to imputing receipt of housing subsidies, data which are not reported in the ACS. As with CPM 2011, we imputed subsidy receipt using data from the Current Population Survey. First we calculated the proportion of California household head renters receiving housing subsidies in the CPS, to determine the proportion of analogous heads to whom to assign subsidies in the ACS, and then we developed a linear probability model to predict subsidy receipt in the CPS, with this model then applied to the ACS to assign receipt to renter household heads until we reached the designated proportion of heads receiving subsidies. For CPM 2011, we predicted and assigned incidence of subsidy receipt separately for elderly versus non-elderly household heads, as incidence is quite

[1] See 2011 Technical Appendices: http://www.ppic.org/content/pubs/other/1013SBR_appendix.pdf

different for these two subgroups. For CPM 2012, we additionally predicted and assigned subsidy receipt separately for non-elderly heads with and without children. This additional step was needed to achieve an acceptable match between the number of children and non-elderly adults with imputed subsidy receipt in the ACS using our imputation model as compared to the number of children and non-elderly adults with reported subsidy receipt in the CPS. We then used the same procedure as for CPM 2011 to calculate the value of housing subsidies for those with imputed receipt.

Medical Out-of-Pocket Expenses. We followed an identical approach to imputing medical out-of-pocket expenses for CPM 2012 as for CPM 2011, but we corrected some errors in coding that had a minor impact on imputed values, resulting in somewhat smaller estimated MOOP expenses. Using the corrected MOOP approach with the 2011 data leads to a 0.2 percentage point decrease in CPM poverty rates overall and for the subpopulation of elderly adults, and a 0.1 percentage point decrease in the CPM poverty rate for children and working age adults. The corrections also result in a 0.1 to 0.2 percentage point decrease in the impact of excluding medical-out-of-pocket expenses on CPM poverty rates in 2011 for the overall population and the subgroups of children, working-age adults, and elderly.

Tax Liabilities and Credits. For CPM 2012, some minor changes were made to the imputation strategy for taxes compared to the methods used for CPM 2011. As with CPM 2011, our estimated statewide aggregate EITC amount and number of EITC filers was substantially lower than totals from IRS administrative data. Thus as for 2011, we adopted some strategies to increase EITC claiming to better match administrative data. As for CPM 2011, dependents of non-tax filers and dependent tax filers who were not claimed as EITC dependents were reassigned to another tax filer in the household in order to maximize EITC claiming. For CPM 2012, we additionally reassigned dependents to another tax filer in the household when a filer had more than three assigned dependents, and thus had exceeded the maximum number of dependents for which EITC can be claimed, again in order to increase our aggregate EITC amount and filers to better match administrative totals. This new change affected only 1.1 percent of tax filers. In addition, a few errors in the general algorithm for assigning dependents to tax filers were corrected.

We also slightly changed our approach to accounting for income tax filing among unauthorized immigrants. As with CPM 2011, we began with the assumption that all unauthorized immigrants filed income taxes, using an Individual Taxpayer Identifier Number (ITIN) rather than a Social Security Number (SSN). However, as with CPM 2011, our calculated number of tax filers flagged as unauthorized immigrants substantially exceeded the number of ITIN tax filers in administrative data, so as for 2011 we randomly selected some unauthorized immigrants to file taxes with a SSN instead (thus being eligible to claim the EITC), in order to reduce the number of ITIN filers and increase the number of EITC filers to better match administrative totals. For CPM 2011, we assigned SSN-filer status until we matched the number of ITIN filers in administrative totals. In contrast, for CPM 2012 we randomly assigned SSN-filer status to immigrants until our percentage, not number, of ITIN filers matched the percentage of ITIN filers in administrative data. The choice to match the percentage rather than number of ITIN filers was rooted in the fact that our overall number of tax filers differed somewhat from IRS totals.

Finally, for CPM 2012 we corrected our calculated EITC credit amounts for a minor discrepancy discovered between EITC rules and the procedures used to calculate EITC by TAXSIM, our external tax calculator. Per IRS rules, tax filers with no EITC qualifying dependents may only claim the EITC if they are between the ages of 25 and 64. TAXSIM, however, does not exclude filers without dependents who are outside of the age eligibility range, instead allowing EITC for tax filers of all ages who meet the relevant income criteria. We thus subtract the calculated EITC credit for filers without dependents who are age-ineligible for the EITC. This change has only a minor impact on calculated tax amounts, as the EITC amounts for childless tax filers are generally very small, with a maximum credit of less than $500.

Using this slightly modified approach to assigning tax unit dependents, accounting for unauthorized immigrant tax filers, and removing EITC for age-ineligible childless tax filers with the 2011 data leads to minor changes in CPM poverty rates for 2011 compared to our original 2011 approach. CPM poverty in 2011 declines by 0.1 percentage points for the population overall, and by 0.3 percentage points for children. The poverty rate after excluding tax aid is also 0.1 to 0.2 percentage points higher compared to our original 2011 estimates for the overall population and for children, working-age adults, and elderly.

Combined Impact of MOOP and Tax Methodology Changes. The changes made to the methods for imputing MOOP and taxes in 2012 have a small but generally additive effect on calculated CPM poverty rates. Applying these changes together to the 2011 data results in a 0.3 percentage point decrease in the overall CPM poverty rate, with a 0.4 percentage point decline in poverty for children and a 0.1 percentage point decline for elderly, compared with our original 2011 CPM estimates. Rates of deep poverty and near poverty for all groups were virtually unchanged.

Table I-1
Original and revised CPM estimates for 2011

	Original	Revised MOOP alone	Revised EITC alone	Revised MOOP and EITC
A. Under 100% of CPM poverty (%)				
All persons	22.1	21.9	22.0	21.8
Children	25.1	25.0	24.8	24.7
Adults	21.4	21.3	21.4	21.3
Elderly	18.9	18.8	19.0	18.8
B. Exclude MOOP from expenses (percentage point difference)				
All persons	-4.2	-4.1	-4.1	-4.0
Children	-4.0	-4.2	-3.7	-3.9
Adults	-3.8	-3.6	-3.8	-3.6
Elderly	-7.0	-6.8	-7.0	-6.8
C. Exclude EITC/CTC from resources (percentage point difference)				
All persons	3.2	3.3	3.2	3.3
Children	6.0	6.1	6.2	6.3
Adults	2.6	2.7	2.5	2.6
Elderly	0.5	0.7	0.3	0.4

Appendix A: General Methodology

Overview of Poverty Measurement

The federal government began measuring poverty in the 1960s. Using the assumption that families spent a third of their income on food, the poverty "line"—or threshold—was set at three times the cost of the economy food plan published by the U.S. Department of Agriculture. This assumption has its limitations (one being that families now spend roughly one fifth of their budgets on food), but for nearly half a century this method for measuring poverty—the Official Poverty Measure (OPM)—has remained unchanged. In 2009, however, the Office of Management and Budget created an Interagency Technical Working Group (ITWG) to consider the creation of a new, complementary poverty measure. The result was the Supplemental Poverty Measure (SPM), which is based primarily on the recommendations of a 1995 report published by the National Academy of Sciences (NAS) entitled *Measuring Poverty: A New Approach* (ITWG, 2010; Citro and Michael, 1995; Short, 2011). Table A1 provides a brief overview of the major differences between the OPM and the SPM approaches to measuring poverty.

Table A1
Key components of OPM and CPM/SPM measures

	OPM approach	CPM/SPM approach
Family	Unmarried cohabiters and foster children excluded.	Unmarried cohabiters and foster children included.
Poverty thresholds	Thresholds developed in the 1960s and updated for inflation each year.	Average of the 33rd - 36th percentile of national expenditures on food, clothing, shelter, and utilities, based on five most recent years of the Consumer Expenditure survey, multiplied by 120% to account for other "key" spending. Thresholds are also adjusted for the regional cost of living.
Resources	Pre-tax cash income (includes earnings, investments, and cash-based government transfer programs).	Includes cash income, in-kind government programs, and net taxes/tax credits.
Expenses	N/A	Out-of-pocket expenses for commuting and other work expenses, medical costs, and child care are subtracted from resources.

The development of the SPM is a significant step forward in measuring poverty, but it is just the beginning. The details of the measure's implementation have ignited significant debate among policymakers, researchers, and various stakeholders regarding best practices for measuring poverty grounded in the NAS recommendations (see Meyer and Sullivan, 2012; Blank, 2011; Levitan et al., 2011; Wimer et al., 2011; Blank, 2008).

The task of measuring poverty can typically be divided into two parts. The first is the creation of a poverty threshold—a representation of the amount of resources necessary to achieve some minimum level of material well-being. The second part is to then estimate families' resources to ascertain their ability to meet the expenses embodied in that threshold. The SPM methodology fits into that paradigm, although the many adjustments made to better represent family resources and expenses in the SPM do not always fall neatly into the threshold and resources dichotomy.

In general, we follow the approach that researchers in other states have taken to date in creating state-level SPM-style measures (Cable, 2013; Chung et al., 2012b; NYC Center for Economic Opportunity, 2012; Wheaton et al., 2011). Note that there is no standard method, as yet, that can be applied to every state, given the differences in safety net programs across the states. Another important source of variation in methods involves differences in access to and type of administrative data with which to validate and augment the survey data. While this makes direct comparisons between different states' results difficult, it also allows individual states and localities to take advantage of the best information available and to set their own priorities with regard to measuring poverty.

Main Methodological Tasks

We split the task of creating the CPM into a number of sub-tasks: (1) defining the family or "poverty unit," (2) creating poverty thresholds, (3) calculating family resources, and (4) calculating family expenses. The CPM, simply put, compares net family resources (step 3 minus step 4) within a poverty unit (step 1) to the appropriate threshold (step 2). Individuals in families with net resources below their threshold are considered to be living in poverty, according to the CPM.

This procedure is in essence the same as is used in calculating supplemental poverty measure rates. However, in each step we introduce data and methods to accurately reflect both the cost of living in California and the major sources of family resources. Appendices B through D describe and validate these steps.

A common theme in these appendices is our use of auxiliary data to supplement what is known about family economic well-being from the main survey data source we use, which we describe in the next section. Official poverty measures (and to some extent the national SPM estimates) rely on only self-reported household survey information. While we also depend on large-scale survey data, we exploit auxiliary data to correct for known sources of error and to supply information missing from such surveys.

Another common theme is reflected in our intent to ultimately generate reliable estimates for subgroups within California. This includes estimates for California's regions, age groups, and racial/ethnic subgroups. This initial report presents statewide estimates and estimates by age group. For example, we acquired detailed auxiliary data to preserve to the extent possible differences in program participation and benefits across regions and race/ethnic groups. The base data for our analyses are provided by the American

Community Survey, a large representative survey undertaken by the Census Bureau. We describe in the following appendices the auxiliary data we use to augment self-reported information.

Primary Data Source: The American Community Survey

Our analyses rely on representative survey data from the 2012 American Community Survey (ACS). The ACS includes detailed economic and demographic information on individuals and households in the United States as well as in individual states and in smaller geographies (multicounty, county, and even smaller areas, depending on population size). The ACS asks less-detailed questions about program participation and income sources than the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) samples used to create the research SPM. (Appendix F discusses additional similarities and differences between the CPS-ASEC and the ACS.) However, the ACS has the significant advantage of very large sample sizes, and we follow others in using it to create the CPM (Cable, 2013; Chung et al., 2012b; NYC Center for Economic Opportunity, 2012; Wheaton et al., 2011).

The 2012 ACS includes a sample size of 368,047 respondents in California. (The survey entirely excludes those in institutional settings, such as prison or college, as well as homeless individuals.) We exclude individuals residing in group quarters from the poverty universe. Group quarters include prisons, nursing homes, and university housing.[2] Following the approach of the Institute for Research on Poverty (IRP) at the University of Wisconsin-Madison, we also exclude from the poverty universe a subset of undergraduates who are neither living in university housing nor living with relatives. This group is intended to include only those students who are receiving substantial financial support from their families and should not be considered poor, regardless of their reported incomes (Chung et al., 2012b). To operationalize the concept, we follow IRP in restricting this group to be between the ages of 18 and 23, with earnings under $5,000 in the past year, typical weekly hours of work less than 20 hours, and less than 13 weeks of work in the past year. With these restrictions, we exclude an estimated 107,160 Californians (and 810 observations in the California sample of the 2012 ACS) from the poverty universe. This is a far smaller group than all college undergraduates (22,017 observations) or even all college undergraduates between the ages of 18 and 23 (12,734 observations). In other words, most college students are working more hours and/or more weeks, or they live in group housing, or they live with their families.[3] Our final sample size is thus 351,172individuals.

[2] Note that this excludes college students who live in dormitories but not those who live in off-campus private housing. In future work we will test the sensitivity of our estimates to the possible inclusion of some college students. For example, we can exclude individuals ages 18-24 who are in school but do not live with their parents.

[3] Bishaw (2013) presents estimates of the effect on state and local official poverty estimates of excluding college students from the poverty universe. The concept of college student used in that paper is broader than ours.

The large California sample enables robust one-year CPM poverty rate estimates, including at the county level. Still, only 34 of the 58 counties are separately identified in public-use ACS data. Table A.2 provides a list of all counties and county groups separately identified in the ACS with corresponding sample sizes that reflect the sample restrictions just described.

Table A2
CPM analysis sample, American Community Survey

County	Sampled individuals	Weighted children	Weighted adults 18-64	Weighted seniors 65+	Weighted population
Alameda	15,062	342,015	996,809	177,464	1,516,288
Alpine/Amador/Calaveras/Inyo/Mariposa/ Mono/Tuolumne	1,717	32,408	105,859	39,314	177,581
Butte	2,200	44,891	134,556	34,569	214,016
Colusa/Glenn/Tehama/Trinity	1,446	31,796	72,809	19,400	124,005
Contra Costa	9,148	259,504	667,356	140,902	1,067,762
Del Norte, Lassen, Modoc, Plumas, Siskiyou	1,760	25,587	70,053	23,222	118,862
El Dorado	1,624	39,031	109,096	29,798	177,925
Fresno	8,566	277,527	555,132	94,939	927,598
Humboldt	1,436	26,475	84,079	18,730	129,284
Imperial	1,324	50,417	95,157	18,713	164,287
Kern	6,934	254,994	490,446	79,030	824,470
Kings	1,269	41,437	78,242	11,774	131,453
Lake, Mendocino	1,422	31,736	90,529	25,843	148,108
Los Angeles	97,817	2,350,842	6,297,487	1,109,606	9,757,935
Madera	1,126	43,061	83,647	17,699	144,407
Marin	2,203	52,416	150,165	45,309	247,890
Merced	2,331	80,404	148,968	25,501	254,873
Monterey, San Benito	4,651	129,481	281,564	52,213	463,258
Napa	1,615	30,970	82,228	20,953	134,151
Nevada, Sierra	881	17,779	61,199	21,404	100,382
Orange	27,907	733,915	1,933,809	369,857	3,037,581
Placer	3,473	84,369	212,537	60,463	357,369
Riverside	20,960	619,147	1,329,337	278,401	2,226885
Sacramento	13,521	361,575	896,738	165,540	1,423,853
San Bernardino	16,587	583,574	1,255,051	194,463	2,033,088
San Diego	26,949	722,657	1,982,988	371,379	3,077,024
San Francisco	6,986	109,975	576,962	113,839	800,776
San Joaquin	6,242	198,420	414,054	74,853	687,327
San Luis Obispo	2,167	49,784	161,067	43,987	254,838
San Mateo	6,903	158,980	468,300	101,452	728,732
Santa Barbara	3,813	97,417	253,080	55,534	406,031
Santa Clara	17,718	433,707	1,159,285	207,839	1,800,831
Santa Cruz	2,288	54,708	165,971	31,479	252,158
Shasta	1,938	38,938	104,813	321,46	175,897

Solano	3,869	98,548	259,810	49,995	408,353
Sonoma	4,527	104,617	304,094	72,495	481,206
Stanislaus	4,594	144,969	312,383	58,365	515,717
Sutter, Yuba	1,772	46,174	99,389	199,67	165,530
Tulare	4,665	144,328	257,976	43,439	445,743
Ventura	8,068	207,977	512,327	103,369	823,673
Yolo	1,693	43,461	124,231	21,591	189,283
California total	35,1172	9,200,011	23,439,580	4,476,836	37,116,430

SOURCE: ACS 2012, accessed via the Integrated Public Use Microdata Series (IPUMS).

The timing of the administration of the ACS and the fact that the month in which respondents are surveyed is suppressed in the public-use data means that respondent twelve-month "reference periods" reach back before 2012. For example, an individual surveyed in the beginning of July 2012 reported annual income earned between July 2011 and June 2012. Because we intend our results to be conceptually reflective of 2012, we address these timing issues by using a Census-provided adjustment factor that aims to standardize the reference period across individuals surveyed throughout the year.[4]

Poverty Unit Construction

We follow the approach of the Census Bureau in creating poverty units for purposes of the research SPM (Short, 2012). These units are created to accurately reflect the sharing of resources and expenses among individuals who reside together. In the simplest case, a nuclear family living alone shares all household resources and expenses, and each individual is then included in the same poverty unit. The concept of nuclear family, however, does not capture all living situations in which individuals share resources and expenses. For example, we create poverty units that include unmarried partners (and their children) living together. We also include foster children and other children categorized as "unrelated" in the ACS in larger poverty units.

Methodology and Limitations

We rely on variables in the ACS defining interrelationship within a household to define poverty units. While detailed, this interrelationship information does have its limitations. In particular, the data provide the most detail on relationships of household members to the head of the household, but less detail on relationships between other members.

[4] Internal Census Bureau files use a factor that varies by month; however, due to privacy concerns, these 12 factors are averaged into a single adjustment factor for public use data. See https://usa.ipums.org/usa/acsincadj.shtml for additional information.

With that caveat in mind, we define the basic poverty unit relative to the head of the household. A poverty unit thus consists of the head of the household and his or her relations, unmarried partner, unmarried partner's children, foster children, and other unrelated children. Although any remaining individuals may be part of the same household, they are considered to be adults unrelated to the head of the household and are thus grouped into their own poverty units based on their relationships. The Census Bureau refers to these as unrelated subfamilies. Poverty units are formed for individuals in subfamilies that are related to each other. After forming these subfamilies, the remaining unassigned individuals are considered to be adults unrelated to anyone in the household, and we place them into their own (single person) poverty units. This last category could explain, for example, two single adults in roommate type situations. Table A.3 contrasts ACS household counts with poverty unit counts according to the definition just outlined.

Table A3
CPM poverty units in American Community Survey, 2012

Unit definition	Sampled units	Weighted units
ACS households	129,099	13,141,590
CPM poverty units	139,092	14,493,170

SOURCE: ACS 2012.

NOTE: Group quarters and excluded college students omitted from all columns.

Finally, we note that the poverty unit is not necessarily the correct concept for assigning program benefits and tax liabilities. We use the same interrelationship variables in the ACS to create Supplemental Nutrition Assistance Program (SNAP) units, Temporary Assistance for Needy Families (TANF) units, and tax filing units according to federal and state law and regulation. We describe these procedures in Appendix C.

Unauthorized Immigrants

Because the treatment of unauthorized immigrants has implications across many of the modules of the CPM, we here discuss our procedure for handling this important demographic group.

Unauthorized immigrants are not eligible for most federal and state safety net programs due to their legal status. However, unauthorized immigrant families earn less, on average, than the native-born and are twice as likely to fall below federal poverty thresholds (Passel and Cohn, 2009). Our CPM approach, which assigns benefits to eligible families to account for underreporting or lack of data, would likely assign too many benefits to units with unauthorized immigrants because of their income level, if a correction is not made for their eligibility.

Because California is home to a large number and share of immigrants, misassignment at the unit level could result in understating poverty rates, especially for demographic subgroups. As of 2012, an estimated 2.8 million unauthorized immigrants resided in California (Baker and Rytina, 2013), more than any other state.

We assign a status of "likely unauthorized" to immigrants in our ACS sample based on methodology developed in Passel and Cohn (2009) and Hill and Johnson (2011) and then use that status to properly assign eligibility for benefits in the SNAP, TANF, EITC, and federal housing subsidy programs. Because the CPM is primarily an estimate of poverty within relatively large population subgroups (region, race, age), our methodology is not required to correctly identify *individual* unauthorized immigrants. Rather, as is the case with many of the components of the CPM, it is important that we reasonably assign status within population subgroups. This is convenient, since very little is known directly about the characteristics of unauthorized immigrants. Few surveys ask respondents about their legal status, and no survey representative at the state level does.

The ACS is no exception. This survey records an individual's place of birth as well as legal status only to the extent of native-born, naturalized, and noncitizen. The noncitizen response is likely for unauthorized immigrants (though reporting error may also factor in) but also would apply to legal permanent residents, refugees, work visa holders, and student visa holders, none of whom are unauthorized (unless they have overstayed a visa).

There is also no source of reliable data on the number of unauthorized immigrants within California's regions and demographic subgroups of interest. Hill and Johnson (2011) provide county and zip code level estimates of the population, and Passel and Cohn (2009) provide national demographic distributions, but no source provides these jointly.

To surmount these obstacles, we assign "likely unauthorized" status to individuals in the ACS using reported "non-citizen" status as well as other socioeconomic characteristics (following Passel and Cohn, 2009) and matching population totals at the county level using the estimates of Hill and Johnson (2011). Specifically our assignment procedure follows these broad steps: (1) identify all noncitizen immigrants in the ACS, (2) exclude those with a very high likelihood of being authorized via widespread amnesty and visa programs, (3) exclude those likely to be authorized by marriage, (4) from the remaining pool of noncitizens, randomly assign "likely unauthorized" status to individuals, using Hill and Johnson (2011) as county control totals. We validate this procedure using the 2008 ACS sample, since that year matches Hill and Johnson's California county estimates precisely (as well as the Passel and Cohn breakdowns for the nation overall). In carrying the procedure forward to future years, we assume the Hill and Johnson distribution of unauthorized immigrants across counties is constant, and we apply the distribution to the estimated number of unauthorized immigrants in California in 2012, according to DHS estimates (Baker and Rytina, 2013).

In the 2012 ACS we estimate that out of the 37.2 million California residents, 5.31 million were noncitizen immigrants (step 1) and of those, 3.34 million are potentially unauthorized (steps 2 and 3; for more detail see Bohn et al, 2013). After step 3, we would have an 18% overcount of unauthorized immigrants were we to assign status to all in the pool. We next randomly assign likely unauthorized status to persons from the potential pool (step 4), matching as closely as possible to the DHS estimate of unauthorized in California in 2012 (2.82 million) and the county distribution in Hill and Johnson (2011). We assign a random number to each individual—or unit, if members of the same household remain in the pool—and select from the pool until the weighted total matches county-level estimates. In counties where the ACS pool underestimates the county total we are aiming to match, we assign unauthorized status to all in the pool and allow for the resulting undercount. The results of this assignment are presented in Table A4. Following the selection procedure, we estimate a total of 2.79 unauthorized immigrants in California, a slight (1%) undercount of the official estimate. Table A4 shows that, in most counties, our estimates match control totals (and shares) quite closely. Generally, the largest errors occur in the smallest counties.

Table A4
Results of unauthorized immigrant identification procedure, county estimates

		Unauthorized Counts		Unauthorized Share of Population	
County	Population	Our estimate	Control totals	Our estimate	Control totals
Alameda	1,520,267	119,388	121,649	7.9%	8.0%
Alpine, Amador, Calaveras, Inyo, Mariposa, Mono, Tuolumne	177,581	2,606	2,453	1.5%	1.4%
Butte	215,818	4,042	3,924	1.9%	1.8%

Colusa, Glenn, Tehama, Trinity	124,225	4,868	9,810	3.9%	7.9%
Contra Costa	1,069,034	75,716	77,502	7.1%	7.2%
Del Norte, Modoc, Lassen, Siskiyou	118,862	987	981	0.8%	0.8%
El Dorado	178,778	3,530	3,924	2.0%	2.2%
Fresno	928,883	48,147	48,071	5.2%	5.2%
Humboldt	130,699	2,187	1,962	1.7%	1.5%
Imperial	164,326	12,839	20,602	7.8%	12.5%
Kern	825,319	46,224	45,128	5.6%	5.5%
Kings	131,503	8,983	8,829	6.8%	6.7%
Lake, Mendocino	248,143	14,365	13,735	5.8%	5.5%
Los Angeles	9,786,798	898,800	898,633	9.2%	9.2%
Madera	144,407	11,809	11,772	8.2%	8.2%
Marin	148,108	5,041	7,848	3.4%	5.3%
Merced	256,441	21,648	21,583	8.4%	8.4%
Monterey, San Benito	463,931	61,421	60,824	13.2%	13.1%
Napa	134,150	15,656	15,697	11.7%	11.7%
Nevada, Plumas, Sierra	100,470	957	1,962	1.0%	2.0%
Orange	3,048,005	283,673	283,521	9.3%	9.3%
Placer	357,369	7,881	7,848	2.2%	2.2%
Riverside	2,234,385	143,419	143,232	6.4%	6.4%
Sacramento	1,426,417	64,313	63,768	4.5%	4.5%
San Bernardino	2,036,191	145,075	147,156	7.1%	7.2%
San Diego	3,087,151	194,319	194,246	6.3%	6.3%
San Francisco	806,064	29,463	29,431	3.7%	3.7%
San Joaquin	687,460	53,757	52,976	7.8%	7.7%
San Luis Obispo	257,595	8,540	8,829	3.3%	3.4%
San Mateo	729,645	53,990	53,957	7.4%	7.4%
Santa Barbara	412,020	36,336	36,298	8.8%	8.8%
Santa Clara	1,804,556	176,888	176,587	9.8%	9.8%
Santa Cruz	255,178	18,601	20,602	7.3%	8.1%
Shasta	176,040	1,210	981	0.7%	0.6%
Solano	408,642	24,348	23,545	6.0%	5.8%
Sonoma	482,035	36,395	40,223	7.6%	8.3%
Stanislaus	515,794	38,652	38,261	7.5%	7.4%
Sutter, Yuba	165,690	8,855	8,829	5.3%	5.3%
Tulare	445,743	28,463	28,450	6.4%	6.4%
Ventura	824,403	64,612	72,597	7.8%	8.8%
Yolo	195,463	12,036	11,772	6.2%	6.0%
Total	37,223,590	2,790,040	2,819,998	7.5%	7.6%

SOURCE: Authors' calculations from ACS 2012 and comparison with the DHS total (Baker and Rytina, 2013) distributed across counties according to Hill and Johnson (2011).

Finally, we compare the socioeconomic characteristics of the likely unauthorized immigrants assigned in the 2012 ACS for California to those estimated by Passel and Cohn (2009) in the 2008 CPS for the United States (Table A5). Admittedly, this is not an apples-to-apples comparison for a few reasons. Characteristics may differ due to the year surveyed, the surveys themselves (CPS vs. ACS), or substantive differences between the California and U.S. unauthorized populations. However, given the dearth of detailed information on the unauthorized population, this is the best comparison we have. Table A5 shows that our procedure yields a likely unauthorized population with education, age, labor force participation and birthplace characteristics distributed similarly to that developed in previous research.

Table A5
Socioeconomic characteristics of immigrants assigned likely unauthorized status

Characteristic	2012 ACS assignment procedure for California	2008 Passel and Cohn (2009) procedure for United States
Education		
Less than high school	51%	47%
High school graduate	29	27
Some college	10	10
College graduate	10	15
Age		
Child (<18)	12	13
Adult	88	87
Gender		
Male	51	59
Female	49	41
Labor force participation of men (ages 18-64)		
No	10	6
Yes	90	94
Labor force participation of women (ages 18-64)		
No	41	42
Yes	59	58
Birthplace (select regions)		
Mexico	63	59
Central America	10	11
South America	2	7
South and East Asia	13	11

SOURCE: Authors' calculations from ACS 2012 and comparison with Passel and Cohn (2009).

We use the procedure presented here to flag individuals in the California ACS who are likely to be unauthorized. This allows us to exclude them from the pool of eligible recipients of certain program income. In general, for the CPM we assume that individuals share resources within households (or families). Thus, even if an unauthorized immigrant is excluded from the calculation of receipt and benefit amount for official purposes, in the ultimate calculation of family resources, all share equally. The specific exclusions, assumptions, and program rules are described in detail in the corresponding resource and expense appendices.

Appendix B: Thresholds

The poverty thresholds calculated in this paper are based on the most recently published, national-level SPM thresholds for 2012. Following the recommendations suggested in the 1995 NAS report and the body of research that followed, these thresholds include expenditures on food, clothing, shelter, and utilities (FCSU), with an additional 1.2 multiplier to account for other necessities. The SPM thresholds are based on roughly the 33rd percentile of expenditures by families with two children and are derived by the Bureau of Labor Statistics (BLS) from five years of Consumer Expenditure (CE) survey data (Garner and Gudrais, 2012). The threshold for the reference family is typically adjusted for other family types using what is called an "equivalence scale." For alternative poverty measures, the Census Bureau typically uses a three-parameter equivalence scale developed by David Betson, and we adopt that method in this paper (Betson, 1996).

Adjustment for Housing Costs, County Level

For local poverty measures such as the California Poverty Measure (CPM), the next step in creating accurate thresholds is to create a "geographic adjustment" that captures the relative costs of the components of the poverty threshold in California's counties as compared to those costs in the nation as a whole. The Official Poverty Measure (OPM) makes no distinction across geographic areas: The poverty line is the same in San Francisco and Los Angeles as it is in rural Mississippi. For national SPM measures, geographic adjustments are performed at the metropolitan area level (Renwick, 2011), while other state and local variants of the SPM are performed at the county level (Chung et al., 2012b) or the city level (NYC Center for Economic Opportunity, 2012). We operationalize the geographic adjustment within California at the county level—the smallest geographic unit where we can reliably match housing cost and ACS data. Implementing this adjustment makes sense in California, given the wide variation in housing costs across the state. For example, many inland counties have housing costs close to the U.S. average, whereas coastal areas have among the highest housing costs in the entire nation.

So how should poverty thresholds in California be adjusted? One possibility is to use what is called a "triple index." That is, one would create not one threshold for everyone but three thresholds depending on a family's housing arrangement, divided into three types: renters, owners with a mortgage, and owners without a mortgage. Each threshold would then be adjusted by the relative housing costs of that group. So for renters, we would adjust for the relative costs of renting in each of California's 58 counties versus the costs of renting in the nation as a whole. For owners with a mortgage, we would adjust for the relative costs of owning with a mortgage versus owning with a mortgage in the nation as a whole (and so forth).

This approach, however, has been largely abandoned in favor of what is called a "rental only index." Under this approach, which the Census has adopted (see Renwick, 2011), only the adjustment factor for renters would be used, and it would be applied to all three housing groups. So, for example, if the national SPM thresholds for the three groups were $20,000, $25,000, and $30,000 for owners without mortgages, renters, and owners with mortgages, respectively, each would be inflated (or deflated) by the relative costs of *renting* in a specific locale versus the nation as a whole. This approach was adopted in response to a problem identified with the triple index at an April 2011 meeting at the Brookings Institution (Renwick, personal communication). Essentially, the problem identified was related to the question of geographic comparability of mortgage expenditures. Mortgage expenditures depend on many factors, such as the length and terms of the typical mortgage, that do not reflect the true cost of buying a new home in a particular area. For this reason, the "owners with mortgages" component of the triple index was deemed too potentially problematic, and, instead, the renters' component of that index was deemed a sufficiently good proxy for the increased (or decreased) costs of buying a new home in a given area.

One problem with this approach in California is that Proposition 13 (1978) capped increases in property taxes, with the implication for owners without mortgages—who have likely been in their homes for many years—that housing costs may be quite low relative to the nation as a whole.[5] Put another way, if California is a much more expensive place to live given high rental costs, this simply may not apply when one owns a home without a mortgage. Indeed, we find this to be the case when we break out relative housing costs for the three groups outlined above. Whereas rental costs, on average, are approximately 40 percent higher in California than in the nation as a whole, and housing costs for owners with mortgages are roughly 60 percent higher, relative housing costs for owners without mortgages are only about 6 percent higher in California.

For these reasons, we have elected to use a "dual index" for the state. After applying three base thresholds for Californians based on one's housing status (own with mortgage, own with no mortgage, rent), we adjust geographically in one of two ways. We use a rental adjustment for families that rent and families that pay a mortgage, and a separate adjustment for families that own their home free and clear (based on their much lower relative costs). To calculate our final thresholds, we inflate the shelter and utilities portion of each SPM threshold by the difference in housing costs between each county (or county group) and the nation for households in two and three bedroom dwellings of the appropriate tenure (and with adequate plumbing facilities). We use five-year data on housing costs from the ACS for 2008-2012. Using a five-year average will tend to moderate housing costs relative to pre-recession years. For the renter and mortgage thresholds, we

[5] The lower relative housing costs are due to voter-passed Proposition 13 (1978), which caps property tax increases for existing owners at 2 percent annually.

use median gross rents. For the non-mortgage threshold, we use median monthly ownership costs that include insurance, utilities, and taxes.

Table B1
CPM thresholds for a family of four (two adults, two children)

	Renters		Owners with mortgage		Owners without mortgage	
County	Threshold	Difference from official threshold (%)	Threshold	Difference from official threshold (%)	Threshold	Difference from official threshold (%)
Alameda	$31,018	33%	$32,031	38%	$22,705	-2%
Alpine	$26,234	13%	$26,976	16%	$22,338	-4%
Amador	$26,234	13%	$26,976	16%	$22,338	-4%
Butte	$25,297	9%	$25,987	12%	$20,687	-11%
Calaveras	$26,234	13%	$26,976	16%	$22,338	-4%
Colusa	$24,348	5%	$24,985	7%	$20,116	-14%
Contra Costa	$30,877	33%	$31,882	37%	$22,725	-2%
Del Norte	$24,502	5%	$25,147	8%	$20,646	-11%
El Dorado	$27,491	18%	$28,304	22%	$23,561	1%
Fresno	$24,220	4%	$24,849	7%	$20,340	-13%
Glenn	$24,348	5%	$24,985	7%	$20,116	-14%
Humboldt	$24,746	6%	$25,405	9%	$20,523	-12%
Imperial	$23,065	-1%	$23,629	1%	$20,687	-11%
Inyo	$26,234	13%	$26,976	16%	$22,338	-4%
Kern	$24,181	4%	$24,808	7%	$20,238	-13%
Kings	$23,963	3%	$24,578	6%	$19,851	-15%
Lake	$25,977	12%	$26,705	15%	$21,767	-7%
Lassen	$24,502	5%	$25,147	8%	$20,646	-11%
Los Angeles	$30,197	30%	$31,164	34%	$21,869	-6%
Madera	$24,323	4%	$24,957	7%	$21,074	-9%
Marin	$34,841	50%	$36,069	55%	$26,068	12%
Mariposa	$26,234	13%	$26,976	16%	$22,338	-4%
Mendocino	$25,977	12%	$26,705	15%	$21,767	-7%
Merced	$23,976	3%	$24,592	6%	$20,197	-13%
Modoc	$24,502	5%	$25,147	8%	$20,646	-11%
Mono	$26,234	13%	$26,976	16%	$22,338	-4%
Monterey	$28,838	24%	$29,727	28%	$21,298	-9%
Napa	$30,659	32%	$31,651	36%	$23,092	-1%
Nevada	$27,619	19%	$28,440	22%	$23,602	1%
Orange	$32,917	41%	$34,036	46%	$22,745	-2%
Placer	$29,338	26%	$30,256	30%	$23,500	1%
Plumas	$24,502	5%	$25,147	8%	$20,646	-11%
Riverside	$28,094	21%	$28,941	24%	$22,154	-5%
Sacramento	$26,914	16%	$27,695	19%	$21,135	-9%
San Benito	$28,838	24%	$29,727	28%	$21,298	-9%

San Bernardino	$27,183	17%	$27,979	20%	$20,605	-12%
San Diego	$30,608	31%	$31,597	36%	$22,093	-5%
San Francisco	$35,700	53%	$36,977	59%	$23,153	-1%
San Joaquin	$26,285	13%	$27,031	16%	$21,115	-9%
San Luis Obispo	$29,607	27%	$30,540	31%	$22,440	-4%
San Mateo	$35,457	52%	$36,719	58%	$23,235	0%
Santa Barbara	$31,724	36%	$32,776	41%	$22,399	-4%
Santa Clara	$33,802	45%	$34,971	50%	$23,907	3%
Santa Cruz	$33,007	42%	$34,131	47%	$22,868	-2%
Shasta	$25,798	11%	$26,516	14%	$20,952	-10%
Sierra	$28,838	24%	$29,727	28%	$21,298	-9%
Siskiyou	$24,502	5%	$25,147	8%	$20,646	-11%
Solano	$29,479	27%	$30,405	31%	$20,931	-10%
Sonoma	$30,364	30%	$31,340	35%	$22,970	-1%
Stanislaus	$25,900	11%	$26,624	14%	$20,972	-10%
Sutter	$24,271	4%	$24,903	7%	$20,483	-12%
Tehama	$24,348	5%	$24,985	7%	$20,116	-14%
Trinity	$24,348	5%	$24,985	7%	$20,116	-14%
Tulare	$23,271	0%	$23,846	2%	$19,667	-16%
Tuolumne	$26,234	13%	$26,976	16%	$22,338	-4%
Ventura	$32,134	38%	$33,210	43%	$22,582	-3%
Yolo	$28,556	23%	$29,429	26%	$22,236	-4%
Yuba	$24,271	4%	$24,903	7%	$20,483	-12%

SOURCE: Authors' calculations as described in the text.

Table B1 highlights two points: (1) There is wide variation across counties in CPM thresholds, with high-cost counties having roughly 50 percent or higher thresholds for renters and owners with mortgages compared to the official poverty threshold; and (2) The separate adjustment for owners without mortgages makes a big differences, as the poverty thresholds for this group are uniformly very close, or lower than, the official poverty threshold across the state.

Appendix C: Resources

The CPM, like other national and state-level supplemental poverty measures, aims to provide a more thorough accounting of the income and resources used by low-income families. In a perfect world, researchers would have access to detailed information on every income stream and in-kind resource that families use over the course of a year; however, the ACS provides information on only a handful of income sources. Many resources vital for the financial well-being of poor families, such as the EITC or low-income housing subsidies, are not asked about in the ACS. Even for those income sources the ACS explicitly requests from respondents, researchers must confront the systemic underreporting of participation in, and income from, social safety net programs such as SNAP (formerly known as food stamps) and TANF (or "welfare income").

This appendix describes our approaches to accurately estimating important family income sources. Major income sources discussed in this section are SNAP, TANF, tax credits (and liabilities), housing subsidies, and the school lunch and breakfast programs.

In our tabulation of overall resources for a CPM poverty unit, we include several cash income sources directly from the ACS without making major adjustments to reported amounts. These income sources include wage and salary income, self-employment income, income from Social Security (including Social Security Disability Income), income from interest and dividends, and income from the Supplemental Security Income (SSI) program. We make only small adjustments to these self-reported income sources, removing extreme outliers and reclassifying some income streams into other categories (for example, we reclassified SSI income that exceeded SSI maximum benefit amounts as income from Social Security). We also adjusted all cash income amounts for the rolling reporting period of the ACS, as discussed above.

Table C1 provides a list of all the resources aggregated to the poverty unit and a general description of our estimation approach. It should be noted that several categories of income, such as unemployment compensation, alimony payments, and veteran's benefits, are combined into an "all other income sources" field in the ACS and cannot be examined individually.

Table C1
CPM resources and estimation approach

Income source	In ACS?	Adjustments for CPM estimate
Wage and salary Income	Yes	No
Self-Employment income	Yes	No
Social Security Income	Yes	No
"Welfare" income	Yes	Yes (Underreporting adjustment for TANF)
Interest and dividend income	Yes	No
Pension Income	Yes	No
SSI income	Yes	No
Alimony, veteran's benefits, child support	Yes (but lumped into "all other income"field, cannot be separated)	No
SNAP (food stamps)	Yes (but only participation, not dollar amount)	Yes (Underreporting adjustment and benefit Imputation)
Tax credits (EITC, CTC)	No	Yes (Imputation)
School meals	No	Yes (Imputation)
Housing subsidies	No	Yes (Imputation)

There are two near-cash resources included in the Census' Supplemental Poverty Measure that are not included in the CPM: the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), the Low Income Home Energy Assistance Program (LIHEAP). Data on participation in these programs are not available in the ACS. As these are relatively small programs that have only a minor impact on SPM poverty rates in CPS data, it is unlikely that their exclusion substantially affects poverty rates under the CPM. Future work could consider the role of these programs as well by identifying administrative data sources from which to impute receipt into the ACS, as this version of the CPM has done for SNAP, TANF, and school lunch and breakfast programs. Future work could also examine the feasibility of incorporating additional near-cash resources targeted to meeting needs for food, clothing, shelter, and utilities which are currently included in neither the CPM nor the SPM, such as the Child and Adult Care Food Program (CACFP) and summer school meals.

TANF/CalWORKs and GA

The two largest welfare programs providing direct cash grants to families are the Temporary Assistance for Needy Families (TANF) program and General Assistance (GA). TANF (known as CalWORKs in California) mostly serves families with children, given its dual goal of reducing extreme poverty among children and assisting adults in moving their families toward self-sufficiency. The much smaller GA program serves indigent adults.

Since TANF and GA provide cash grants to individuals or families, both are included in the official poverty statistics. The CPM pays particular attention to income from these welfare programs in order to accurately measure their impact on poverty rates. To arrive at accurate estimates of program participation and benefit amounts, we confront two key problems in the ACS. The first is underreporting of program income, and the second involves ambiguities of the ACS question wording for our purposes. We discuss each below.

Defining TANF and GA Income in the ACS

The ACS asks respondents about the sum total of welfare income received in the previous year. Unfortunately, in this question, TANF, GA, and any other (relatively smaller) welfare programs are not separately identified. We apply a set of assumptions to sort out the source of welfare income as best we can.

TANF primarily serves families with children, whereas GA almost exclusively serves single adults. Thus, we assign income reported as "welfare" in the ACS according to whether the Census household contains children or not. We take the self-reported presence of children in a household as given, a strong assumption, but given the small size of GA relative to TANF imparts a small degree of error to our estimates. Since GA in California is a fraction of the size of CalWORKs, even if we assign all welfare income to TANF, we will only overstate TANF by 10 percent in the aggregate (the GA caseload as of June 2010 was approximately one-tenth of the TANF caseload during the same month, according to administrative statistics).[6] Table C2 summarizes the number of people and households reporting TANF and GA in the ACS under these assumptions. About 545,000 households in the survey report receipt of "welfare income," and our assumptions split these respondents into 394,000 TANF-reporting households and 150,000 GA-reporting households.

[6] See California Public Assistance Facts and Figures: http://www.cdss.ca.gov/research/PG370.htm.

Table C2
TANF and GA in California Sample of the 2012 ACS

Household type	In units reporting TANF		In units reporting GA	
	Number of people	Number of households	Number of people	Number of households
Children only	291	161	n/a	n/a
Single adult	n/a	n/a	42,173	42,173
Multiple adults, no children	n/a	n/a	315,114	108,228
Single parent	318,204	92,965	n/a	n/a
Multiple adults, children	1,586,179	300,428	n/a	n/a
Total	1,904,774	393,554	357,287	150,401

SOURCE: Authors' calculations from the ACS.

NOTES: Figures represent weighted population counts. TANF or GA receipt is allocated at the household level for this table. The ACS asks individuals ages 15 and older about their receipt of income, including income from "welfare." Those receiving TANF income in the table have one or more dependent children in the household. Those categorized as having income from GA have no dependent children in the household.

Table C2 highlights potential sources of mismatch between the ACS and household concept in the ACS and the unit concept for TANF and GA program participation. There are few child-only households in the ACS that report TANF, because: 1) in the ACS, income questions are only asked of household members over age 15 and 2) there are few households comprised only of children (below age 18). However, we know from administrative data that the child-only caseload of TANF is quite large. TANF benefits in California are often granted to children alone if parents fail to meet work requirements. Clearly there is a mismatch between the concept of household in the ACS and that of a family or "unit" for the purposes of TANF program participation. This mismatch would not necessarily be problematic for estimating an accurate CPM were it not for the high degree of underreporting of welfare income in the ACS. But because TANF is underreported and we aim to correct that using administrative data, we must take additional steps to align the ACS and administrative concept of TANF participation. We discuss these efforts in the following section.

TANF/GA Underreporting in the ACS

Both welfare program participation and benefit amounts are underreported in household surveys (Wheaton, 2007). Using custom tabulations of administrative data on TANF participation for 2012, we estimate an undercount of TANF units in the ACS of about 49 percent; we provide further details below. In addition, the dollar amount of benefits claimed in California in 2012 was about $3.2 billion[7] compared to ACS self-reported TANF income of about $1.6 billion. Due to both sources of underreporting, we develop a two-step procedure for correcting TANF underreporting. Other SPM-style estimates generally do not correct for underreporting of welfare income.

[7] Estimated from California Department of Social Services "Public Assistance Facts and Figures", January 2012-December 2012, http://www.cdss.ca.gov/research/PG370.htm

While GA is subject to this underreporting issue, it is a small program, and thus we take participation and income received as given. Since the caseload is so small and expenditures are low relative to other programs, we did not focus our efforts on refining GA income assignment or amounts for this version of the CPM. Note that in the cases reporting GA income (as allocated) in the ACS, the average annual income from GA was about $4,900, with a state total of about $740 million. In the future, we could consider efforts to better identify potential recipients in the ACS to match what is known about the geographic distribution of GA cases (for example, Los Angeles County is home to about 70 percent of the state caseload, but we estimate 30 percent of the caseload is in the city of Los Angeles). And we could attempt to impute income amounts to account for misreporting or underreporting (we currently have an overestimate of total dollars spent on GA statewide in the ACS).

To correct TANF for underreporting we must inflate the number of recipients and adjust or impute benefit amounts. Common to our procedure on a number of benefit and expense pieces of the CPM, our method for correcting TANF is aimed at matching administrative totals as closely as possible. We use custom, detailed tabulations of actual TANF participation in California. These allow us to match participation at the county-race level for California, which is important since we aim to calculate the CPM within these dimensions. Furthermore, we use administrative data on the overlapping TANF and SNAP program participants to refine our assignment of participation. TANF recipients are categorically eligible for SNAP, and our procedure takes this joint participation into account. And finally, we use administrative data on timed-out and sanctioned adults to adjust ACS reported and assigned TANF participation to better approximate the child-only TANF caseload.

The procedure to correct TANF reports includes the following steps:

1. Split Census households using relationship flags to create TANF units in ACS data. These are defined identically to SNAP units, since information on the status of adults (sanctioned, timed out, etc.) is not available in the ACS;
2. Exclude individuals who are assigned unauthorized immigrant status or who report SSI income from consideration of TANF participation;
3. Take as given TANF participation for units that report receipt of TANF income, according to the rules implemented above;
4. Use income and unit information to flag TANF eligibility among units that did not report TANF income;
5. Randomly assign TANF receipt to a fraction of eligible units who are also eligible or received SNAP to match administrative totals of units receiving benefits from both programs at the county-race group-household type level;
6. Randomly assign TANF to an additional fraction of eligible units to match administrative totals of units that received TANF but not SNAP, also at the county-race group level;

7. Estimate a benefit model in the administrative data and predict monthly benefit amounts for units that reported TANF and for units for which we imputed TANF receipt in the ACS;
8. Multiply the monthly benefit amount by a randomly assigned number of months that a unit received TANF over the twelve-month period to match distributions created in the administrative data.

Administrative Data Sources

Assigning TANF participation and months on TANF

We use custom tabulations from the longitudinal statewide administrative database for California that records monthly receipt of TANF and SNAP for individuals. This database, known as the Medi-Cal Eligibility Determination System (MEDS), does not contain the dollar amount of benefit received, only whether an individual participated in the program. We aggregate these counts to cells defined by characteristics of the SNAP unit (number of adults, number of children, county, race, etc.). In total, we define 1378 cells in the TANF administrative caseload. Within these cells, we create a distribution of months on TANF over 2012, as well an unduplicated count of persons and units ever on the program in 2012. These tabulations were created in collaboration with the state's Department of Social Services. We have two versions of the tabulations for the purposes of TANF assignment: the case counts of SNAP units that also received TANF (specifically someone in the SNAP unit received TANF) and the total case counts of TANF participants. Because these case counts are slightly different concepts given the regular presence of unaided adults, we also use the two data sources described next.

Accounting for unaided adults in units that receive TANF

We use a rough adjustment to TANF caseload to account for the presence of unaided adults in households and units in the ACS.[8] We rely on county-level administrative reports, publically available, to construct a ratio described in the procedure below. These reports include the caseload movement report, CA 237 CW, and welfare-to-work monthly activity report, WTW 25.

[8] It is alternatively possible to create a routine to exclude adults from ACS data, but we have found no variable upon which this could be imputed or randomly assigned in a systematic manner. In addition, in future work we may be able to construct administrative TANF cell totals accounting for the presence of unaided adults directly.

Imputing TANF benefit amounts.

As part of the U.S. Department of Agriculture's quality control program, each state, under the auspices of the Research and Development Enterprise Project (RADEP), draws a sample of TANF cases each month to verify recipient eligibility and benefits. We use the 2012 fiscal year California sample, which contains monthly benefit and unit characteristic data for over 5,000 TANF households, to model monthly benefit amounts by household demographic characteristics and income sources.

TANF Assignment Procedure

Steps 1 and 2 of the assignment procedure are described in more detail in the following section. We assume that TANF units are identical to SNAP units for our purposes. While not precisely correct, ACS data provide no additional information with which to redefine TANF units. In particular, we do not know whether a parent has reached the 60- or 48-month TANF time limit, and we do not know whether a parent has received a sanction for failure to participate in required TANF work activities and is not included in the case.[9] To better approximate the presence of adults in TANF cases in the ACS, we inflate administrative totals using county-specific rates of sanctioned or timed-out adults. Essentially, we "add" adults to TANF cases counted in administrative data to match administrative reports on sanctioning.[10] In the ACS, only those age 15 and older report receipt of welfare income (on behalf of themselves or their children). Thus, we necessarily have an over-count of the number of true TANF recipients in the ACS.[11] That over-count is reflected in Table C3, which compares units in the ACS that self-report TANF along with our adjustments to administrative totals (result of Steps 1 through 3). Note that because of the limitations of ACS data, columns 1-3 reflect counts of people in units that report receiving TANF, whereas column 4 reflects actual aided TANF members from administrative records.

[9] California switched from a 60-month to a 48-month lifetime time limit for adults in July 2011.
[10] These county-level rates are calculated from 237 and WTW25 reports. We calculate the fraction of excluded adults as [number of cases with a timed out adult(s) + number of cases with a sanctioned adult(s)]/[number of non-safety net cases], and we apply this to administrative totals of TANF cases with at least one child.
[11] We are experimenting with methods that may improve this step in the procedure.

Table C3
Individuals in units reporting TANF receipt by case type, 2011

	Census households	Split into SNAP/TANF units	SSI and unauthorized removed	Administrative totals (adjusted)
	(1)	(2)	(3)	(4)
Child only	291	1,684	160,788	473,755
Single parent	318,204	646,896	524,348	984,726
Multiple adults and children	1,586,179	647,317	469,051	727,812
Adult only	N/A	94,542	76,732	30,141
Total	1,904,774	1,390,439	1,230,919	2,216,435

SOURCES: Authors' calculations from the 2012 ACS (weighted) and California administrative data, including MEDS, 237, and WTW25.

NOTES: Column 1 based on self-reported welfare income received by at least one individual in a household on the ACS. Columns 2 and 3 adjust self-reported information according to a variety of assumptions described in the text. Column 4 provides an unduplicated count of TANF units observed to receive TANF for at least one month during the year from administrative records.

The number of people in ACS units reporting TANF income is 45 percent less than the number of Californians aided by TANF in 2012; again, this actually *understates* the *underreporting* in ACS due to the problem of identifying aided adults. However, in terms of case counts, the total number of cases reflected in Column 3 is 405,487 and in Column 4 is 794,679; this indicates an undercount of about 49 percent based on cases.

To determine eligibility for TANF (step 4), we use an income cutoff of 125 percent of the federal poverty threshold. To qualify for TANF in a given quarter, a family must, among other conditions, have income less than the "minimum basic standard of adequate care." This standard varies both by family size and region. Because ACS income is reported annually, likely fluctuates over the year for the TANF eligible population, and is well-understood to be misreported for those with multiple or marginal jobs, we cannot directly compare ACS-reported income to the TANF eligibility income thresholds (Abraham, Haltiwanger, and Sandusky, 2009). We therefore approximate the TANF cutoff using a ratio of the federal poverty line (which varies similarly by family size) slightly above what is required for "minimum basic standard of adequate care" (to account for the ACS income mismatch issues). For the modal family size, the augmented TANF cutoff is roughly 106-119 percent of FPL, so we use 125 percent as our income cutoff.

Table C4
Individuals in TANF units, according to eligibility and unit type

Unit type	Self-reporters (adjusted)	Income eligible non-reporters	Administrative totals
	(1)	(2)	(3)
Child only	160,788	712,859	473,755
Single parent	524,348	1,543,263	984,726
Multiple adults, children	469,051	1,607,388	727,812
Adult only	76,732	24,247	30,141
Total	1,230,919	3,887,757	2,216,435

SOURCE: Author's calculations in the ACS and MEDS.

NOTE: Number of individuals within each category of unit size, weighted at the person-level in the ACS.

From this pool of eligible non-reporters (Table C4), we assign TANF participation in two steps: first, the joint TANF-SNAP cases (step 5) and then the TANF-alone cases. The joint TANF-SNAP units comprise the majority of the TANF caseload (step 6). To match the administrative totals, we assign reported or eligible TANF units in the ACS receipt randomly within county and unit type (child only, single parent, etc.) cells, totaling over 1300. For the SNAP-TANF joint caseload, we also match within race/ethnic fields.[12] Where not enough households in the ACS could be found to match administrative cell totals, we aggregated cells with the largest neighboring county. In other cells, the ACS self-reports overstate administrative totals, in which case we take self-reports as true. The ACS is a population-weighted survey and therefore we cannot always select sampled units to force unit weights[13] to match administrative counts exactly. We instead select units so that the weighted difference between ACS and administrative cell counts is between 0-3 percent of the actual in the case of the joint SNAP-TANF caseload and between 0-50 percent of the actual for the TANF-only caseload.[14]

The results of this detailed two-step TANF assignment procedure are summarized in Table C5.

[12] We randomly assign participation within county, race/ethnic group, and household type. While an assignment based on likelihood of participation (perhaps modeled in an external data set like the CPS or SIPP) is appealing, we are concerned that this approach may reinforce the underreporting problem we are trying to overcome. For example, if higher income units are less likely to report participation across all similar surveys, a conditionally random assignment like we use may be preferable. Nonetheless, these are concerns that we plan to address in future work.

[13] Our unit weight is the person weight of the oldest person in the SNAP unit.

[14] The TANF-only larger factor is necessitated by small cell size to which we are trying to impute. An alternative would be to split unit weights to generate an exact match with administrative counts. This complicates the overall CPM, however, as a number of modules use similar imputation procedures. We will explore the impact of these two methods in future work.

Table C5
Individuals in TANF units as reported, assigned, and in administrative data

Unit size/type	Self-reporters	TANF-SNAP joint receipt (reported and assigned)	TANF-alone receipt (reported and assigned)	Final TANF receipt	Administrative totals
	(1)	(2)	(3)	(4)	(5)
Child only	160,788	356,257	76,420	432,677	473,755
Single parent	524,348	905,439	90,201	995,640	984,726
Multiple adults, children	469,051	542,633	200,174	742,807	727,812
Adult only	76,732	13,513	65,063	78,576	30,141
Total	1,230,919	1,817,842	431,858	2,249,700	2,216,435

SOURCE: Authors' calculations from California ACS sample and California administrative data for 2012.

NOTE: Person-weighted counts in columns (1)-(4).

The TANF assignment results in a slight over count (1.5%) in the number of people in units receiving TANF. This may stem from our assignment procedure of randomly selecting units that are "too large" (for example that have more children), or from the presence unaided members in units that receive TANF and/or from assuming TANF self-reported participation (under our assumptions) is accurate. However, based on case counts instead of number of individuals, the imputation yields assignment of TANF to 784,410 cases in the ACS, a 1% undercount of the administrative total of 794,679 cases.

The final step in our TANF correction procedure is to impute benefit amounts to cases that were assigned receipt. This is based on detailed administrative survey data that allows us to model monthly benefit amounts as a function of a variety of unit characteristics (as in the SNAP model below). For consistency and as a simple method to correct for underreporting of benefit level, we use this benefit model to assign benefit amounts to self-reported TANF units as well.[15] Table C6 provides the simple OLS model used to predict monthly TANF benefits, based on the administrative survey data.

[15] We also create benefit amount estimates from self-reported income and from administrative reports of statewide average monthly benefits for various types of TANF units. These two additional benefit calculations are created for the purpose of sensitivity testing, and we find that they have little effect on CPM estimates.

Table C6
TANF monthly benefit model

Variable	Description	Coefficient estimate	Standard error
Intercept	Intercept	242.3	5.46
Number of Adults	Count of all adults in unit	107.5	3.94
Number of Children	Count of children in unit	80.6	2.07
Young Head	Head of unit is a minor	11.5	8.02
Elderly Head	Head of unit is elderly	66.1	16.5
Observations	3,311		
R-squared	0.388		

SOURCE: California TANF quality control sample for 2012 (RADEP).

To obtain annual TANF estimates, we next apply a distribution of months on aid based on administrative data in order to inflate monthly estimates to annual figures. This months-on distribution yields CalWORKs benefits ranging from $320/year to about $14,800/year, with the mean TANF unit receiving $4,100/year. Table C7 shows the resulting averages for all imputed TANF cases across case types for the model-based approach and self-reported amount. The first column shows the model-based approach using coefficients in monthly averages, and the second presents self-reported amounts.

Table C7
CalWORKs annual benefit amounts by case type, 2011

Case type	Benefit model	Self-reported
Annual averages		
Child only	$3,795	$275
Adult only	2,171	4,039
Mixed	4,346	4,745
California overall	4,027	3,917
Annual totals		
Child only	$ 774,257,421	$ 17,928,060
Adult only	137,352,495	251,603,950
Mixed	2,247,281,569	1,318,952,956
California overall	3,158,891,486	1,588,484,966

SOURCE: Authors calculations from ACS and RADEP.

NOTE: Case-weighted averages for cases either imputed or reporting benefits.

SNAP/CalFresh and CFAP

The federal Supplemental Nutrition Assistance Program (SNAP), until October 2008 known as the Food Stamp Program, has served a rapidly increasing number of low-income families in the years during and after the Great Recession. In California, the number of individuals receiving in-kind assistance from CalFresh (the state program name) nearly doubled from 2.8 million in 2009 to 4 million in 2012.[16] An additional 30,000 to 40,000 individuals received assistance from the California Food Assistance Program (CFAP) over the same time period, the state program which provides food assistance to qualified non-citizen residents who do not qualify for federal benefits.[17]

Considering both the size of the program and its substantial role in reducing poverty, accurately measuring SNAP participation and benefit amounts is imperative for the CPM or any state-level measure. At the same time, the ACS collects relatively little information on SNAP. The survey asks respondents only whether "any member of the household "(not which member(s) of the household) participated in the program, and does not gather any data on the dollar amount of benefits received. There is also growing evidence that SNAP receipt is under-reported in the ACS, as it is in the CPS.

Therefore, we augment the ACS with California administrative data. We follow the general imputation approach of other state and local-level SPM-style measures, modifying it to reflect California demographics, program rules, and available administrative data (Isaacs, Marks, Thornton, and Smeeding, 2011a; NYC Center for Economic Opportunity, 2012). To implement our imputation approach, we augment the ACS with two administrative data sources, described below. The approach exploits the administrative data at an aggregate level in order to assign benefits to members of ACS households to match aggregate administrative statistics. Our methodology combines the SNAP and CFAP programs for the purposes of estimating household participation in food assistance programs. In what follows when we refer to "SNAP" this is shorthand for "SNAP and CFAP". The CFAP program is small relative to SNAP in California, so the choice to combine the two is not of major consequence. However, the wording of the ACS questionnaire makes it likely that respondents would report SNAP or CFAP participation in the survey.

As mentioned in the TANF discussion above, for the vast majority of TANF recipients, we assign SNAP and TANF benefits jointly in the procedure described here. When possible—as is the case for us, thanks to rich administrative data at the California Department of Social Services—it is preferable to consider TANF and SNAP program participation jointly. Program rules imply that most TANF recipients are categorically eligible for SNAP. And, in fact, most TANF households in California are also enrolled in SNAP. Thus, assigning TANF and SNAP separately could greatly misallocate the total amount of benefits received by

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[16] California Department of Social Services (CDSS) "CalFresh Program Total, Public Assistance and Nonassistance Persons, July 2009-January 2014" (http://www.cdss.ca.gov/research/PG350.htm)—number of individuals receiving CalFresh benefits in July of each year cited.
[17] California Department of Social Services (CDSS) "California Food Assistance Program Total, Public Assistance and Nonassistance Persons, July 2009-January 2014" (http://www.cdss.ca.gov/research/PG350.htm)—number of individuals receiving CFAP benefits in July of each year cited.

units in the ACS. How assigning TANF as part of the SNAP assignment procedure functions practically is highlighted as we outline the overall method below.

Described in more detail below, our overall strategy has the following structure:

1. Split Census households using household relationship flags to create SNAP benefit units in the ACS;
2. Exclude individuals who are assigned unauthorized immigrant status or who report SSI income from consideration of SNAP participation;
3. Take as a given SNAP participation for units that report;
4. Use income data to flag SNAP eligibility among units that did not report SNAP receipt;
5. Randomly assign SNAP receipt to a fraction of the eligible units to match administrative totals at the county-race-household type level;
6. Estimate a benefit model in the administrative data and predict monthly benefit amounts for units that reported SNAP and units for which we imputed SNAP receipt in the ACS; and
7. Multiply the monthly benefit amount by a randomly assigned number of months that a unit received SNAP over the twelve-month period to match distributions created in the administrative data;
8. Adjust annual benefit at the county level to more closely match administrative totals on dollars spent on SNAP in 2012.

Administrative Data Sources

Imputing SNAP participation and months on SNAP

We use custom tabulations from the longitudinal statewide administrative database for California that records monthly receipt of CalFresh for individuals. This database, known as the Medi-Cal Eligibility Determination System (MEDS), does not contain the dollar amount of the SNAP benefit received, only whether an individual participated in the program. We aggregate these counts to cells defined by characteristics of the SNAP unit (number of adults, number of children, county, race, etc.). We use these data to create a distribution of months on SNAP over 2012, as well an unduplicated count of persons and units ever on the program in 2011. Both SNAP and CFAP participants are included in these counts. These tabulations were created in collaboration with the state Department of Social Services.

Imputing SNAP benefit amounts

As part of the U.S. Department of Agriculture's quality control program, each state draws a sample of SNAP cases each month to verify recipient eligibility and benefits. We use the 2012 fiscal year California sample, which contains monthly benefit and unit characteristic data for over 5,000 SNAP households. We use these data to model monthly benefit amounts by household demographic characteristics and income sources.

Aggregate SNAP benefits issued by county

The California Department of Social Services publishes monthly reports on SNAP participation and benefits paid ("DFA 256 - Food Stamp Program Participation and Benefit Issuance Report"). These reports include detail on aggregate totals for all counties in the state. While the participation information is not particularly useful because the concept of participation varies between these reports and the ACS survey data, the monthly benefits issued can be used to benchmark the success of our individual level benefit model.

Creating SNAP Units in the ACS

The first step to imputing SNAP benefits is to assign individuals to SNAP units as defined by program rules. Because these units differ slightly from poverty units, SNAP receipt may vary within the same CPM poverty unit. Regardless, we finally aggregate SNAP resources to the CPM unit.

We redefine ACS households into SNAP units according to program rules. This involves a number of judgment calls with regard to relationships between individuals in the ACS. For example, an adult sibling who lives with a mother-child dyad would not be required to apply for SNAP together with the others if the three do not generally prepare and eat meals together. Employing the convention used by other state SPM researchers, we split households into the maximum number of units possible according to program rules (Isaacs et al., 2011a; NYC Center for Economic Activity, 2012). Essentially, we keep nuclear families intact, but move related and unrelated adults into their own units (along with any of their children). In addition, we move foster children into single person units and assign them SNAP receipt.

In cases where we split households that reported SNAP receipt, we voided SNAP receipt for any split unit that has income above 175 percent of FPL. In practice, SNAP units where receipt is voided in this manner have quite high incomes—averaging over $58,000—so we are reassured that this correction is not overly restrictive. We apply this correction only for split households, to handle the problem stemming from the SNAP question in the ACS. For all households that are not split to construct proper SNAP units, we apply no income test.

For units that report TANF or GA income (see previous section) but do not report SNAP participation, we assign SNAP participation. This aligns the self-reports in ACS with program rules on categorical eligibility.

In addition, we remove two types of ACS respondents from SNAP units:

- SSI recipients: California automatically augments monthly Supplemental Security Income (SSI) payments by $10 in lieu of SNAP eligibility. While SSI recipients in California are categorically ineligible for SNAP (the so-called SSI "cash-out"), other members of the household can still qualify for benefits. After creating SNAP units in the ACS, we remove self-reported SSI recipients.[18] Note that we do not exclude SSI recipients' other sources of income in the calculation of SNAP unit total income. In households that report SNAP receipt, we assume the remainder of the household receives SNAP (unless one or multiple split units do not meet the income test described just above).

- Unauthorized immigrants: "Unauthorized" or "undocumented" immigrants are ineligible for SNAP. However, the other, authorized members of the household can qualify for SNAP. We follow the same procedure as for SSI removals: Unauthorized members are removed from the unit for the purpose of calculating unit size but not from the calculation of unit income. We follow the procedure for identifying likely unauthorized immigrants described earlier in this appendix.

Table C8 illustrates the implications of these decisions on both the distribution of individuals across unit types—categorized by the presence of adult(s) and children—and the overall number of individuals self-reporting SNAP receipt in the ACS (Steps 1-3). Comparing columns 1 and 2 of the table makes it clear that defining SNAP units out of Census households creates many more small units. This is exactly as expected, given the working definition of SNAP units for purposes of the CPM (along with other ACS-based state poverty measures).

Removing unauthorized immigrants and SSI recipients from units (column 3) reduces the number of individuals in households that report SNAP receipt by roughly 22 percent. Roughly three-quarters of the decline comes from the exclusion of unauthorized immigrants, and one-quarter from the exclusion of SSI recipients. These steps dramatically increase the number of child-only units, because the steps effectively remove ineligible adults from the units.

Table C8
Individuals in units reporting SNAP receipt by case type in ACS, 2011

	Census households	Split into SNAP units	SSI and unauthorized immigrants removed	Administrative totals
	(1)	(2)	(3)	(4)
Child only	743	32,000	525,082	788,787
Single adult	103,828	926,794	726,165	1,083,433
Multiple adults, no children	661,101	308,500	235,435	237,738
Single parent	566,788	1,581,716	1,235,659	1,963,629
Multiple adults, children	3,736,885	1,865,065	1,242,692	1,794,741
Total	5,069,345	4,714,075	3,965,033	5,868,328

SOURCE: Authors' calculations from the 2012 ACS (weighted) and California administrative data.

NOTE: Column 1 is based on self-reported SNAP receipt by households in the ACS. Columns 2 and 3 adjust self-reported information according to a variety of assumptions described in the text. Column 4 provides an unduplicated count of SNAP units observed to receive SNAP for at least one month during the year from administrative data for 2012.

In sum, we are left with an undercount of roughly 1.9 million people (32%) on SNAP in 2012 in the ACS as compared to administrative actuals. While dividing households that report SNAP receipt into multiple units

[18] SSI receipt is only reported by individuals over the age of 15 in the ACS; if received by children, it is likely to be reported by a parent. At this time, we do not have a reliable way to assign SSI to children in the ACS. Future work will examine alternative assumptions on how to handle this shortcoming of the data on SSI recipients.

is an important intermediary step, the ACS falls substantially short of matching the actual number of individuals who received SNAP in 2012 recorded in administrative totals.[19] In terms of number of cases, administrative records suggest 2.7 million cases participated in the program, whereas 1.75 million units in the ACS report SNAP participation in 2012, a 35% undercount.

Simulating Eligibility among Non-Reporters

In order to correct for the nearly two million missing SNAP participants in the ACS, we simulate receipt of SNAP (steps 4 and 5). We create a pool of units that did not report SNAP receipt who are likely eligible for the program based on SNAP income rules. We used an annual income cut-off of 175 percent of FPL, adjusted for SNAP unit size (or, in the case of units with excluded members that remained in the household, household size). Although the official SNAP monthly eligibility threshold is 130 percent of FPL, the higher income limit allows for some variability between monthly and annual income.[20] In other words, families with annual incomes above 130 percent of the FPL may still qualify and participate in SNAP if their income dips below 130 percent of the FPL for a month or span of months. In the ACS, income is reported annually, not monthly.

Table C9 compares the number of self-reporting, simulated eligible units (based on the 175 percent FPL cutoff) and administrative totals. Self-reporting units in the ACS total about 4 million people (or about 1.8 million units). To approximate the administrative total of 5.9 million (column 3), we assign participation to a fraction of the 8.6 million cases in the eligibility pool so that the total self-reported plus assigned cases matches the administrative total.

Table C9
Individuals in SNAP units, according to eligibility and unit type

Unit type	Self-Reporters (adjusted)	Income eligible non-reporters	Administrative totals
	(1)	(2)	(3)
Child only	525,082	502,707	788,787
Single adult	726,165	3,759,448	1,083,433
Multiple adults, no children	235,435	1,049,661	237,738
Single parent	1,235,659	1,287,351	1,963,629
Multiple adults, children	1,242,692	1,965,516	1,794,741
Total	3,965,033	8,564,683	5,868,328

SOURCE: Author's calculations using the ACS and MEDS.

NOTE: Table shows number of individuals within each category of unit size, weighted at the person-level in the ACS.

Matching ACS Units to Administrative Totals by Cells

[19] That total includes individuals in group quarters, which are removed from our ACS sample. In the ACS, individuals in group quarter housing that reported food stamps represented less than 2% of self-reporters.
[20] The 130 percent FPL threshold applies to most CalFresh applicants, but there are exceptions for some groups. See Schirm and Kirkendall (2012) for an assessment (using the SIPP) of the difference between monthly and annual income.

As other state-level supplemental poverty research relying on the ACS has done, we randomly selected units from the pool of eligibles who did not report receipt, then added those units to the self-reporters and categorically eligible to match state administrative totals.

In order to ensure our ACS sample of SNAP recipients reflected the California administrative caseload along demographic and geographic dimensions, we created 2582 cells in the administrative data defined by county (or county group), number of adults (0-2+), number of children (0-2+), TANF receipt, and by race/ethnic categories (white, black, Hispanic, and all other). We believe the granularity of these cells to be necessary, considering the differences in the county administration of SNAP and variation in take-up among different demographic groups. The size and rich administrative data in California makes this possible, whereas other state SPM estimates are more constrained by these factors.

We define TANF receipt in the administrative data as any member of the SNAP unit receiving TANF benefits at any point in 2012, and race as the race/ethnicity of the head of household (as self-reported on the benefits application). To proxy for head of household we use the race/ethnicity of the oldest case member. Cells were matched at the unit level—in other words, ACS SNAP units were selected to match into administrative cells, and then receipt was given to all individuals in the unit.

Where not enough households in the ACS could be found to match administrative cell totals, we aggregated cells with the largest neighboring county. Where too many households in the ACS overpopulated a cell, self-reports were taken as given. In practice, this over-count is relatively small, roughly amounting to a 3 percent over-count of administrative totals (if all other cells are imputed to 100 percent of actuals). In all other cases, SNAP units in the ACS are randomly selected within a cell to match administrative totals as closely as possible. The ACS is a population-weighted survey, and thus we cannot always select sampled units to force unit weights[21] to match administrative counts. Instead, we select units so that the weighted difference between ACS and administrative cell counts is between 0-3 percent.[22]

Table C10 presents the results of this imputation method for the ACS SNAP units. The first column provides the number of self-reporting SNAP units (as above), and the last column gives the administrative totals to which we match. Our imputed SNAP units in the ACS match well with the administrative caseload.

[21] Our unit weight is the person weight of the oldest person in the SNAP unit.
[22] An alternative would be to split unit weights to generate an exact match with administrative counts. This complicates the overall CPM, however, as a number of modules use similar imputation procedures. We will explore the impact of these two methods in future work.

Table C10
Individuals in SNAP units by case type, 2012

Unit Size/Type	Self-Reporters (adjusted)	SNAP receipt following assignment	Administrative totals
	(1)	(2)	(3)
Child only	525,082	792,709	788,787
Single adult	726,165	1,093,005	1,083,433
Multiple adults, no children	235,435	286,818	237,738
Single parent	1,235,659	1,858,940	1,963,629
Multiple adults, children	1,242,692	1,793,010	1,794,741
Total	3,965,033	5,824,482	5,868,328

SOURCE: Authors' calculations from California ACS sample and California administrative data for 2012

NOTE: The weight of the oldest person in the SNAP unit is used to compute the distributions in columns 1 and 2.

Our assignment procedure within detailed geographic and demographic cells results in a robust overall match to administrative data. We underestimate the number of people in units that receive SNAP by just 0.7 percent and understate the number of cases by 2 percent (2.65 million cases assigned, compared to 2.7 million in administrative counts).

Estimating Monthly Benefit Amounts

Using the California SNAP quality control sample for 2012, we estimated monthly dollar benefit amounts based on a range of characteristics (step 6). We used an ordinary least squares regression to estimate monthly benefit using case size, household composition, and flags for income received from other programs. Specifically, we estimate a case-level model of the following form:

$$Monthly\ Benefit_{ic} = \beta_1 unit\ size_{ic} + \beta_2 children_{ic} + +\beta_4 any\ TANFGA_{ic} + \beta_6 any\ SSI_{ic} + +\beta_8 any\ SS_{ic} + \boldsymbol{\gamma_c} + \varepsilon$$

where c indexes county and γ a set of county dummy variables. Parameter estimates are given in Table C11, the county group Alpine-Amador-Calaveras-Inyo-Mariposa-Mono-Tuolume is the reference county.

Table C11
SNAP monthly benefit model

Variable	Description	Coefficient estimate	Standard error
Unit size	Count of all individuals receiving CalFresh	81.27	3.45
Number of children	Count of children in unit	19.05	4.00
Any SSI	Any member in household receives SSI income	17.95	7.16
Any SS	Any member in unit receives Social Security income	-82.69	6.17
Any TANF/GA	Any member in unit receives CalWORKs or General Assistance income	55.37	3.67
County fixed effects		Yes	
Observations	4,289		
R-squared	0.736		

SOURCE: California SNAP quality control sample for 2012.

According to program rules, SNAP benefits are computed based on unit size and amount of earned and unearned income. Intuitively, the size of the household has the largest effect on monthly benefit totals. It is important to note, however, that many variables included in the model above actually proxy for earnings. For example, the coefficient for number of aided children is positive, not because children are entitled to a higher benefit based on program rules, but rather because children do not typically contribute earned income to the household (which, all else equal, lowers the benefit). Similarly, while income from a welfare program such as TANF or General Assistance technically counts against the overall SNAP benefit, these variables proxy for households with zero or very low levels of earnings, and so their estimates are in fact positive.

Unlike other sub-national SPMs which typically report negative coefficients for SSI, our estimate is positive. We presume this is due to California's unique SSI "cash-out" policy (see p. 33). Because Californians with SSI income are categorically excluded from receiving SNAP benefits, income from an SSI recipient in a household receiving SNAP is not counted against the SNAP unit's resources in awarding benefits. Take for example a grandfather on SSI who serves as the primary caretaker for two children. While the grandfather is not eligible for SNAP, the children are. Because the children rely at least partially on their grandfather's income for support, and have no earnings of their own, they qualify for a very high benefit amount.

We include dummy variables for each of the 41 California county and county groups in the ACS to account for possible, unobserved geographic variations in the SNAP caseload. Los Angeles County serves as our “base” variable. While thirty-five of the county dummy estimates are significant at the 10 percent level, we used all county dummy estimates in predicting monthly benefit amounts.

We use the coefficients from this model to predict monthly dollar benefit amounts for every SNAP unit in the ACS with self-reported or imputed receipt. We then apply minimum and maximum monthly benefit tests to ensure that the model does not predict benefit levels outside legislated levels. The minimum amount of $16/month is applied to cases with 2 or fewer persons, and maximums are applied according to unit size, ranging from $200/month for a single person unit to $1,800/month for a 12 person unit. In practice, few cases are predicted SNAP benefits outside these ranges in our data. Table C12 compares our predicted monthly benefit in the ACS with estimates from an administrative sample.[23] Our model appears to perform quite well across different case types.[24]

Table C12
Predicted and actual SNAP monthly benefit by unit type, 2012

Case type	California administrative sample	Predicted in ACS
Child only	$331	$292
Adult only	192	158
Mixed (children and adults)	444	410

SOURCE: For administrative sample, authors calculations from FFY 2012 SNAP public-use Quality Control samples.

NOTE: Survey years are not entirely comparable (fiscal year vs calendar year), but amounts are presented for reference. ACS estimates apply to both self- and imputed-reporters in 2012.

Estimating Time on Aid

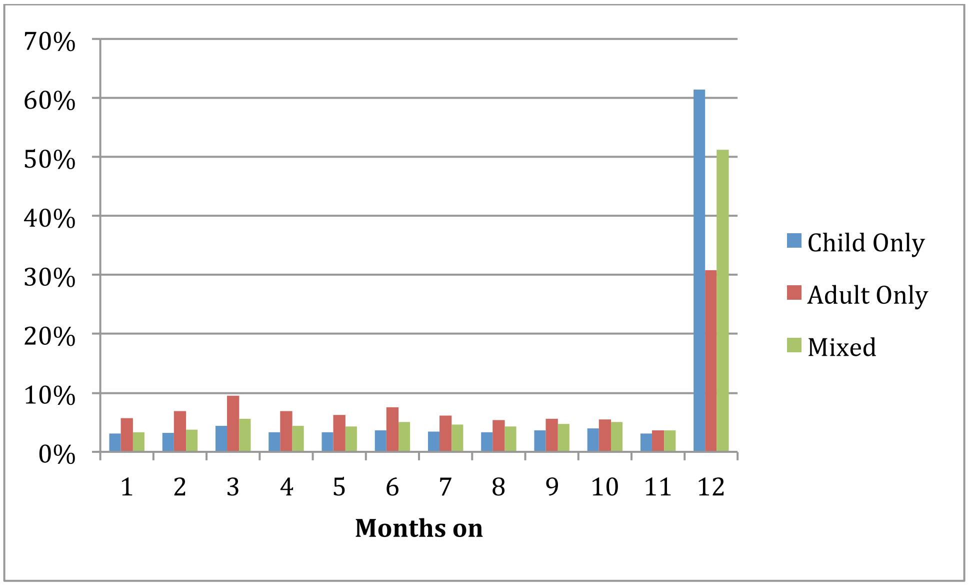
As noted above, the ACS does not collect information on the exact composition of units or the dollar value of benefits received, nor does it ask respondents how long they have participated in SNAP. Households which do report the receipt of SNAP benefits could have participated in the program for only a month, perhaps while a primary earner was between jobs, or they could have been participating in the program for multiple years.

The amount of time a household receives SNAP benefits over the course of a year obviously has a significant bearing on the annual resources available to that household, and in turn on that household’s poverty status in the CPM. Unfortunately, since state administrative data lack annual dollar benefit information for households, we are only able to estimate the amount of one month’s worth of benefits.

[23] Unfortunately, no monthly benefit microdata that capture the entire universe of CalFresh recipients in each month of 2012 exists.
[24] In instances where the model predicted monthly benefits above the legal maximum given unit size, the monthly benefit level was set at the legal maximum. In instances when the model predicted negative benefits, the benefit level was set at zero.

In order to impute the number of months a household in the ACS might have received SNAP benefits, we computed a distribution of months on SNAP from administrative data based on case type and county (or county group) of residence (step 7). Our three case types consisted of child-only units, adult-only units, and mixed units. Overall, we created 123 distributions of months spent on SNAP, each with more than 224 cases. Figure C1 provides an example and shows the statewide distribution of months on SNAP by the three case types.

Figure C1
Distribution, months on SNAP, by case type



SOURCE: Authors' calculations from California administrative data for 2012.

Among SNAP units with only aided children, 61 percent received SNAP for the entire calendar year, as did 51 percent of units with both aided adults and children. Among adult-only SNAP units (a more volatile population), intra-annual turnover was considerably higher—31 percent were on the program all 12 months and 26 percent were on the program for six months or less.

After applying these distributions to SNAP units in the ACS, we multiplied the number of months assigned to a unit by that unit's imputed monthly benefit amount, yielding an annual estimate of SNAP benefits.

To improve the match on administrative dollars spent, we apply one final adjustment to SNAP unit benefits (step 8). We use administrative totals of SNAP benefits issued by county, the "CA 256" reports described above, to benchmark our model-imputed totals. We adjust all unit-level SNAP benefit amounts within a county upwards or downwards so that the average benefits imputed matches the average benefits in administrative data. Note the average actual benefits are computed using CA 256 data on dollars spent and the unduplicated count of units ever on SNAP in 2012 from our custom tabulations of MEDS data. In essence we globally adjust benefits – within a county – so that SNAP benefits paid within a county in our model are off from administrative actuals by only as much as the estimated caseload is off. Finally, we re-apply the minimum and maximum SNAP benefit test to ensure that this reweighting did not artificially push any unit above or below known thresholds.

Table C13 compares average and total annual benefits by case type.

Table C13
Predicted SNAP Annual Benefit by Unit Type, 2012

Case type	Predicted in ACS for all SNAP-assigned units	Predicted in ACS for only SNAP self-reporting units
Annual averages		
Child only	$3,221	$3,458
Single adult	1,239	1,286
Multiple adult, no child	2,011	2,049
Single parent	3,707	3,865
Multiple adults, children	4,980	5,132
California overall	2,731	2,834
Annual totals		
Child only	$1,204,632,676	$ 802,348,935
Single adult	1,355,171,683	934,035,500
Multiple adult, no child	256,998,818	213,567,989
Single parent	2,408,826,431	1,632,336,544
Multiple adults, children	2,007,253,314	1,400,104,557
California overall	7,232,882,925	4,982,393,527

SOURCE: Authors' calculations from 2012 ACS using model parameters derived from the California SNAP quality control sample for 2012.

Administrative records indicate $7.3 billion was spent on SNAP benefits in 2012. If self-reporters alone are imputed benefits in the ACS, the annual total is underestimated by $2.3 billion. After assigning receipt to other eligible units to match administrative records on participation, we estimate a total of $7.2 billion was spent on SNAP. This underestimates the actual total by about 0.78 percent.[25]

[25] Before applying the county-level adjustment in the last step, the statewide SNAP benefits imputed totals $6.4 billion, understating the administrative total by a larger margin.

School Meals

The National School Lunch Program (NSLP) and the School Breakfast Program (SBP) are U.S. Department of Agriculture-administered, school-based nutrition programs. The U.S. Department of Agriculture (USDA) reimburses schools for meals that meet its specified nutritional guidelines and that are served to three categories of students:

- Those with incomes under 130 percent of FPL, who are eligible for free meals;
- Those with incomes between 130 and 185 percent of FPL, who are eligible for reduced price meals;
- All other students, who are eligible for full-price meals.

Students typically either apply to receive free or reduced price meals, or they are determined automatically eligible (and are simply sent a letter of notifying them of their enrollment) via a data match to SNAP and TANF records ("direct certification"). Students can apply at any point during the school year; and once they have been approved, they remain eligible through September of the following school year, regardless of any changes in their family economic circumstances. Although the USDA reimbursement is larger for eligible free meals claimed, even full price meals are subsidized to a small extent.[26] The USDA also provides in-kind "commodities" to schools, and California adds an additional amount to the federal reimbursement rate (these amounts are discussed below). Both the NLSP and the SBP serve mainly students in public and charter schools. According to data from California Department of Education, roughly 95% of public schools in California served lunches that could be claimed under the NSLP in fall 2012, while about 80% of public schools served breakfasts that could be claimed under the SBP.

Unlike the CPS-ASEC, the ACS does not include questions about participation in school meals, and the Census Bureau SPM estimates for California in 2012 attribute a 0.8 percentage point reduction in poverty for children due to the NSLP program. [27] The SPM does not include estimates of SBP participation. In California we are fortunate to have been able to make use of administrative claiming data for both the NLSP and the SBP, so we take the same approach to imputing SBP. The imputation approach we describe below relies heavily on the National Academy of Sciences recommendations for identifying students eligible for free and reduced price meals in the ACS (Schirm and Kirkendall, 2012).

[26] Under certain circumstances, schools can offer free meals to their entire student bodies and receive a set amount from USDA. Such schools (either "Provision 2" or "Provision 3" status schools) do not require students to apply for the program. However, schools in these categories must demonstrate high poverty rates, implying that a high fraction of students are eligible for free meals.

[27] California SPM rate for children in 2012 was 26.7 percent, and with school lunch excluded was 27.5 percent., per authors' analysis of CPS 2012 data.

Methodology

Defining students

Following Schirm and Kirkendall (2012, p. 237), we define students in the ACS as those who:

- Answer "yes" to the question of whether they attended public school or public college at some time during the past 3 months;
- Report the highest degree or level of school completed as "none" through "twelfth grade;"
- Have a reported age of under 20 years old.

Defining students automatically eligible for school meals

There are several categories of children who are categorically eligible for free school meals (if meals are offered at their school). These groups of children include:

1. Foster children
2. Children in households receiving TANF/CalWORKs
3. Children in households receiving SNAP/CalFresh
4. Children in households receiving benefits from the Food Distribution Program on Indian Reservations (FDPIR)
5. Children enrolled in Head Start or Even Start as low-income students
6. Children who are homeless, migrants, or runaways.

We identify children in the first three categories above and assign them to receive free meals. The information provided in the ACS does not permit us to assign categorical eligibility based on the fourth through sixth categories. We assign categorical eligibility based on imputed receipt of TANF and SNAP (as described earlier in this appendix). We rely on self-reported family relationships to determine foster care status, implying that we undercount categorically eligible foster children. The ACS estimate of the number of foster children in California in 2012 is 26,935, while the actual monthly average number of foster children in California in 2012 was roughly 55,000.

We do not consider immigration status in imputing school meal receipt for two reasons. First, most children are citizens or legal immigrants; second, schools do not determine the immigration status of students for the purposes of providing them with school meals.

Defining economic units

USDA regulations specify the "economic unit" as the income unit for making school meals eligibility determinations, with the economic unit defined as "a group of related or unrelated individuals who are not residents of an institution or boarding house but who are living as one economic unit, and who share housing and/or significant income and expenses of its members. Generally, individuals residing in the same house are an economic unit. However, more than one economic unit may reside together in the same house." Generic USDA application instructions appear to adhere to a broader household resident definition. In the end, Schirm and Kirkendall (2012) implement the narrower economic unit definition.

Schirm and Kirkendall specify five possibilities for calculating economic units in the ACS. They recommend using the so-called EU4, which is the second-most broad definition they consider (pp. 261-263). EU4 first removes foster children who are treated as economic units (and automatically assigned eligible status).[28] Then the "core family" (defined as all related individuals plus an unmarried partner of the householder) is defined as one economic unit. If there are no unrelated adults in the household (except an unmarried partner), then any unrelated students (plus any other unrelated children who are not students) are combined with the core family as one economic unit. However, if there are unrelated adults (in addition to an unmarried partner), all unrelated individuals (except an unmarried partner) are combined into a separate economic unit. This approach makes 70 percent of unrelated students part of the economic unit of the core family.

Defining income for the purposes of school meal eligibility

The ACS collects data on the gross money income for household members ages 15 and older, so the economic unit's income can be compared with 130 percent and 185 percent of the applicable poverty guideline. Schirm and Kirkendall note that the definition of income for the purposes of school meals applications and the definition of income in the ACS appear to be quite close. While the panel concluded that the income definitions were sufficiently similar, the span of time for income reporting is different. For school meals, the typical reference period used in applications is a recent or upcoming month. In the ACS, the reference period is a moving 12-month window (depending on survey month, which is not a publicly available data element).

For this reason, we include a 33 percent "padding" factor to the income eligibility cut-off amounts of 130 percent and 185 percent of the applicable federal poverty guideline. In other words, we use income eligible cut-offs of 173 percent (for free meal eligibility) and 246 percent (for reduced price meal eligibility) of FPL. This augmentation of the thresholds for free and reduced price meals allows for monthly fluctuations in income that may make a student eligible for part of the year. Column 1 of Table C15 shows the estimated total number of students in California and in each county/county group, and column 2 shows the estimated number of students eligible for free meals.

[28] See http://www.childsworld.ca.gov/PG2864.htm for California's approach to this policy, part of the federal Healthy Hunger-Free Kids Act of 2010.

Imputation approach, receipt of school meals

We assign receipt of free or reduced price meals to the public school students whom we have flagged as eligible by filling cells created using administrative data. In particular, we first assign all those we flag as categorically eligible to receive free meals. We then add participants by randomly assigning those flagged as eligible for free or reduced price meals until we meet or exceed 95 percent of the relevant administrative benchmark. We use 95 percent rather than 100 percent as a stopping point because the weights assigned to respondents are greater than 1, and we generally overshoot the administrative target if we select participants until the total is greater than or equal to 100 percent of the administrative benchmark.

To create the administrative benchmarks, we use administrative data at the level of the school that records meal-claiming for the 2012-13 school year. These administrative data, produced from the CDE's databases, represent monthly counts of the number of meals that schools served and the number of days meals were served for federal and state reimbursement for each month of the year. We use daily average meals served for the period September 2012 through December 2012 to create benchmarks for participation.

The benchmarks we created are specific to the program (lunch or breakfast), program segment (free or reduced price meal), and county or county group identified in the ACS. To account for varying participation among younger and older students, we further disaggregate the benchmarks by categorizing schools into elementary grades, junior high grades, high school grades, and other schools (often K-12 schools). This information comes from the Public Schools Database (see http://www.cde.ca.gov/ds/si/ds/pubschls.asp).[29] Finally, we adjust the counts of meals claimed using a county-specific attendance factor that we computed using average daily attendance and fall enrollment statistics recorded for all California school districts (see http://www.ed-data.k12.ca.us/). This attendance factor means that we assign receipt of some school meals to more children, but then assign a smaller dollar value for those meals (because children are assumed to receive school meals for somewhat fewer days over the course of the school year due to absenteeism).

Table C15 lists the imputed number of students receiving free meals for the state and for each county/county group (columns 4 and 7), and compares these estimates with the average daily number of meals claimed divided by the attendance factor for each county or county group (columns 3 and 6). (Counts of students participating in reduced price meals are not shown in the table, but estimates are available from the authors upon request.) Statewide, our procedure for imputed free school meals results in matching 95 percent of school lunch participation and 96 percent of school breakfast participation. Certain counties have higher imputed participation than the administrative benchmark. The over-counts are almost always within a few

[29] We first assign students flagged as eligible who are in the relevant age range for each of these school types. We then assign eligible students of all ages to fill out the "other" school category.

percentage points of the benchmark. The county group Nevada/Sierra has the largest percentage differential between the imputed counts and the administrative benchmark.

Table C15
Estimated California imputed students in ACS and participating students from California administrative data – free meals

	Estimated total public school students	Estimated students eligible for free meals	CDE–NLSP participation	ACS–imputed receipt, lunch	Ratio (4)/(3)	CDE–SBP participation	ACS–imputed receipt, breakfast	Ratio (7)/(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Statewide	6,719,477	2,879,952	2,367,309	2,260,561	0.95	1,155,086	1,107,896	0.96
Alameda	237,004	84,562	58,770	56,021	0.95	21,784	20916	0.96
Alpine/Amador/Calaveras/Inyo/ Mariposa/Mono/Tuolumne	25,947	8,334	6,502	6,376	0.98	3,328	3250	0.98
Butte	33,432	13,492	12,846	12,416	0.97	7,681	7588	0.99
Colusa/Glenn/Tehama/Trinity	24,304	10,244	10,214	9,824	0.96	5,324	5094	0.96
Contra Costa	196,100	57,630	42,762	41,053	0.96	19,223	18477	0.96
Del Norte/Lassen/Modoc/Plumas	19,451	8,995	5,710	5,955	1.04	3,358	3526	1.05
El Dorado	30,610	7,813	6,033	6,399	1.06	2,770	2764	1.00
Fresno	206,430	123,092	102,738	98,129	0.96	53,163	50766	0.95
Humboldt	18,368	5,076	5,379	5,342	0.99	2,867	2863	1.00
Imperial	40,314	20,813	16,919	16,527	0.98	7,423	7501	1.01
Kern	187,862	102,318	88,103	84,090	0.95	41,619	39682	0.95
Kings	30,790	17,513	12,730	11,983	0.94	7,324	7186	0.98
Los Angeles	1,710,373	825,182	673,736	640,359	0.95	370,878	352531	0.95
Madera	31,095	18,172	16,030	15,414	0.96	6,823	7178	1.05
Lake/Mendocino	24,109	13,245	9,903	9,838	0.99	5,853	5881	1.00
Marin	33,439	7,444	4,874	4,732	0.97	2,506	2505	1.00
Merced	63,644	37,294	31,929	30,704	0.96	15,685	15174	0.97
Monterey/San Benito	96,007	46,039	37,162	35,582	0.96	15,885	15266	0.96
Napa	22,068	5,636	5,235	5,174	0.99	2,983	3038	1.02
Nevada/Sierra	13,987	4,880	1,925	2,528	1.31	555	472	0.85
Orange	535,189	193,364	155,504	148,047	0.95	60,339	57587	0.95
Placer	63,020	14,622	11,331	11,253	0.99	4,629	4522	0.98
Riverside	470,513	205,402	173,445	165,297	0.95	77,013	73357	0.95
Sacramento	265,685	122,914	98,073	93,393	0.95	40,552	38627	0.95
San Bernardino	438,136	215,395	191,574	182,381	0.95	76,732	73774	0.96
San Diego	525,737	201,323	162,155	154,476	0.95	89,329	85205	0.95
San Francisco	59,394	20,766	17,998	17,260	0.96	5,169	5068	0.98
San Joaquin	146,047	65,477	62,537	59,698	0.95	29,248	27984	0.96
San Luis Obispo	38,103	10,670	7,847	7,846	1.00	4,894	4965	1.01
San Mateo	104,329	27,938	21,130	19,933	0.94	10,930	10876	1.00
Santa Barbara	71,037	28,541	24,825	23,604	0.95	11,146	10853	0.97
Santa Clara	296,494	80,505	67,001	63,871	0.95	33,039	31598	0.96

Santa Cruz	40,646	11,755	13,482	12,925	0.96	9,370	8949	0.96
Shasta	28,992	10,687	10,493	10,222	0.97	5,217	4941	0.95
Solano	69,595	21,420	18,965	18,295	0.96	8,315	8399	1.01
Sonoma	78,758	26,217	19,756	19,032	0.96	11,391	11492	1.01
Stanislaus	108,749	54,906	47,848	45,748	0.96	23,858	22991	0.96
Sutter/Yuba	37,634	17,515	14,353	13,903	0.97	8,451	8144	0.96
Tulare	111,936	72,341	50,588	48,114	0.95	25,925	24965	0.96
Ventura	151,873	48,702	39,197	37,391	0.95	19,329	18663	0.97
Yolo	32,276	11,718	9,704	9,426	0.97	3,180	3278	1.03

SOURCE: Authors' calculations from the 2011 ACS and CDE administrative data.

NOTES: Students estimated to be eligible for free meals includes categorically eligible students. As described in the accompanying text, participation counts reflect average daily meals claimed between September and May multiplied by a county-specific factor to reflect absenteeism.

Our imputations produce the following summary estimates of participation in school meals: 55 percent of California public school students did not participate in free or reduced price school meals in 2012, while 27 percent participated in school lunch alone, 13 percent participated in both school lunch and school breakfast, and 6 percent participated in school breakfast alone (Table C16).

Table C16
Imputed receipt of free and reduced price school meals among California public school students

Does not participate	54.8%
School lunch only	26.5%
School breakfast only	6.0%
Both lunch and breakfast	12.7%

SOURCE: Authors' calculations from the 2012 ACS and CDE administrative data.

Benefit calculation

Table C17 shows the daily reimbursement amounts and an example of the school year reimbursement amounts we assigned to students imputed to receive school meals. (Annual amounts vary somewhat across counties and depend on the attendance factor, described above.) These amounts are the average of the 2010-11 and 2011-12 federal and state reimbursement amounts.

Table C17
Imputed annual amounts for school meals

	School breakfast	School lunch
Free	$321.32	$515.29
Reduced price	$274.27	$452.69
Full price	-	-

NOTES: Amounts include both federal and state reimbursements and represent statewide averages. County-by-county amounts vary somewhat due to differing attendance adjustments.

Another approach to calculating the amount of the benefit would be to use the actual price of a full-price meal. This would be the cost to the student of receiving a school meal if he/she did not qualify for the federal program. However, school districts set this price, and prices across the state are not generally published.

A final, potentially quite attractive approach would be to use a value equivalent to that needed for a family to provide a meal of similar quality to the student. At the same time, a recent, USDA-sponsored evaluation of a summer meal program in several states (the Summer Electronic

Benefits Transfer for Children Demonstration) replaces the value of school lunch and school breakfast received at school with the federal reimbursement amounts on an EBT card for use during the summer months when most schools are out of session (Collins et al., 2013). The approach that we take is in the same spirit.

Limitations

We make two simplifying assumptions in our calculations: first, that students who ever enroll in school meals do so at the beginning of the school year and remain enrolled throughout the year; and second, that students not identified as public school students do not receive school meals.

Housing Subsidies

The ACS lacks information on whether families reside in publicly subsidized housing. Although they reach smaller numbers of families than programs like SNAP, the two main government-supported housing programs—public housing and rental subsidies such as Section 8—provide quite sizable benefits for families. Thus, it is important to estimate the receipt and value of these subsidies in the ACS in order to accurately measure poverty for the purposes of the CPM.

Methodology

Calculating families' housing subsidies involves two steps: 1) assigning incidence of subsidized housing receipt, and 2) calculating the value of subsidies for participating families. The research SPM, which uses the CPS, contains information on whether families receive public housing or rental subsidies. For these families, the Census links to administrative Housing and Urban Development (HUD) data to estimate the market value of the family's housing unit. The value of the housing subsidy is then the difference between the family's estimated rental payments and the market value of the family's housing unit. Because this "income" can only be used to meet a family's shelter costs, the housing subsidy's value is capped at the difference between the shelter portion of the poverty threshold and the family's estimated rental payments.

Our approach to the first step in calculating housing subsidies in the ACS is to impute incidence of subsidy receipt from the CPS. We first calculate the proportion of California household heads who are renting in a pooled three-year CPS public-use data file. This is the proportion of analogous renting heads in the 2012 California ACS data file for whom we want to assign incidence. Because the incidence is quite different for elderly versus non-elderly heads, we predict and assign incidence separately for these two subgroups. We also predict separately for non-elderly heads with and without children. We then predict the probability of reporting the receipt of a housing subsidy in the pooled CPS file using a linear probability model. The covariates in this regression model are the natural log of household income, dummies for SNAP and cash welfare receipt, dummies for racial/ethnic category, a dummy for official poverty status, a second dummy for falling under 150 percent of the official poverty line, and sex, age, education level of the head of household, the number of adults and number of children living in the household, and marital status. The estimated coefficients from these models are available upon request.

We next calculate the predicted probability of subsidy receipt in the ACS using the coefficients from this regression model. We then use the proportion of renting heads of households calculated above and take the same percentage of heads with the highest predicted probability of receiving a subsidy and assign them an imputed subsidy receipt. If all members of the household are identified as likely unauthorized immigrants by our algorithm (see Technical Appendix A), we disallow subsidy receipt.

The next step is to calculate the value of this imputed subsidy. Because we lack administrative data with which to calculate the market value of housing units, we use Fair Market Rent data for each county by number of bedrooms to calculate an approximate market value for the unit. Tenant payments are estimated to be 30 percent of total household income. The difference between these two values is then treated as the value of the housing subsidy, after applying a cap, defined as the difference between the shelter portion of the threshold and the estimated rental payments. Because all of these parameters are estimated at the household level, the housing subsidy is then prorated to the individual level and reaggregated to the poverty unit level. For example, if a four-person household was given a $4,000 housing subsidy value, and the household consisted of a three-person poverty unit and a single individual poverty unit, the former would be given a value of $3,000 and the latter a value of $1,000.

This process yields approximately 1.3 million subsidy recipients in California in 2012 (or 3.5 percent of the total population).[30] The median housing subsidy value for this group is approximately $8,100 (Table C19). While only a small percentage of Californians receive a housing subsidy, the value of this subsidy to those who receive it can be quite large.

[30] This translates to roughly 575,000 households with a housing subsidy in the ACS. The number of households in the CPS receiving a subsidy is similar. Administrative records show roughly 475,000 federally subsidized housing units in California.

Table C19
Imputed housing receipt and subsidy amounts for selected groups

Characteristic	ACS 2012	CPS 2012
All		
Number of recipients	1.286 million	1.323 million
Median subsidy	$8,098	$7,406
Minimum subsidy	$3	$136
Maximum subsidy	$26,968	$21,938
Children		
Number of recipients	493,320	430,377
Median subsidy	$10,137	$10,051
Minimum subsidy	$6	$176
Maximum subsidy	$26,968	$21,938
Adults		
Number of recipients	610,758	672,795
Median subsidy	$7,914	$7,406
Minimum subsidy	$3	$136
Maximum subsidy	$26,968	$21,938
Elderly		
Number of recipients	182,375	219,553
Median subsidy	$5,076	$4,873
Minimum subsidy	$6	$141
Maximum subsidy	$21,417	$11,057

SOURCES: Authors' calculations based on the ACS and CPS-ASEC for 2012.

Table C20 demonstrates the extent to which including housing subsidies using the procedure just described alters CPM-measured poverty. Overall, including housing subsidies results in a 1.2 percentage point lower poverty rate. The role of housing subsidies is largest for children and for older adults in the CPM.

Table C20
CPM with and without housing subsidies

	With housing subsidy imputation	Without housing subsidies (percentage point difference)
All persons	21.8%	1.2%
Children	24.9	1.9
Adults	20.9	0.9
Elderly	19.7	1.6

SOURCES: Authors' calculations based on the ACS 2012 and auxiliary data sources as described in these appendices.

Tax Liabilities and Credits

The ACS does not ask respondents about the amount they pay in taxes or receive in federal and state income tax credits (which, for many low-income taxpayers, exceed their total income-tax liability). ACS-based poverty measures such as the CPM must thus impute federal and state tax liability to survey respondents. The Census Bureau must also simulate a tax return in the SPM, since the CPS does not ask respondents for detailed information about tax liabilities and credits.

To accomplish this end, we adapt two pre-existing tax simulation models for national survey data: the Brookings Metropolitan Policy Program's "MetroTax Model," which we use to determine tax unit composition and filing status in the ACS, and the TAXSIM program of the National Bureau of Economic Research (NBER), which we use to model net federal, state, and payroll taxes paid.

Due to data limitations in the ACS, we are unable to simulate all of the detailed information often contained in individual tax returns. The ACS lacks detail about certain sources of taxable income—such as unemployment insurance benefits or capital gains—that would be included in a fully comprehensive tax calculation. Moreover, the two publicly available tax simulation models we use are unable to simulate some or all of the complexity of the tax code. These limitations include an inability to account for retirement plan contributions or student loan interest payments. The ACS does include, however, reported wages and self-employment income, which are the primary inputs determining the value of the Earned Income Tax Credit and refundable Child Tax Credit, as well as the value of payroll taxes. Thus ACS data allows for reasonably robust estimation of the low-income tax credits and payroll taxes that comprise the tax policy components with the largest impact on poverty as measured under SPM-like measures such as the CPM.

Creation of Tax Units

We use the "MetroTax Model" to create tax return units, identify filing status (single, married filing joint, and head of household), and identify which individuals in the ACS file tax returns.[31] Detailed information about the MetroTax Model is included in the technical appendix on the Brookings Metropolitan Policy Program's website.

[31] We recode "married filing separate" units as single filers because TAXSIM cannot make tax calculations for "married filing separate" returns. All married-filing-separate units created in the MetroTax Model have no dependents.

The MetroTax model uses the ACS variables on relationship to the householder to identify families, subfamilies, and unrelated individuals and assign them to separate tax units. The model uses information on age, disability, and school enrollment to identify likely adult and child dependents.

We modify the MetroTax model in the creation of EITC-eligible tax units by reassigning "qualifying children" (dependents that allow a tax filer to claim the EITC) within a household in cases where those qualifying children would otherwise remain unclaimed. This occurs in cases where individuals who could claim them as dependents do not file a return because they do not meet federal income filing thresholds, because the filers are themselves dependents, or because the filers have already claimed three dependents and thus have received the maximum allowable EITC benefit for their income level. We assume that all individuals eligible for the EITC do indeed file in our model, so it is mostly individuals with no earned income or individuals dependent on others in the household for support whose children are reassigned to others. This reassignment procedure reflects common tax filing strategies among low-income households (Tach & Halpern-Meekin, 2014), and better approximates the actual amount of EITC dollars paid out to filers in the state in 2012 per administrative data.[32]

We calculate income and payroll taxes for all tax units with incomes above the 2012 tax-year income filing thresholds (minimum income amounts that require tax units to file). We thus implicitly assume that all individuals required to file taxes do in fact file. Tax units with incomes that fall short of federal filing requirements do not receive a simulated tax return, with the exception that tax units falling short of federal filing thresholds but that still qualify for the EITC are included as filers. Table C21 shows how the profile of tax filers in our CPM tax model compares to IRS administrative data for California. Overall, the total number of filers compares favorably to state administrative totals. We find somewhat more single filers using our model, and fewer head of household filers.

[32] It should be noted that this reassignment procedure resulted in tax units where individuals not related to the dependents claimed them as qualifying children—a violation of the EITC's "relationship test." Also, the TAXSIM program does not distinguish between adult and child dependents, which in some cases leads to non-disabled adult dependents being claimed for EITC purposes.

Table C21
CPM tax model vs. administrative data: filing status

Filing status	Administrative data returns filed	Administrative data % of returns	CPM model returns filed	CPM model % of returns
Single	7,952,240	47%	7,341,428	47%
Married filing joint	6,136,590	36	5,871,350	38
Head of household	2,592,340	15	2,592,340	15

SOURCES: Administrative tax return data from IRS Statistics of Income for California, tax year 2012. CPM tax model from authors' calculations in 2012 ACS data, using Brookings' MetroTax model and NBER's TAXSIM program.

NOTE: Three percent of filers in the CPM tax model are "dependent" filers (filers claimed as dependents by another individual in the household). These filers are not included in the CPM model totals.

Tax Calculator

We use NBER's TAXSIM calculator to compute federal income tax liability, California state income tax liability, and payroll taxes for Social Security and Medicare. As part of those calculations, TAXSIM also determines a tax unit's eligibility for and amount of EITC, Child Tax Credit, and Child and Dependent Care Tax Credit. For more information on TAXSIM, see Feenberg and Coutts description of the TAXSIM model (1993), as well as the TAXSIM website.[33]

Several categories of income that routinely appear on a tax return are excluded from our calculation of tax liability because of insufficiently detailed information in the ACS. These include dividend income, property income, alimony income, and unemployment benefits. In order to calculate the mortgage interest deduction, we follow the convention used by other state-level SPM researchers and take 80 percent of reported monthly mortgage payments in the ACS as interest paid, and then annualize that total (Betson et al., 2011).

We also make one correction to the calculated federal income taxes to account for a discrepancy between IRS rules and TAXSIM procedures for determining EITC eligibility for childless tax filers. Tax filers with no qualifying dependents are only allowed to claim the EITC, per IRS rules, if they are between the ages of 25 and 64. TAXSIM, however, does not exclude filers who are outside of this age range, instead calculating EITC credits for childless tax filers of all ages. We thus correct the calculated federal income taxes by subtracting EITC amounts assigned to tax filers without dependents who are less than 25 or more than 64 years old. This correction affects 277,067 weighted filers, and reduces the total calculated EITC amount by $66.3 million, or about 1 percent. The change in total EITC is small because EITC credits for childless tax filers are generally quite small, with a maximum credit of less than $500.

[33] TAXSIM user interface website: http://users.nber.org/~taxsim/

Adjustments for Unauthorized Immigrants

Federal law requires all U.S. residents, including unauthorized immigrants, to file income taxes. All unauthorized immigrants do not in fact file taxes, but a substantial proportion do. Estimates of the proportion of unauthorized immigrants who file federal income taxes range from about half up to more than 80 percent (Hill & Johnson, 2011).

For the CPM tax model, we assume that all individuals identified as unauthorized immigrants in our sample file federal and state income taxes using an Individual Taxpayer Identification Number (ITIN). (For more information on how we identify unauthorized immigrants in the ACS, see the "Unauthorized Immigrant" section in Appendix A.) This assumption likely overestimates of the proportion of unauthorized immigrants actually filing income taxes, but a more nuanced approach would require additional assumptions to assign tax filer or non-filer status within the population of unauthorized immigrants. Future development of the CPM may examine the feasibility of more in-depth modeling of the tax filing behavior of unauthorized immigrants.

Since the federal tax code prohibits individuals who lack a valid social security number from claiming the EITC, we eliminate EITC eligibility for those tax units in which we identify the tax return filer to be a likely unauthorized immigrant. All other portions of the tax model remain the same. This methodological decision has implications for the total amount of EITC generated statewide in our model and ultimately on overall CPM poverty rates.

When we assume that all of the individuals whom we classify as unauthorized immigrants use an ITIN when filing their tax returns, the result is an over-count of the number of ITIN filers statewide, compared to the most recent administrative data available. At the same time, our aggregate tax estimates show an under-count of the number of filers claiming the EITC statewide, compared to administrative data. Thus we adjust our tax estimates by randomly selecting some unauthorized filers to file with Social Security numbers rather than ITINs until our percentage of ITIN filers matches available administrative data. An effect of this change is that these filers become eligible to claim the EITC. This modification was adopted in order to simultaneously reduce the proportion of ITIN filers and increase the number of EITC claims to better match administrative data. This procedure resulted in 205,442 filers identified as likely unauthorized immigrants receiving the EITC – about 6.3 percent of all EITC filers in our model. It is important to clarify that we are not claiming that this percentage of California EITC filers in 2012 were in fact unauthorized immigrants—there is little evidence of unauthorized immigrants claiming the

EITC at such levels. Instead, we seek to correct for the error inherent in our survey data and imputations in order to approximate the impact of tax policy at the statewide level. Table C22 compares the CPM tax model's treatment of ITIN filers to available administrative data.

Table C22
ITIN filers in CPM tax model

Model	Total returns	ITIN returns	ITIN share of total (%)
Tax year 2012 administrative data	14,881,581	1,006,176	6.8
CPM tax model	15,899,643	1,081,413	6.8
CPM tax model without random selection of ITIN filers filing with SSN	15,899,643	1,476,670	9.3

SOURCE: IRS 2012 state ITIN filers data downloaded from Brookings Metropolitan Policy Program's "EITC Interactive" website. CPM tax model calculations from 2012 ACS data.

Comparison to IRS Tax Totals

Table C23 compares the results of our CPM tax simulation to IRS data publicly available for California. The table also includes the results of an alternative simulation where we do not flag unauthorized filers and eliminate any assigned EITC benefit. The results suggest that we fairly closely approximate the population of total filers across the state, but somewhat underestimate the total amount of refundable tax credit dollars flowing to Californians. This is especially true in the case of the CTC, where we capture only a bit over 60 percent of refundable dollars claimed by state residents. ITIN filers can claim the CTC; and if the amount of their CTC is greater than the amount of income tax they owe, they can also claim the Additional Child Tax Credit (ACTC), which our model takes into account. Improving the CPM tax model to more accurately reflect administrative totals is an area for future CPM estimates.

Table C23
Major tax credits: CPM tax model vs. administrative data

Return figure	IRS data	CPM tax model	Ratio
Total state returns	14,881,581	15,899,643	1.07
EITC amount	$6,900,647,141	$ 6,557,315,072	0.95
EITC filers	2,955,085	3,237,697	1.10
CTC amount	$2,876,806,779	$ 3,145,820,160	1.09
CTC filers	2,505,688	2,497,154	1.00
ACTC amount	$3,482,569,726	$ 2,638,526,464	0.76
ACTC filers	2,486,405	2,021,005	0.81
Filers with AGI between $1 and $25K	5,872,374	5,269,998	0.90
Filers with AGI between $25K and $50K	3,502,508	3,658,946	1.04

SOURCES: IRS data for California for tax year 2012 downloaded from Brookings Metropolitan Policy Program's "EITC Interactive" website.. CPM tax model figures from authors' calculations using 2012 ACS data.

Limitations

As mentioned earlier and as reflected in the above comparison to administrative tax records, our tax simulation procedures are limited by the level of detail available in the ACS. It is also important to note that our assumption that every individual and family eligible to claim the EITC does indeed file a tax return does not take into account known variation in EITC participation rates by ethnicity. For example, recent research suggests a lower EITC take-up rate among Hispanic families and among those who live in the western United States (Short, Donahue, and Lynch, 2012).

The disparity between the aggregated statewide EITC benefit produced by our model and that reported by the IRS for 2012 may be attributable to several factors. These include errors in the identification and claiming of qualifying children and dependents, the identification of unauthorized filers, and the inability to identify filers who claim children not living full-time within their household of residence.

Sensitivity Analysis and Comparison to Census SPM

Appendix F provides a comparison of the Census SPM one-year estimates for California (using the 2012 CPS-ASEC) and the CPM estimates if we exclude the EITC and the refundable portion of the CTC. Overall, we find comparable reductions in poverty due to the EITC and CTC.

Table C24 illustrates the role of various components of the tax code on CPM poverty rates, as well as alterations to some of the basic assumptions of the CPM tax model. In a simulation where we test the effect of removing all net federal taxes—payroll plus income tax liability or refund—we find a roughly one percentage point increase in the poverty rate overall and a three percentage point increase in the child poverty rate. The role of payroll taxes was smaller than can be expected in future years because 2012 was the year of the so-called "payroll tax holiday"—payroll tax rates for Social Security and Medicare were substantially reduced.

Table C24
CPM tax model: sensitivity analysis

	Poverty rates (%)			
	All persons	**Children**	**Adults (18-64)**	**Seniors (65 and older)**
CPM rate	21.8	24.9	20.9	19.7
Remove payroll taxes	20.0	22.6	19.2	19.2
Remove all federal taxes (payroll tax plus income tax liability/refund)	22.7	28.4	21.1	19.5
Remove state income tax liability/refund	21.7	25.0	20.9	19.7

SOURCE: Authors' calculations using 2012 ACS data and auxiliary data sources as described in the text.

Appendix D: Adjustments to Resources—Expenses

The ACS lacks sufficient detail to determine who pays medical, child care, and other work-related expenses, and how much they pay. Although the Census Bureau incorporates reported annual medical out-of-pocket (MOOP) and child care out-of-pocket expenses in the CPS-ASEC, the ACS does not address these issues. We discuss below our approach to using self-reported expenses in the CPS-ASEC and other sources to create values for the 2012 California ACS sample for these three types of non-discretionary expenses.

Medical Out-of-Pocket Expenses

To impute MOOP for the CPM measure, we estimate a series of regression models. We begin with a protocol developed by Trudi Renwick, Chief of the Poverty Statistics Branch of the U.S. Census Bureau. Using SAS 9.3, we first use the 2012 Annual Social and Economic Supplement to the Current Population Survey Data to model MOOP expenses for four groups: 1) families with a nonelderly head, 2) the elderly, 3) non-elderly unrelated individuals, and 4) the uninsured and individuals with public health insurance. In the case of the first three groups, we use three models for each group: 1) predicting premium amounts using a generalized linear model assuming a Poisson distribution, 2) predicting whether or not they have other out-of-pocket expenditures using a logistic regression model and, if so, 3) predicting the amount of these other out-of-pocket expenditures using a generalized linear model assuming a Poisson distribution. In the case of the fourth group—the uninsured and those with public health insurance—we use two models, first predicting whether or not they have other out-of-pocket expenditures using logistic regression, and, if so, the amount of those expenditures using a generalized linear model assuming a Poisson distribution.

The variables used to predict health insurance premiums, the probability of having MOOP expenses, and the value of such expenses from the CPS include family composition, number of adults in the family, number of persons in the family, household head age, household head age squared, log of family income, type of health insurance coverage (private, employer, Medicaid, Medicare, Medicare and Medicaid, any public insurance coverage, none), and state.[34] Regression equations are generated from CPS data and then used to assign probabilities or values to families or individuals in the ACS. For the probability predictions, either a 0 or 1 value is assigned via random assignment to 0 or 1 based upon the predicted probability. For continuous variables, actual predicted values are used.

Table D1
Model estimates, CPS-ASEC

A. Regression models predicting premium amounts				
	Families with nonelderly head	Elderly	Nonelderly insured unrelated individuals	
Family composition				
Single	-0.1089			
	(0.0)			
Couple	-0.1285			
	(0.0)			
Number of adults in family	0.1526			
	(0.0)			
Number of persons in family	0.0500	-0.0047		
	(0.0)	(0.0)		
Household head age	-0.0197	-0.0255	-0.0055	
	(0.0)	(0.0)	(0.0)	
Household head age squared	0.0003	0.0002	0.0002	
	(0.0)	(0.0)	(0.0)	
Type of health insurance coverage				
Medicaid		-0.9559		
		(0.0002)		
Medicare		-0.1932		
		(0.0)		
Both Medicare and Medicaid		0.7170		
		(0.0002)		
Any public			-0.3285	
			(0.0)	

[34] For the details of each model, see Renwick, Short, Bishaw, and Hokayem (2012), "Using the American Community Survey (ACS) to Implement a Supplemental Poverty Measure (SPM)," Social, Economic, and Housing Statistics Division (SEHSD) Working Paper #2012-10 available at http://www.census.gov/hhes/povmeas/publications/poor/RenwickShortBishawHokayemPAA.pdf.

Private			0.1040	
			(0.0)	
Employer			0.4414	
			(0.0)	
Log of family income	0.0794	0.1062	-0.0012	
	(0.0)	(0.0)	(0.0)	
Type of coverage for families				
Private	0.6603			
	(0.0)			
Employer	0.1129			
	(0.0)			
Constant	7.0794	7.5901	7.4109	
	(0.0001)	(0.0007)	(0.0001)	
N	24,087	11,586	10,857	
AIC	92,126,757,990	39,323,150,659	31,562,962,322	

Note: State fixed effects not shown but included in all models.

B. Logistic regression models predicting probability of having additional MOOP

	Families with nonelderly head	Elderly	Nonelderly insured unrelated individuals	Uninsured/Public health insurance
Number of adults in family	-0.0693			
	(0.00122)			
Number of persons in family	-0.0612	0.1773		
	(0.000496)	(0.000494)		
Household head age	-0.0266	0.0198	-0.0728	0.000853
	(0.000406)	(0.00229)	(0.000323)	(0.000233)
Household head age squared	0.000072	-0.00006	0.000518	-0.00025
	(.000004726)	(0.000015)	(.000003994)	(.000002908)
Type of health insurance coverage				
Medicaid		0.4578		0.1358
		(0.00800)		(0.00118)
Medicare		-0.7039		-0.5477
		(0.00188)		(0.00240)
Both Medicare and Medicaid		0.4548		0.0578
		(0.00816)		(0.00333)
Any public			0.4815	

			(0.00217)	
Private			0.0792	
			(0.00343)	
Employer			-0.2533	
			0.00377	
Log of family income	-0.1549	-0.1808	-0.0626	-0.0371
	(0.000246)	(0.000292)	(0.000286)	(0.000153)
Type of coverage for families				
Private	-0.1076			
	(0.00371)			
Employer	0.1773			
	(0.00581)			
Any public	0.9669			
	(0.00158)			
None	0.9964			
	(0.00163)			
Constant	-0.4804	-1.5351	0.2150	-0.3261
	(0.00785)	(0.0853)	(0.00599)	(0.00445)
N	44,968	23,446	18,839	14,518
AIC	22,762,732	23,679,456	19,970,609	29,497,181

C. Regression models predicting amount of additional MOOP				
	Families with nonelderly head	Elderly	Nonelderly insured unrelated individuals	Uninsured/Public health insurance
Number of adults in family	0.1572			
	(0.0)			
Number of persons in family	0.1238	-0.0373		
	(0.0)	(0.0)		
Household head age	-0.0183	-0.0753	0.0440	0.0649
	(0.0)	(0.0)	(0.0)	(0.0)
Household head age squared	0.0004	0.0006	-0.0003	-0.0005
	(0.0)	(0.0)	(0.0)	(0.0)
Type of health insurance coverage				
Medicaid		-0.5455		0.0683
		(0.0001)		(0.0)
Medicare		0.0115		0.2591
		(0.0)		(0.0)

Both Medicare and Medicaid		0.0778		-0.6714
		(0.0001)		(0.0001)
Any public			0.1943	
			(0.0)	
Private			0.2804	
			(0.0)	
Employer			-0.0305	
			(0.0)	
Log of family income	0.1609	0.1452	0.0092	-0.0137
	(0.0)	(0.0)	(0.0)	(0.0)
Type of coverage for families				
Private	0.3597			
	(0.0)			
Employer	0.0367			
	(0.0)			
Any public	-0.2923			
	(0.0)			
None	-0.1362			
	(0.0)			
Constant	5.3592	8.2721	5.5352	4.6011
	(0.0001)	(0.0007)	(0.0001)	(0.0001)
N	43,035	21,289	16,889	10,400
AIC	208,920,649,485	89,143,764,165	51,495,351,237	32,908,052,543

NOTE: State fixed effects not shown but included in all models.

Table D2 provides summary statistics for imputed insurance premiums and additional MOOP (above and beyond premiums).

Table D2
Predicted MOOP values

A. Insurance premiums (mean)	
Families with nonelderly head	$3,982
Elderly	$2,308
Nonelderly insured unrelated individuals	$2,212
B. Additional MOOP expense (probability)	
Families with nonelderly head	0.044
Elderly	0.085
Nonelderly insured unrelated individuals	0.090
Uninsured/Public health insurance	0.256
C. Additional MOOP expense (mean)	
Families with nonelderly head	$2,185
Elderly	$1,316
Nonelderly insured unrelated individuals	$994
Uninsured/Public health insurance	$672

SOURCE: Authors' calculations from the CPS-ASEC and the ACS, as described in the text.

Table D3 provides a comparison between the SPM and the CPM calculations for California, with and without the inclusion of MOOP. Calculated in the CPS-ASEC, MOOP increases the poverty rate for the elderly by about 8 percentage points, from about 14 percent to about 23 percent. Calculated in the ACS, MOOP increases the poverty rate for the elderly by about 7 percentage points, from 12.5 percent to 19.7 percent. For children and working-age adults, the increase in the poverty rate due to the inclusion of MOOP in the CPM is about 4 percentage points, while it is about 3 percentage points in the SPM. Thus the CPM somewhat overstates MOOP for children and working-age adults, and understates MOOP for seniors, relative to the SPM.

Table D3
CPM and SPM for California if medical expenses excluded

	CPM absent medical expenses	Percentage point difference from CPM	SPM absent medical expenses	Percentage point difference from SPM
A. Under 100%				
All persons	17.4%	-4.4%	19.8%	-3.4%
Children	20.4	-4.5	23.8	-2.9
Adults 18-64	17.2	-3.7	19.3	-2.6
Adults 65+	12.5	-7.2	14.7	-8.1
B. Under 50%				
All persons	4.6%	-1.3%	5.3%	-1.3%
Children	4.2	-0.9	4.9	-1.1
Adults 18-64	5.2	-1.1	5.9	-1.1
Adults 65+	2.7	-2.5	3.2	-2.5
C. 50 - 99%				
All persons	12.8%	-3.1%	14.5%	-2.1%
Children	16.2	-3.6	18.9	-1.8
Adults 18-64	12.0	-2.6	13.4	-1.5
Adults 65+	9.8	-4.7	11.4	-5.7

SOURCE: Authors' calculations from ACS and CPS-ASEC/IPUMS 2012 data as described in the text.

Child Care Out-of-Pocket Expenses

To assign values for child care expenses to ACS respondents, we begin by estimating two sets of regression models to predict child care expenses for the California CPS-ASEC sample for 2010-2012, and we do this at the level of the SPM unit by selecting the oldest working-age adult within each SPM unit, or an older adult if there is no working-age adult in the unit. We use the IPUMS version of the CPS-ASEC (King et al., 2010).

We exclude from the sample all SPM units with no children, all SPM units with no adult earners (age 18 or older), and all SPM units that have more adults than adult earners in the unit. We assign $0 out-of-pocket child care expenses to all three of these types of units. SPM units with no children have mean child care expenses of $0 in CPS data. SPM units with no adult earners and those with more adults than adult earners are categorically assigned child care expenses of $0 by the SPM work-related expenses capping methodology, which caps child care expenses at the amount of earnings of the adult in the poverty unit with the lowest earned income.

We stratify the remainder of the sample into two groups: those with a youngest child under age 6 and those with a youngest child ages 6-17. The first group is our preschool age sample and the second group is our school age sample. The sample sizes for these two groups are 1,388 and 2,404, respectively. Sample size limitations precluded a disaggregation into groups defined more narrowly by youngest child's age.

We estimate two models for the preschool age sample and the school age sample. Table D4 provides the estimation results. The first (logistic regression) models (Columns 1 and 3) predict whether an SPM unit has any child care expenses. The second (linear regression) models (Columns 2 and 4) predict, for those who have any expenses, the amount of those expenses.

We include in the models a set of family demographic, economic, and regional characteristics. In particular, we include a set of dummy variables for the number and ages of adults (capped at three) and of children in the unit (capped at four), a set of dummy variables describing the age of adults and of youngest children in the unit, dummies for race/ethnic background, dummies for the highest level of education completed by a unit member, a flag indicating whether anyone in the unit is foreign-born, dummies indicating whether the unit reported income from SNAP or TANF/GA, and, finally, eight regional dummies according to the California counties identifiable in the CPS-ASEC. The included variables are identical across the participation and the amounts models, and all models are weighted using the health insurance weight that is described further at https://cps.ipums.org/cps-action/variables/HINSWT#description_tab. Columns 1 and 3 include all observations for SPM units in the CPS-ASEC 2010-2012 California with the sample characteristics described above. Columns 2 and 4 include only unit observations for units with positive child care expenses.

Table D4
Model estimates, child care expenses

	Preschool age sample (youngest child under age 6)		School age sample (youngest child age 6-17)	
	Any child care expense	Child care expense amount	Any child care expense	Child care expense amount
	(1)	(2)	(3)	(4)
One adult	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Two adults	-0.21	430.74	-0.08	682.91
	(0.20)	(705.73)	(0.15)	(602.31)
Three or more adults	-0.43	-237.11	-0.36	-730.19
	(0.29)	(1047.42)	(0.27)	(905.39)
Any adult age 18-24	-0.12	-530.69	-0.43	-163.54
	(0.21)	(737.15)	(0.26)	(887.17)
Any adult age 65 or older	-1.13	11634.31	-0.92	-4103.29
	(0.89)	(1841.97)	(0.65)	(1709.78)
One child	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Two children	0.55	2661.13	-0.32	-41.70
	(0.14)	(561.54)	(0.13)	(592.34)
Three children	0.11	3326.77	-0.45	365.61
	(0.19)	(1421.11)	(0.18)	(832.76)
Four or more children	0.30	2791.24	-0.32	-808.14
	(0.27)	(972.10)	(0.31)	(988.50)
Youngest child preschool age	0.80	2059.00		
	(0.16)	(733.29)		
Youngest child elementary school age	-	-	3.11	2676.47
			(0.27)	(864.34)
White, non-Hispanic	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Black, non-Hispanic	0.07	-3622.36	-0.17	-1340.49
	(0.31)	(916.56)	(0.28)	(1259.08)
Asian, non-Hispanic	-0.34	-1895.66	-0.23	-309.23
	(0.23)	(988.84)	(0.22)	(1079.19)
Other race, non-Hispanic	-0.44	-2579.10	0.37	-1680.42
	(0.36)	(2010.25)	(0.39)	(972.35)
Hispanic, any race	-0.16	-3534.84	0.10	-1877.62

	(0.16)	(836.26)	(0.16)	(573.63)
Any member foreign born	0.16	1097.69	-0.27	-537.94
	(0.15)	(673.32)	(0.14)	(576.75)
Highest adult education, no HS degree	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Highest adult education, HS degree	-0.46	982.26	0.02	-114.21
	(0.27)	(956.59)	(0.25)	(992.13)
Highest adult education, some college	-0.17	1106.87	0.18	-661.15
	(0.25)	(941.26)	(0.24)	(1000.10)
Highest adult education, college	0.27	3703.61	0.69	947.97
	(0.26)	(1004.95)	(0.24	(1028.20)
Any TANF/GA (self-reported)	-0.67	-1469.92	-1.94	-1334.70
	(0.34)	(719.13)	(0.78)	(1217.26)
Any SNAP (self-reported)	-0.67	-2075.53	-0.30	-826.44
	(0.24)	(596.68)	(0.31)	(657.77)
Bay Area /Northern Coastal	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Central	-0.01	-3460.08	-1.26	-1164.39
	(0.29)	(1069.36)	(0.31)	(1046.42)
Los Angeles	-0.32	-1914.97	-0.15	680.52
	(0.21)	(1228.04)	(0.19)	(806.80)
Orange/San Diego	0.08	-2931.26	-0.53	218.96
	(0.22)	(966.29)	(0.20)	(800.06)
Southern Coastal	-0.33	-1407.10	-0.84	-472.04
	(0.30)	(1149.95)	(0.36)	(1087.73)
Northern Inland	-0.03	-3268.64	-0.54	-940.14
	(0.24)	(1075.52)	(0.22)	(769.31)
Inland Empire	-0.20	-3738.32	-0.59	-76.97
	(0.24)	(1014.42)	(0.24)	(1230.10)
Unidentified counties (in CPS)	0.34	-814.26	-0.46	741.56
	(0.24)	(1156.13)	(0.22)	(1182.70)
Reference period: 2012	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Reference period: 2011	-0.31	-703.04	0.13	-322.01
	(0.15)	(732.40)	(0.14)	(689.71)
Reference period: 2010	-0.17	-578.95	0.11	-1109.14
	(0.15)	(722.11)	(0.14)	(640.17)
Constant	-0.53	5254.86	-3.48	2996.29
	(0.39)	(1742.45)	(0.39)	(1306.49)
Observations	1,388	615	2,404	500
Pseudo-R-squared/ R-squared	0.07	0.26	0.18	0.11

SOURCES: Authors' calculations from the 2010-2012 CPS-ASEC (IPUMS) and the 2012 ACS (IPUMS).

NOTES: Standard errors in parentheses. Columns 1 and 3 are logistic specifications and columns 2 and 4 are linear regressions. Regressions weighted by the health insurance unit weight (HINSWT) developed by the State Health Access Data Assistance Center (SHADAC). This weight zeros out wholly imputed observations in the CPS-ASEC and reweights the remainder of the sample. See https://cps.ipums.org/cps-action/variables/HINSWT#description_tab.

We impute values for the California ACS sample using the model parameters developed in the CPS. We first predict the probability of any expenses of each type, then rank the predicted probabilities and select the weighted fraction that corresponds to the weighted CPS fraction of respondents with any expenses of that type in each of the two samples. In the case of those with a youngest child under age 6, it is the top 44 percent of predicted probabilities. In the case of the sample of those with a youngest child age 6-17, it is the top 21 percent. After predicting expense amounts using the second set of models, we recode any predicted negative amounts to zero.

Panel A of Tables D5 provides the distribution of self-reported child care expenses in the 2010-2012 California CPS-ASEC sample, summed across SPM poverty units, and compares it to the distribution we calculated in the ACS using the procedure just described. Our calculated distribution again approximates the CPS distribution; we do have relatively more large values of child care expenses (12% have imputed child care expenses of $4,500 or more in the ACS, as compared to 8% in the CPS).

Table D5
Mean values for out-of-pocket child care expenses, California samples

	CPS/ Census	ACS/CPM
A. Distribution of out-of-pocket expenses		
$0	83%	85%
$1 to $499	1	0
$500 to $1,499	2	0
$1,500 to $2,499	2	0
$2,500 to $3,499	2	0
$3,500 to $4,499	1	1
$4,500 or more	8	14
B. Mean out-of-pocket expenses, selected groups		
Any child	$1,032	$1,232
Any child, positive out-of-pocket expenditures	$6,034	$8,300
No adults with earnings, or more adults than adult earners in poverty unit	$232	$0*
All adult(s) report earnings, youngest child infant or preschool age	$3,298	$4,300
All adult(s) report earnings, youngest child elementary school age or older	$1,034	$1,367

SOURCE: Authors' calculations from the 2011-2013 CPS-ASEC (IPUMS) and the 2012 ACS (IPUMS).

*Units in these two categories assigned $0 child care expenses in the CPM.

In Panel B we provide examples of mean values for child care expenses for several different types of CPM units. Overall, we overestimate child care costs for all poverty units with children by a modest amount ($199, or about 19%). For poverty units that have positive out-of-pocket expenses, we overstate these costs by $2,266, or 38%). We understate out-of-pocket costs for poverty units with no adult earners, or more adults than earners, because we constrain the out-of-pocket costs for these units to be $0. For poverty units with young children, we show costs that are $1,002 (30%) higher than in the CPS, and for units with older children, we impute costs that are on average $332 (32%) higher. In sum, we tend to somewhat overstate out of pocket child care expenses in the ACS relative to the self-reported amounts in the CPS, although the differences noted are a relatively small fraction of the poverty thresholds. Final imputed, unit-level child care expenses in the ACS range between $0 and $15,873.

After imputing out-of-pocket child care expenses, we cap these costs in tandem with work expenses by summing unit-level child care expenses and person-level work expenses (described below) and capping the total at the earnings of the lowest-earning adult in the unit.[35] Table D10 below provides a comparison of the CPM estimates with and without capped work-related expenses.

Commuting and Other Non-Discretionary Work Expenses

We impute non-childcare, non-discretionary work expenses to working individuals in the ACS and deduct those expenses from family resources when determining a family's poverty status. The ACS contains relatively limited data on work expenditures. Survey respondents are not explicitly asked how much they spend traveling to and from work, or the cost of self-provided work supplies.

To impute these costs at the individual level, we adopt the general approach used by the Census Bureau and recommended by the National Academy of Sciences' Panel on Poverty and Family Assistance, with some additional modifications. We first assign a flat weekly expense to every employed member of the poverty unit.[36] We then multiply that weekly base amount by the reported number of weeks worked by an individual over the past 12 months, capping the figure

[35] Higher earning adults in the unit have only their work expenses capped at their earnings.
[36] This represents a slight variation upon Census procedures, which only assign non-discretionary work-related expenses to adults age 18 and over. Our model includes individuals 16 and over who report working at least one week over the past year, as in our estimation those individuals are likely to incur non-discretionary work-related expenses.

at an individual's earned income over the same period (so that imputed work expenses can never exceed total income derived from employment).[37] Finally, we use ACS data on commuting method to assign a smaller level of work expense to three types of workers with presumably lower commuting costs: individuals who work from home, individuals who bike to work, and individuals who walk to work.

Calculation of Weekly Work Expenses Base Amount

Per the Census Bureau's procedures, we use 85 percent of median weekly work expenses as reported in the SIPP as our base weekly work-related expense amount. This amount aggregates spending on three primary categories of expenses asked about in the SIPP: (1) "mileage expenses," which assign a cost to the number of miles typically driven to and from work in a typical week; (2) "annual expenses," which includes expenditures on items such as uniforms, union dues, licenses, and permits, and (3) "other expenses," which include non-mileage related work costs such as bus fares or parking fees (Short, Shea, and Eller, 1996). In 2012, the median value of work expenses reported in Wave 8 of the 2008 SIPP was $38.85.[38] We calculate 85 percent of this amount to obtain a base amount of weekly non-discretionary work-related expenses for the 2012 CPM: $33.02 per week. We then multiply that weekly base amount by the reported number of weeks worked by an individual over the past 12 months. Individuals with positive earned incomes in 2012 averaged 45 weeks of work, while working individuals in households below the official poverty line averaged 39 weeks.

Adjustments for Individuals with Presumably Minimal Commuting Costs

While the ACS lacks data on how much individuals spend on their commute, it does contain relatively detailed information about the method of transport by which individuals get to work. Using the TRANWORK—"means of transportation to work"—variable, we make adjustments to the weekly work expenses imputation for three types of workers with presumably lower

[37] We use the "WKSWORK2—Weeks worked last year, intervalled" variable from the ACS/IPUMS file to determine the number of weeks worked by each individual 16 and older in our sample (only individuals 16 and older report the number of weeks worked over the past year). Because this variable is intervalled, we take the midpoint of each relevant interval and multiply that midpoint by the base weekly expense amount to calculate annual work-related expenses. For example, if an individual indicates that he/she worked between 1 and 13 weeks in the previous 12 months, we assign the person a "weeks worked" value of 7 and multiply that by the weekly expense amount (e.g., 7*$33.02=$231.14).

[38] Amount obtained from Kathleen Short of the U.S. Census Bureau in 2014.

commuting costs: 1) individuals working from home, 2) individuals who walk to work, and 3) individuals who bike to work.

It is important to note that there is some mismatch between reference periods for the transportation variable and the income variable we are adjusting. The former pertains to the *week* before the survey, whereas the income variables pertain to the *year* before the survey. We are thus assuming that means of transport last week are equivalent to means of transport in the prior twelve months.

Short et al. (1996) estimate that 82 percent of non-discretionary work expenses reported in the SIPP are derived from the mileage cost of driving to and from work. We thus simply remove 82 percent from our base weekly work expense and assign the remaining amount ($5.94) as our weekly expense for low-commuting cost workers. This approach broadly imitates that deployed by the New York City Center for Economic Opportunity (NYC CEO, 2012) in its city-level supplemental poverty measure, which imputes different weekly commuting costs based on different self-reported modes of transit (car, bus, subway, railroad, etc.) However, although the Center focuses exclusively on commuting costs, it imputes no expense whatsoever ($0) for walkers, bikers, and individuals who work from home. In contrast, we assign the $5.94 to capture non-commute related work expenses and other miscellaneous expenses associated with those workers.

As Table D6 illustrates, the number of individuals who work from home or who walk or bike to work represents a meaningful portion of the poor. Cumulatively, these three categories of worker represented 10.9 percent of working individuals in households below the CPM poverty thresholds in 2012. Table D7 shows that assigning lower weekly work expenses for these workers results in substantially lower average annual expenses. We believe that assigning these individuals a lower weekly work-related expenditure more accurately reflects the actual variation in non-discretionary work costs across California.

Table D6
Commuting mode for working Californians age 16 and older living in "poor" households, CPM definition of poverty

Means of transport to work	Estimated number of individuals	Percent of individuals
Auto, truck, or van	1,795,934	77.4
Bus or trolley bus	197,592	8.5
Bicycle	41,113	1.8
Walked	102,558	4.4
Worked at home	108,177	4.7

SOURCE: Authors' calculations from 2012 ACS.
NOTES: Not inclusive of every means of transport to work reported in ACS. Table displays percentage of working individuals in poverty under CPM poverty definition who report a means of transportation to work in the last week.

Table D7
Average imputed annual work expenses by commuting method for Californians age 16 and older with earnings, CPM definition of poverty

Poverty Status	Drivers	Bikers/Walkers/ Work at Home	All
All workers	$1,558	$274	$1,444
All workers under 100% CPM	1,405	245	1,275

SOURCE: Authors' calculations in 2012 ACS.

Limitations

There are some limitations to our work expenses imputation model. For one, the Census routine at the heart of our procedure—using 85 percent of median work-related expenses as reported in the SIPP as the base expenditure amount for all working individuals—may underestimate the true cost of work-related expenses for Californians. The self-reported cost estimates derived from SIPP reflect *national* commuting costs, not commuting costs specific to California. Factors that contribute to higher average commuting costs for Californians relative to the nation as a whole—higher gas prices, longer commuting times, higher public transit fares—are thus likely understated when a national average is used for imputation purposes. Indeed, other research into imputing commuting costs in the ACS suggest significantly higher household expenditures than those imputed by our model. Research by Rapino et al. (2011) suggest that alternative methods of estimating commuting costs, such as using external data on average driving speed in major urban areas to compute miles driven to and from work, could yield significantly higher cost estimates for California. For example, using the General Services Administration's federal standard for mileage reimbursement, Rapino et al. estimate that the median commuting cost for drivers in the

Lancaster-Palmdale area is $7,795—substantially larger than the statewide average of $1,125 produced by our methodology.

Effect of Child Care and Other Work-Related Expenses on CPM Poverty

Before these work-related expenses are subtracted from household resources to determine CPM poverty status, these expenses are combined with child care expenses, and the total is capped at the earnings of the adult in the unit with the lowest earnings. As noted above, the methodologies and estimates for both child care and other work-related expenses differ somewhat between the CPM and the SPM. However, the net effect of capped combined child care and other work-related expenses on poverty rates is similar in the CPM compared to the one-year estimates for California in the SPM. Table D10 compares these effects, showing that the capped combined child care and work expenses in the CPM have a slightly larger effect on child poverty than child care plus work expenses in the one-year SPM.

Table D10
SPM for California and CPM if child care and other work-related expenses are excluded

	CPM poverty rates absent child care and other work expenses (%)	Percentage point difference from CPM	SPM poverty rates absent child care and other work expenses (%)	Percentage point difference from SPM
A. Under 100%				
All persons	19.1	-2.7	20.6	-2.6
Children	21.3	-3.6	23.4	-3.3
Adults 18-64	18.3	-2.6	19.3	-2.6
Adults 65+	19.0	-0.7	21.9	-0.9
B. Under 50%				
All persons	5.2	-0.7	5.9	-0.7
Children	4.4	-0.7	5.4	-0.6
Adults 18-64	5.5	-0.8	6.1	-0.9
Adults 65+	5.0	-0.2	5.7	-0.0

SOURCE: Authors' calculations from ACS and CPS-ASEC/IPUMS 2012 data as described in the text.

NOTE: California sample for March 2013 CPS-ASEC has 20,466 observations. Negative percentage point differences shown in the table imply that the CPM poverty rate is higher when work expenses are subtracted from resources.

Appendix E: Supplemental Tables

The tables below provide greater detail and additional estimates beyond the tables and figures presented in the main report.

Table E1 presents CPM poverty rates by age group with 99% confidence intervals, using the replicate weights created by Census and included on the public-use file. The standard errors presented in Table E1 are not corrected to reflect the imputation of several types of resources and expenses to ACS respondents. These imputations reduce the sampling variability of the estimates, implying that the standard errors presented here are understated. The choice of a 99% confidence interval represents a first approximation to correcting for the understated standard errors. Future research will explore the calculation of imputation-corrected standard errors.

Table E1
Californians in poverty and deep poverty

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
All persons	21.8 [21.6-22.4]	6.0 [5.8-6.2]	16.0 [15.6-16.4]
Children	25.2 [24.5-26.0]	5.2 [4.8-5.6]	20.0 [19.3-20.7]
Adults 18-64	21.1 [20.7-21.5]	6.4 [6.2-6.6]	14.7 [14.3-15.1]
Adults 65+	19.8 [19.1-20.4]	5.2 [4.9-5.6]	14.6 [13.9-15.2]

SOURCES: Authors' calculations from the California sample of the 2012 ACS (351,172 observations) and auxiliary data sources as described in these technical appendices.

NOTE: Estimates correspond to Figures 1 and 2 in the report. Confidence intervals, calculated using replicate weights, in brackets (99% level).

Table E2 presents CPM poverty rates by age group with resources from individual safety net programs excluded.

Table E2
CPM rates in the absence of needs-based social safety net programs

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
CPM with all resources included			
All persons	21.8%	5.9%	15.9%
Children	24.9	5.1	19.8
Adults 18-64	20.9	6.3	14.6
Adults 65+	19.7	5.2	14.5
Excluding CalWORKs (TANF) + GA			
All persons	23.0	6.4	16.6
Children	27.3	6.1	21.2
Adults 18-64	21.8	6.7	15.1
Adults 65+	20.0	5.3	14.7
Excluding SSI			
All persons	23.1	7.1	16.0
Children	25.9	5.6	20.3
Adults 18-64	22.1	7.4	14.7
Adults 65+	22.1	8.2	14.0
Excluding CalFresh (SNAP)			
All persons	24.2	7.1	17.1
Children	29.6	7.6	22.0
Adults 18-64	22.8	7.2	15.5
Adults 65+	20.3	5.4	14.9
Excluding school meals			
All persons	22.4	6.2	16.3
Children	26.4	5.8	20.6
Adults 18-64	21.4	6.5	14.9
Adults 65+	19.8	5.3	14.5
Excluding EITC + refundable CTC			
All persons	25.0	7.2	17.8
Children	31.1	7.5	23.5
Adults 18-64	23.5	7.4	16.1
Adults 65+	20.2	5.4	14.9
Excluding housing subsidies			
All persons	23.0	6.9	16.1
Children	26.8	6.7	20.2

Adults 18-64	21.8	7.1	14.7
Adults 65+	21.3	6.2	15.1
Excluding all programs above combined			
All persons	29.8	13.7	16.1
Children	38.5	18.5	20.0
Adults 18-64	27.4	12.5	15.0
Adults 65+	24.2	10.3	13.9
Excluding Social Security			
All persons	26.9	10.4	16.5
Children	26.5	6.0	20.5
Adults 18-64	23.7	8.4	15.3
Adults 65+	44.6	30.0	14.6
Excluding all programs above including Social Security			
All persons	34.4	18.5	15.9
Children	39.7	19.8	19.9
Adults 18-64	29.8	14.9	15.0
Adults 65+	47.3	35.1	12.2

SOURCES: Authors' calculations from the California sample of the 2012 ACS and auxiliary data sources as described in these technical appendices.

NOTES: CalWORKs and GA are combined. Tax assistance combines the EITC and the refundable portion of the CTC. School meals combines school breakfast and school lunch. Social Security has an extremely large effect on poverty rates (for seniors) compared to all other programs, therefore the effect of all safety net programs combined is shown both without and with Social Security included. Small differences in reported percentage point program effects shown in the table are due to rounding.

CPM rates with expenses excluded are detailed in Table D3 (medical out-of-pocket expenses) and Table D10 (child care and other work expenses) in Appendix D above.

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