PUBLIC POLICY INSTITUTE OF CALIFORNIA

Technical Appendices

The California Poverty Measure: A New Look at the Social Safety Net

October 2013

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In collaboration with the Stanford Center on Poverty and Inequality

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Supported with funding from The Walter S. Johnson Foundation

Abbreviations

CPM	California Poverty Measure
CalFresh	California name for SNAP
CalWORKs	California Work Opportunity and Responsibility to Kids (California TANF program name)
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

Appendix A: General Methodology

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 Public Policy Institute of California and the Stanford Center on Poverty and Inequality.

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 detailed estimates that correspond to the figures presented in the accompanying report. Appendix F summarizes similarities and differences between the CPM and the Census Supplemental Poverty Measure estimates for California.

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 2011 American Community Survey (ACS) IPUMS version (Ruggles et al., 2010). 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 2011 ACS includes a sample size of 351,526 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.[1]

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[1] 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.

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 116,685 Californians (and 853 observations in the California sample of the 2011 ACS) from the poverty universe. This is a far smaller group than all college undergraduates (25,344 observations) or even all college undergraduates between the ages of 18 and 23 (15,515 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.[2]

The large California sample enables robust one-year CPM poverty rate estimates, including at the county level. Still, only 38 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 adults 65+	Weighted population
Alpine/Amador/Calaveras/Inyo/Mariposa/Mono/Tuolumne	1,576	33,522	108,623	36,902	179,047
Alameda	15,178	339,129	982,574	168,328	1,490,031
Butte	2,024	45,314	134,049	33,011	212,374
Del Norte/Lassen/Modoc/Siskiyou	1,606	22,094	59,061	17,384	98,539
Colusa/Glenn/Tehama/Trinity	1,550	31,659	72,578	19,840	124,077
Contra Costa	8,449	259,962	662,632	131,847	1,054,441
El Dorado	1,499	40,628	111,643	27,409	179,680
Fresno	8,315	277,459	551,356	93,619	922,434
Humboldt	1,509	25,938	85,663	17,722	129,323
Imperial	1,518	50,649	95,832	18,675	165,156
Kern	7,232	254,492	488,057	76,473	819,022
Kings	1,423	42,213	79,320	10,872	132,405
Lake/Mendocino	1,384	32,372	91,003	24,534	147,909
Los Angeles	98,677	2,370,658	6,251,177	1,066,397	9,688,232
Madera	1,160	42,116	82,207	17,071	141,394
Marin	2,122	51,356	150,829	42,998	245,183
Merced	2,478	81,148	148,125	24,517	253,790
Monterey/San Benito	4,722	127,593	276,849	48,618	453,060
Napa	1,248	31,172	81,388	20,150	132,710
Nevada/Plumas/Sierra	1,121	22,089	72,242	25,301	119,632

[2] 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.

County	Sampled individuals	Weighted children	Weighted adults 18-64	Weighted adults 65+	Weighted population
Orange	30,364	736,527	1,911,115	354,334	3,001,976
Placer	2,661	85,748	212,687	54,956	353,391
Riverside	19,540	621,217	1,312,453	264,663	2,198,333
Sacramento	12,896	360,469	882,708	162,355	1,405,532
San Bernardino	13,356	590,622	1,242,638	184,571	2,017,831
San Diego	29,197	724,530	1,962,253	351,684	3,038,467
San Francisco	6,810	109,817	568,791	110,045	788,653
San Joaquin	5,891	200,134	406,965	71,874	678,973
San Luis Obispo	2,162	50,157	162,006	41,250	253,413
San Mateo	7,367	159,840	460,560	95,415	715,815
Santa Barbara	4,170	96,304	252,466	53,742	402,512
Santa Clara	17,909	431,288	1,142,721	197,777	1,771,786
Santa Cruz	2,534	54,920	165,709	29,510	250,139
Shasta	1,736	38,631	106,075	30,111	174,817
Solano	3,574	99,855	256,766	47,599	404,220
Sonoma	4,334	105,446	304,389	67,402	477,237
Stanislaus	4,780	145,950	311,774	54,478	512,202
Sutter/Yuba	1,658	46,661	99,384	18,988	165,033
Tulare	5,021	144,749	256,473	41,855	443,077
Ventura	8,196	210,375	513,595	96,787	820,757
Yolo	1,726	44,528	124,593	19,671	188,792
California total	350,673	9,239,331	23,132,706	4,270,735	36,572,348

SOURCE: ACS 2011, accessed via the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2010).

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 2011. For example, an individual surveyed in the beginning of July 2011 reported annual income earned between July 2010 and June 2011. Because we intend our results to be conceptually reflective of 2011, 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.[3]

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

[3] 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.

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.

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, 2011

Unit definition	Sampled units	Weighted units
ACS households	129,029	12,468,544
Poverty units	140,067	14,386,610

SOURCE: ACS 2011.

NOTE: Group quarters excluded in 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). Erroneously assigning SNAP or Earned Income Tax Credit (EITC) benefits, for example, to unauthorized immigrants could result in underestimates of poverty under the CPM (or SPM) approach. Incorrectly assigning an unauthorized immigrant SNAP benefits in our model (in the case of a single adult) or erroneously counting unauthorized immigrants in the SNAP unit size (in the case of a multi-person unit) would increase unit resources and could potentially move units across the poverty threshold (or some multiple of it), plausibly decreasing the rate of poverty and overstating the impact of a particular program.[4]

California is home to an estimated 2.8 million unauthorized immigrants as of 2011 (Hoefer, Rytina, and Baker, 2012), more than any other state. Furthermore, the *share* of state population that is unauthorized is higher than in almost any other state at about 7 percent, with the exception being Nevada (Passel and Cohn 2009). It is thus critically important to address unauthorized eligibility while estimating a robust CPM. We develop a methodology for excluding likely unauthorized immigrants from the calculation of benefits in the SNAP, TANF, and EITC programs.

Because the CPM is an estimate of poverty within relatively large population subgroups (region, race, age), we do not necessarily need 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 those population subgroups. This is convenient, since very little is known directly about the characteristics of unauthorized immigrants. Even the number of unauthorized immigrants in the nation or in California is an estimate obtained indirectly by backing out known legal immigrant counts from total (legal plus unauthorized) immigrant counts (referred to as "residual methods"; see Warren and Warren, 2013; Passel and Cohn, 2009, 2011; Hoefer et al., 2012). Few surveys ask respondents about their legal status, and no survey representative at the state level does.[5]

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 non-citizen. There is likely to be reporting error in those designations. Aside from that source of error, the non-citizen category is a heterogeneous mix of immigrants including legal permanent residents, refugees, work visa holders, student visa holders, and visa over-stayers, as well as unlawful border crossers.

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.

We develop a procedure to assign legal status to individuals in the ACS, based on the methods in Passel and Cohn (2009). That work uses the residual method to estimate unauthorized population totals and then uses a wide variety of individual characteristics, probabilistic methods, and other approaches to assign specific legal status in the Current Population Survey. Note, their methods are proprietary. We adapt the general strategy to the ACS and the California context. The first step, estimating the total number of unauthorized immigrants by county, is taken from Hill and Johnson (2011).[6] Then following Passel and Cohn (2009), we

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[4] Note that our methodology of matching SNAP program receipt to administrative totals buffers against this kind of error, since we force the values to match actuals within race, region, and household composition characteristics. However, ignoring the unauthorized immigrant issue may affect the results within subgroups and regions. The issue is impossible to ignore in generating EITC estimates since we do not have similarly rich administrative data.

[5] The Survey of Income and Program Participation (SIPP), a national survey, asks more detailed questions about immigration status than other nationally representative surveys; in particular, the 2008 SIPP asks respondents whether they arrived as a permanent resident, refugee, or "other." These questions, ignoring response error, may allow analysts to deduce somewhat more about legal status than in the ACS or CPS. Indeed, research efforts are exploring the utility of SIPP for imputing status (Judson and Long, 2012).

[6] Hill and Johnson's California county estimates pertain to 2008. We thus validate our procedure using the 2008 ACS first. We also assume that the distribution of unauthorized immigrants across California's counties has not changed systematically between 2008 and 2011. This allows us to apply the shares from 2008 to 2011 unauthorized immigrant totals to obtain the county distribution in 2011. It may be possible to update this method with more recent data in the future.

develop a method to assign legal status to individual immigrants in the ACS. We assign only authorized or unauthorized status, rather than the wide variety of visa categories assigned in Passel and Cohn (2009).

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 "potentially unauthorized," probabilistically assign estimates at the county level to match Hill and Johnson's estimates. 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 is constant, and we apply the distribution to the estimated number of unauthorized immigrants in California in 2011, according to DHS estimates (Hoefer et al., 2012).

We validate the resulting "likely unauthorized" immigrant population by comparing their characteristics to those of the unauthorized population as estimated in Passel and Cohn (2009). Confirming the distributions are as expected, based on what is known from the research literature, we proceed with the legal status assignment in other modules of the CPM.

Table A4 presents the numerous steps we use to refine the pool of potentially unauthorized immigrants in the ACS. The first three rows show how we execute Step 1, which is to narrow the sample to anyone who reports noncitizen status. We take these self-reports as given and do not attempt to correct for misreporting in this survey question. Step 2 is shown iteratively in the remaining rows of Table A.4. Future research will consider the sensitivity of our resulting estimates to changes in this algorithm.

TABLE A4
Procedure to identify unauthorized immigrants in the 2011 ACS

	Sample	Weighted
All Californians	**351,526**	**36,868,080**
1. Restrict to immigrants (not native born and not born abroad to American parents)	95,282	10,090,464
2. Remove any who report being naturalized	46,779	5,356,947
3. Remove those likely legal via Immigration Reform and Control Act (IRCA) legalization (exclude any who arrived before 1980)	40,958	4,749,173
4. Remove likely refugees or amnesties via particular year-country programs: e.g., Nicaraguan Adjustment and Central American Relief Act (NACARA), Haitian Refugee Immigration Fairness Act (HRIFA), etc.	39,746	4,609,894
5. Remove any in occupations or industries requiring citizenship (protective services, military, lawyers, federal and state government)	39,306	4,560,763
6. Remove any likely high skilled visa holders based on occupation (computer, engineering, physical scientists)	37,884	4,401,530
7. Remove any likely visa holders in certain high skilled healthcare occupations (practitioners and technical occupations)	37,267	4,336,805

	Sample	Weighted
8. Remove any likely legal based on high skilled financial specialist occupation (accountant, tax preparer)	36,962	4,306,861
9. Remove likely student visa holders (current college students who arrived in last 10 years)	35,239	4,105,900
10. Remove anyone with a legal spouse	28,451	3,405,064

SOURCES: Authors' calculations from American Community Survey for 2011.

NOTE: Table excludes anyone in group quarters.

Following the procedure summarized in Table A4, we narrow the ACS sample to 3.4 million potentially unauthorized immigrants in California in the 2011. This pool is about 500,000 individuals (20%) larger than the official unauthorized population estimate of 2,830,000 (Hoefer et al, 2012) .

Our next step is to select approximately 2.8 million persons from the pool of potential unauthorized individuals summarized in Table A4 to match the official unauthorized population estimate. We use random assignment within counties or county groups, to match the Hill and Johnson (2011) county distribution of unauthorized immigrants.[7] 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.

Following the selection procedure, we estimate a total of 2,803,643 unauthorized immigrants in California. Note this is a slight (1%) undercount of the official estimate, resulting from the fact that the ACS is a weighted sample. Table A5 shows that the county level distribution is estimated quite closely for all counties, both in terms of the number as well as the share of unauthorized.

TABLE A5
Validating unauthorized immigrant identification procedure, county estimates

	Unauthorized immigrant counts		Unauthorized immigrant share	
	(1) ACS assignment procedure	(2) Best estimate	(3) ACS assignment procedure (%)	(4) Best estimate (%)
Alameda	122,209	122,080	4.4	4.3
Alpine/Amador/Calaveras/Inyo/Mariposa/Mono/Tuolumne	3,016	2,461	0.1	0.1
Butte	3,968	3,938	0.1	0.1
Colusa/Glenn/Tehama/Trinity	4,345	9,845	0.2	0.3
Contra Costa	74,885	77,777	2.7	2.7
Del Norte/Lassen/Modoc/Siskiyou	754	985	0.0	0.0
El Dorado	4,018	3,938	0.1	0.1
Fresno	48,484	48,241	1.7	1.7
Humboldt	1,940	1,969	0.1	0.1

[7] Hill and Johnson (2011) estimates of unauthorized population by county for 2008 is adjusted to the 2011 in the following manner: county X's share of all unauthorized immigrants in the state in 2008 is applied to the 2011 best estimate of the total state unauthorized population from Hoefer et al (2012) to obtain an estimate of the share in county X in 2011. This assumes no systematic shift in the residential pattern of unauthorized immigrants between 2008 and 2011, a potentially strong assumption but our best available estimate.

	Unauthorized immigrant counts		Unauthorized immigrant share	
	(1) ACS assignment procedure	(2) Best estimate	(3) ACS assignment procedure (%)	(4) Best estimate (%)
Imperial	16,670	20,675	0.6	0.7
Kern	48,466	45,288	1.7	1.6
Kings	8,895	8,861	0.3	0.3
Lake/Mendocino	5,913	7,876	0.2	0.3
Los Angeles	902,024	901,819	32.2	31.9
Madera	11,974	11,814	0.4	0.4
Marin	14,187	13,783	0.5	0.5
Merced	21,731	21,659	0.8	0.8
Monterey/San Benito	61,320	61,040	2.2	2.2
Napa	13,423	15,752	0.5	0.6
Nevada/Plumas/Sierra	737	1,969	0.0	0.1
Orange	284,653	284,526	10.2	10.1
Placer	10,457	7,876	0.4	0.3
Riverside	143,901	143,740	5.1	5.1
Sacramento	64,104	63,994	2.3	2.3
San Bernardino	145,655	147,678	5.2	5.2
San Diego	195,707	194,935	7.0	6.9
San Francisco	29,616	29,536	1.1	1.0
San Joaquin	53,860	53,164	1.9	1.9
San Luis Obispo	8,973	8,861	0.3	0.3
San Mateo	54,475	54,149	1.9	1.9
Santa Barbara	36,860	36,427	1.3	1.3
Santa Clara	174,364	177,213	6.2	6.3
Santa Cruz	19,495	20,675	0.7	0.7
Shasta	1,369	985	0.0	0.0
Solano	23,734	23,628	0.8	0.8
Sonoma	29,600	40,365	1.1	1.4
Stanislaus	38,890	38,396	1.4	1.4
Sutter/Yuba	9,246	8,861	0.3	0.3
Tulare	28,860	28,551	1.0	1.0
Ventura	69,000	72,854	2.5	2.6
Yolo	11,865	11,814	0.4	0.4
California total	2,803,643	2,829,998		

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

Finally, we compare the socioeconomic characteristics of the likely unauthorized immigrants assigned in the 2011 ACS for California to those estimated by Passel and Cohn (2009) in the 2008 CPS for the United States (Table A6). 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 A6 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 A6
Validating unauthorized immigrant identification procedure, socioeconomic characteristics

Characteristic	2011 ACS assignment procedure for California	2008 Passel and Cohn (2009) procedure for United States
Education		
Less than high school	52%	47%
High school graduate	28	27
Some college	10	10
College graduate	10	15
Age		
Child (<18)	13	13
Adult	87	87
Gender		
Male	51	59
Female	49	41
Labor force participation of men (ages 18-64)		
No	11	6
Yes	89	94
Labor force participation of women (ages 18-64)		
No	41	42
Yes	59	58
Birthplace (select regions)		
Mexico	64	59
Central America	8	11
South America	2	7
South and East Asia	14	11

SOURCE: Authors' calculations from ACS 2011 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 2011. 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.[8] 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 2007-2011. Using a five-year average will tend to moderate housing costs relative to pre-recession years. For the renter and mortgage thresholds, we use median gross rents. For the non-mortgage threshold, we use median monthly ownership costs that include insurance, utilities, and taxes. Table B1 shows the resultant thresholds for families of four for all 58 California counties.

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	$31,701	39	$32,438	42	$22,296	-2
Alpine	$26,377	16	$26,904	18	$22,088	-3
Amador	$26,377	16	$26,904	18	$22,088	-3
Butte	$25,532	12	$26,025	14	$20,594	-10
Calaveras	$26,377	16	$26,904	18	$22,088	-3
Colusa	$24,659	8	$25,117	10	$19,784	-13
Contra Costa	$31,743	39	$32,482	42	$22,462	-2
Del Norte	$23,856	5	$24,283	6	$20,137	-12
El Dorado	$28,152	23	$28,749	26	$23,210	2
Fresno	$24,518	7	$24,971	9	$20,137	-12
Glenn	$24,659	8	$25,117	10	$19,784	-13

[8] 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.

	Renters		Owners with mortgage		Owners without mortgage	
County	**Threshold**	**Difference from official threshold (%)**	**Threshold**	**Difference from official threshold (%)**	**Threshold**	**Difference from official threshold (%)**
Humboldt	$24,954	9	$25,425	11	$20,054	-12
Imperial	$23,236	2	$23,638	4	$20,386	-11
Inyo	$26,377	16	$26,904	18	$22,088	-3
Kern	$24,307	7	$24,751	9	$19,888	-13
Kings	$24,419	7	$24,868	9	$19,639	-14
Lake	$26,349	16	$26,874	18	$21,300	-7
Lassen	$23,856	5	$24,283	6	$20,137	-12
Los Angeles	$30,785	35	$31,487	38	$21,611	-5
Madera	$24,109	6	$24,546	8	$20,573	-10
Marin	$35,785	57	$36,684	61	$25,639	12
Mariposa	$26,377	16	$26,904	18	$22,088	-3
Mendocino	$26,349	16	$26,874	18	$21,300	-7
Merced	$24,236	6	$24,678	8	$19,888	-13
Modoc	$23,856	5	$24,283	6	$20,137	-12
Mono	$26,377	16	$26,904	18	$22,088	-3
Monterey	$29,518	29	$30,169	32	$21,300	-7
Napa	$31,335	37	$32,058	41	$23,022	1
Nevada	$27,518	21	$28,090	23	$23,064	1
Orange	$33,842	48	$34,664	52	$22,296	-2
Placer	$29,659	30	$30,315	33	$22,877	0
Plumas	$27,518	21	$28,090	23	$23,064	1
Riverside	$28,828	26	$29,451	29	$21,881	-4
Sacramento	$27,518	21	$28,090	23	$20,822	-9
San Benito	$29,518	29	$30,169	32	$21,300	-7
San Bernardino	$27,926	22	$28,514	25	$20,386	-11
San Diego	$31,307	37	$32,028	40	$21,902	-4
San Francisco	$36,349	59	$37,270	63	$22,524	-1
San Joaquin	$26,518	16	$27,050	19	$20,718	-9
San Luis Obispo	$29,954	31	$30,623	34	$22,338	-2
San Mateo	$36,504	60	$37,431	64	$22,898	0
Santa Barbara	$32,109	41	$32,863	44	$21,922	-4
Santa Clara	$34,377	51	$35,220	54	$23,355	2
Santa Cruz	$32,884	44	$33,668	48	$22,836	0
Shasta	$26,025	14	$26,538	16	$20,698	-9
Sierra	$27,518	21	$28,090	23	$23,064	1
Siskiyou	$23,856	5	$24,283	6	$20,137	-12
Solano	$30,166	32	$30,842	35	$20,739	-9
Sonoma	$30,898	35	$31,604	39	$22,732	0
Stanislaus	$26,391	16	$26,918	18	$20,781	-9
Sutter	$24,602	8	$25,059	10	$20,033	-12

	Renters		Owners with mortgage		Owners without mortgage	
County	Threshold	Difference from official threshold (%)	Threshold	Difference from official threshold (%)	Threshold	Difference from official threshold (%)
Tehama	$24,659	8	$25,117	10	$19,784	-13
Trinity	$24,659	8	$25,117	10	$19,784	-13
Tulare	$23,476	3	$23,887	5	$19,535	-14
Tuolumne	$26,377	16	$26,904	18	$22,088	-3
Ventura	$33,433	47	$34,239	50	$22,255	-2
Yolo	$28,884	27	$29,510	29	$21,756	-5
Yuba	$24,602	8	$25,059	10	$20,033	-12

SOURCE: Authors' calculations as described in the text.

NOTE: A positive percentage point difference means that the CPM threshold is higher than the official poverty threshold.

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.

Finally, in Table B2 we show the sensitivity of the estimates to using SPM thresholds calculated with the Census approach. Not surprisingly, across the board the estimates using CPM as opposed to SPM thresholds are lower by 0.8-1 percentage points. Nearly all of this difference is confined to those estimated to be between 50 and 100 percent of the poverty line.

TABLE B2
Sensitivity of CPM estimates to poverty thresholds

	Under 100%		Under 50%		50%-99%	
	Estimate (%)	Percentage point difference from CPM	Estimate (%)	Percentage point difference from CPM	Estimate (%)	Percentage point difference from CPM
Census SPM poverty thresholds						
All persons	22.9	0.9	6.2	0.1	16.7	0.8
Children	26.1	1.0	5.8	0.1	20.3	0.9
Adults 18-64	22.2	0.8	6.6	0.1	15.6	0.7
Adults 65+	19.7	0.8	5.1	0.2	14.6	0.6

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

NOTE: A positive percentage point difference means that the CPM estimate is lower.

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 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).

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 unfortunately lumped into an "all other income sources" field in the ACS.

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 a number of categories of resources that we exclude from the CPM: the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), the Low Income Home Energy Assistance Program (LIHEAP), In-Home Supportive Services (IHSS), Child and Adult Care Food Program (CACFP), summer meals, child support payments, foster care payments, and adoptions assistance payments. These are relatively small programs compared to those we have focused on in this version of 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. In principle the cash-based resources listed above (e.g., child care, foster care, and adoptions assistance) should be reported as "welfare" or "other" income by respondents to the ACS.

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. We confront two key problems in identifying welfare income and measuring the effect of these programs on poverty. The first is underreporting of income, and the latter has to do with ambiguities of the ACS question wording for our purposes. We discuss each in turn.

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. 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).[9] 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 396,000 TANF-reporting households and 149,000 GA-reporting households.

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

TABLE C2
TANF and GA in California Sample of the 2011 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	149	149	n/a	n/a
Single adult	n/a	n/a	45,444	45,444
Multiple adults, no children	n/a	n/a	303,033	104,356
Single parent	318,205	94,040	n/a	n/a
Multiple adults, children	1,577,579	301,849	n/a	n/a
Total	1,895,933	396,038	348,477	149,800

SOURCE: Authors' calculations from the ACS.

NOTES: Figures represent weighted population counts. 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 at least two 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. For example, TANF benefits are often granted to children 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, which we discuss 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 2011, we estimate an undercount of TANF units in the ACS of about 50 percent; we provide further details below. In addition, the dollar amount of benefits claimed in California in 2011 was about $3.4 billion compared to ACS self-reported TANF income of about $2 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.

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 (averaging 153,000 per month according to statewide data) and expenditures are low relative to other programs ($400 million paid in 2011, according to statewide data), 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 $4,300, with a state total of about $720 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 33 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;
6. Randomly assign TANF to an additional fraction of eligible units to match administrative totals of units that received TANF but not SNAP;
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 2011, as well an unduplicated count of persons and units ever on the program in 2011. 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.[10] 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.

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 2011 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.[11] 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.[12] 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.[13] That over-count is reflected in Table C.3, 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.

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[10] 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.

[11] California switched from a 60-month to a 48-month lifetime time limit for adults in July 2011.

[12] 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.

[13] 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	149	1,957	135,683	482,936
Single parent	318,205	634,785	543,491	1,013,743
Multiple adults and children	1,577,579	640,632	459,591	747,363
Adult only	N/A	94,707	77,309	31,252
Total	1,895,933	1,372,081	1,216,074	2,275,293

SOURCES: Authors' calculations from the 2011 ACS (weighted) and California administrative data, including MEDS, CA237, WTW25, and WTW25A.

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 47 percent less than the number of Californians aided by TANF in 2011; 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 403,157 and in Column 4 is 815,000; this indicates an undercount of about 51 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	135,683	706,785	482,936
Single parent	543,491	1,512,408	1,013,743
Multiple adults, children	459,591	1,659,452	747,363
Adult only	77,309	29,328	31,252
Total	1,216,074	3,907,883	2,275,293

SOURCE: Author's calculations in the ACS, 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. 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[14] 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 0-40 percent of the actual for the TANF-only caseload.[15]

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

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	135,683	354,998	71,400	426,398	482,936
Single parent	543,491	936,232	81,275	1,017,507	1,013,743
Multiple adults, children	459,591	598,224	202,677	800,901	747,363
Adult only	77,309	14,539	64,279	78,818	31,252
Total	1,216,074	1,903,993	419,631	2,323,624	2,275,293

SOURCE: Authors' calculations from California ACS sample and California administrative data for 2011.

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

The TANF assignment results in a slight over count (2%) 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 811,000 cases in the ACS, matching very closely the administrative total of 815,000 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.[16] Table C6 provides the simple OLS model used to predict monthly TANF benefits, based on the administrative survey data.

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

[15] 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.

[16] 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	279.3	5.44
Number of Adults	Count of all adults in unit	105. 7	3.91
Number of Children	Count of children in unit	79.7	2.06
Young Head	Head of unit is a minor	16.2	8.29
Elderly Head	Head of unit is elderly	69.7	14.33
Observations	3,504		
R-squared	0.383		

SOURCE: Authors' calculations from the California TANF quality control sample for 2011.

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 $350/year to about $14,800/year, with the mean TANF unit receiving $4,500/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	$4,128	$4,533
Adult only	2,332	4,233
Mixed	4,830	5,079
California overall	4,453	4,867
Annual totals		
Child only	$ 861,776,411	$ 268,251,110
Adult only	184,643,145	267,419,770
Mixed	2,356,114,881	1,426,473,910
California overall	3,373,570,439	1,962,114,790

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 2.1 million in 2007 to 3.9 million in 2011.[17]

Research indicates that SNAP plays an important role in reducing material hardship for low-income families (Tiehen et al, 2012). In addition, estimates from the nationwide SPM indicate that SNAP reduced poverty by 1.5 percentage points overall and 2.9 percentage points for children in 2011 (Short, 2012).

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.

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 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;

[17] California Department of Social Services (CDSS) CalFresh Program, total public assistance and nonassistance persons, July 2007-January 2013 (www.cdss.ca.gov/research/PG350.htm)—number of individuals receiving CalFresh benefits in January 2007 and December 2011.

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 2011.

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 2011, as well an unduplicated count of persons and units ever on the program in 2011. 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 2011 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 16 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.

[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.

TABLE C8
Individuals reporting SNAP receipt by case type, 2011

	Census households	Split into SNAP units	SSI and unauthorized immigrants removed	Administrative totals
	(1)	(2)	(3)	(4)
Child only	1,251	33,082	461,151	767,348
Single adult	86,636	823,811	645,500	966,513
Multiple adults, no children	558,893	260,284	192,053	205,101
Single parent	571,121	1,516,169	1,232,744	1,876,202
Multiple adults, children	3,494,546	1,814,859	1,207,026	1,726,367
Total	4,712,447	4,448,205	3,738,474	5,541,531

SOURCE: Authors' calculations from the 2011 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 2011.

In sum, we are left with an undercount of roughly 1.8 million people (33%) on SNAP in 2011 in the ACS as compared to administrative actuals. While dividing households that report SNAP receipt into multiple units is an important intermediary step, the ACS falls substantially short of matching the actual number of individuals who received SNAP in 2011 recorded in administrative totals.[19] In terms of number of cases, administrative records suggest 2.5 million cases participated in the program, whereas 1.6 million units in the ACS report SNAP participation in 2011, a 36% undercount.

Simulating Eligibility among Non-Reporters

In order to correct for the roughly one 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 3.7 million people (or about 1.6 million units). To approximate the administrative total of 5.5 million (column 3), we assign participation to a fraction of the 8.7 million cases in the eligibility pool so that the total self-reported plus assigned cases matches the administrative total.

[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.

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	461,151	534,560	767,348
Single adult	645,500	3,716,605	966,513
Multiple adults, no children	192,053	1,067,106	205,101
Single parent	1,232,744	1,311,020	1,876,202
Multiple adults, children	1,207,026	2,036,743	1,726,367
Total	3,738,474	8,666,034	5,541,531

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

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

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 2011, and race as the race/ethnicity of the head of household (as defined by oldest 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, 2011

Unit Size/Type	Self-Reporters (adjusted)	SNAP receipt following assignment	Administrative totals
	(1)	(2)	(3)
Child only	461,151	740,165	767,348
Single adult	645,500	978,070	966,513
Multiple adults, no children	192,053	247,106	205,101
Single parent	1,232,744	1,795,764	1,876,202
Multiple adults, children	1,207,026	1,720,662	1,726,367
Total	3,738,474	5,481,767	5,541,531

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

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 1 percent and understate the number of cases by 2 percent (2.45 million cases assigned, compared to 2.5 million in administrative counts).

Estimating Monthly Benefit Amounts

Using the California SNAP quality control sample for 2011, 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:

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

where c indexes county and γ a set of county dummy variables, with Los Angeles the omitted category. We tested alternative models, and present some sensitivity tests at the end of this section. Parameter estimates are given in Table C11.

TABLE C11
SNAP monthly benefit model

Variable	Description	Coefficient estimate	Standard error
Intercept	Intercept (L.A. County base)	48.42	3.70
Unit size	Count of all individuals receiving CalFresh	87.97	1.93
Number of children	Count of children in unit	12.99	2.14
Any SSI	Any member in household receives SSI income	25.99	5.14
Any SS	Any member in unit receives Social Security income	-63.73	5.51
Any TANF/GA	Any member in unit receives CalWORKs or General Assistance income	25.65	2.80
County fixed effects		Yes	
Observations	5,501		
R-squared	0.719		

SOURCE: Authors' calculations from the SNAP quality control sample for 2011.

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. 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, 2011

Case type	California administrative sample	Predicted in ACS
Child only	$301	$284
Adult only	194	167
Mixed (children and adults)	462	420

SOURCE: For administrative sample, authors calculations from FFY 2011 SNAP Quality Control samples.

NOTE: For California administrative sample, authors' calculations from the FFY 2011 SNAP quality control sample.
For Predicted in ACS, authors' calculations using the coefficients from Table C11.

[23] Unfortunately, no monthly benefit microdata that capture the entire universe of CalFresh recipients in each month of 2011 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.

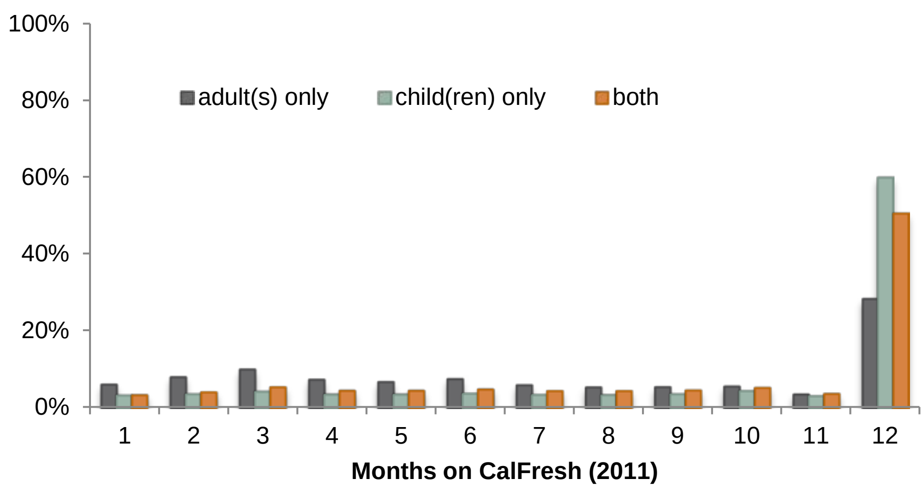
Estimating Time on Aid

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.

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 250 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 2011.

Among SNAP units with only aided children, 60 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—46 percent remained 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 2011 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, 2011

Case type	Predicted in ACS for all SNAP-assigned units	Predicted in ACS for only SNAP self-reporting units
Annual averages		
Child only	$2,963	$2,851
Single adult	1,239	1,184
Multiple adult, no child	2,067	1,880
Single parent	3,673	3,446
Multiple adults, children	4,992	4,681
California overall	2,731	2,584
Annual totals		
Child only	$1,072,756,982	$ 669,046,032
Single adult	1,211,687,657	829,048,361
Multiple adult, no child	228,949,826	175,970,001
Single parent	2,290,164,807	1,573,614,392
Multiple adults, children	1,902,601,891	1,343,661,359
California overall	6,706,161,162	4,591,340,146

SOURCE: Authors' calculations from the coefficients in Table C11 and the ACS for 2011.

Administrative records indicate $6.7 billion was spent on SNAP benefits in 2011. If self-reporters alone are imputed benefits in the ACS, the annual total is underestimated by $2.5 billion, or 38 percent. After assigning receipt to other eligible units to match administrative records on participation, we estimate a total of $6.7 billion was spent on SNAP. This underestimates the actual total by about 1 percent.[25]

Sensitivity Analysis: The Importance of Correcting for Underreporting

Our procedures to correct for SNAP and TANF underreporting in the ACS reduce the CPM poverty rate estimates for all persons by a combined 1.2 percentage points (Table C14). Not surprisingly, the CPM estimate for children is most sensitive to the correction procedures. Poverty among children drops 1.1 percentage points with the correction for SNAP underreporting and by 1.2 percentage points with the correction for TANF underreporting. Using both corrections, poverty for children is 2.3 percentage points lower.

[25] Before applying the county-level adjustment in the last step, the statewide SNAP benefits imputed totals $6.1 billion, understating the administrative total by about 9 percent.

TABLE C14
CPM estimates using self-reported receipt in place of imputed receipt and benefits

	Under 100%		Under 50%		50%-99%	
	Estimate (%)	Percentage point difference from CPM	Estimate (%)	Percentage point difference from CPM	Estimate (%)	Percentage point difference from CPM
Self-reported CalFresh						
All persons	22.7	0.7	6.4	0.3	16.3	0.4
Children	26.3	1.1	6.3	0.6	20.0	0.6
Adults	22.0	0.6	6.7	0.2	15.2	0.3
Elderly	19.2	0.3	5.1	0.2	14.1	0.1
Self-reported CalWORKs						
All persons	22.6	0.6	6.3	0.2	16.3	0.4
Children	26.2	1.1	6.1	0.4	20.1	0.7
Adults	21.8	0.4	6.6	0.1	15.2	0.3
Elderly	19.0	0.1	5.0	0.1	14.0	0.0
Both self-reported CalFresh and self-reported CalWORKs						
All persons	23.3	1.2	6.6	0.5	16.6	0.7
Children	27.3	2.2	6.7	1.0	20.6	1.2
Adults	22.4	1.0	6.9	0.4	15.5	0.6
Elderly	19.3	0.4	5.1	0.2	14.2	0.2

SOURCE: Authors' calculations from the ACS and California administrative data as described in the text.

NOTE: Self-reported CalWORKs amounts shown in the table include GA and are self-reported but not capped. CalFresh amounts are imputed, but receipt is self-reported. A positive percentage point difference means the CPM estimate is lower.

The Census SPM relies on self-reports of SNAP and TANF receipt, so it is also interesting to consider the extent to which both programs reduce poverty rates in California. We make these comparisons in Appendix F.

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.

Typically students apply to receive the appropriate category of meals. They 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 the California Department of Education, all but 39 public schools in California offered the NSLP in 2010-2011, while 7,042 of the 8,136 public schools (or 87%) offered the SBP.

Unlike the CPS-ASEC, the ACS does not include questions about participation in school meals, and the Census Bureau SPM estimates attribute a one percentage point reduction in poverty for children due to the NSLP program (Short, 2012). 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).

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 eligible without application for free school meals (if meals are offered at their school). This is termed categorical eligibility. 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
9. 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

[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.

foster children in California in 2011 is 30,779, while the actual monthly average number of foster children in California in 2011 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 and defines the economic unit 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).[27] 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 C12 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.

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[27] See 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 2010-11 school year. These administrative data, produced from the CDE's databases, represent the number of meals that school districts claimed (on behalf of schools) for federal and state reimbursement for each month of the year. 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).[28] 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 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 percentage points of the benchmark. Marin and the county group Nevada/Plumas/ Sierra have the largest percentage differential between the imputed counts and the administrative benchmark.

[28] 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.

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	6,741,352	3,224,145	2,210,402	2,103,650	95%	992,454	957,345	96%
Alameda	235,865	88,341	52,276	50,103	96%	18,014	17,313	96%
Alpine/Amador/Calaveras/Inyo/ Mariposa/Mono/Tuolumne	25,125	9,599	6,205	6,412	103%	3,071	3,164	103%
Butte	32,487	17,361	11,472	11,077	97%	6,652	6,869	103%
Colusa/Glenn/Tehama/Trinity	22,231	11,138	9,986	9,209	92%	5,069	5,045	100%
Contra Costa	188,950	67,380	39,256	37,529	96%	16,982	17,039	100%
Del Norte/Lassen/Modoc/Siskiyou	15,118	6,950	5,420	5,590	103%	3,024	3,078	102%
El Dorado	32,552	8,844	4,719	4,917	104%	2,284	2,549	112%
Fresno	205,842	132,118	92,179	87,882	95%	45,147	43,165	96%
Humboldt	20,601	8,857	5,221	5,297	101%	2,739	3,038	111%
Imperial	39,618	21,451	16,756	15,715	94%	6,769	6,694	99%
Kern	188,901	107,926	84,676	77,502	92%	37,381	36,012	96%
Kings	30,457	16,061	11,846	11,071	93%	7,053	7,007	99%
Lake/Mendocino	23,487	13,019	9,327	9,027	97%	5,560	5,920	106%
Los Angeles	1,747,121	942,258	641,043	609,288	95%	307,247	292,095	95%
Madera	33,113	19,814	14,470	13,767	95%	5,956	6,051	102%
Marin	33,944	11,051	4,581	5,153	112%	2,302	2,829	123%
Merced	63,557	42,469	29,670	28,359	96%	13,951	13,374	96%
Monterey/San Benito	92,242	45,499	33,363	31,438	94%	13,518	13,033	96%
Napa	23,423	10,953	5,642	5,710	101%	3,284	3,602	110%
Nevada/Plumas/Sierra	15,890	5,192	2,364	2,565	109%	718	862	120%
Orange	527,854	211,865	145,493	138,434	95%	56,783	54,290	96%
Placer	63,584	17,219	10,614	9,594	90%	4,134	4,437	107%
Riverside	455,776	230,097	163,337	155,823	95%	66,467	63,533	96%
Sacramento	261,633	128,111	87,551	83,229	95%	34,514	33,072	96%

	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)
San Bernardino	446,294	241,359	177,726	169,444	95%	64,009	61,426	96%
San Diego	530,613	223,067	149,461	142,264	95%	78,457	74,787	95%
San Francisco	59,829	26,975	17,189	16,417	96%	4,692	4,932	105%
San Joaquin	151,583	76,906	54,403	51,922	95%	22,364	21,471	96%
San Luis Obispo	37,921	16,273	7,756	7,604	98%	4,599	4,529	98%
San Mateo	108,045	33,241	18,815	18,128	96%	10,018	9,708	97%
Santa Barbara	72,409	33,994	23,211	21,940	95%	10,238	9,865	96%
Santa Clara	289,458	90,536	60,858	56,969	94%	28,178	27,227	97%
Santa Cruz	39,467	16,869	12,447	11,575	93%	5,845	5,796	99%
Shasta	27,461	12,196	10,070	9,915	98%	5,203	5,077	98%
Solano	71,641	24,504	17,969	16,489	92%	7,342	7,131	97%
Sonoma	76,874	22,998	18,929	18,160	96%	9,745	9,789	100%
Stanislaus	110,690	63,263	44,445	42,467	96%	20,214	20,167	100%
Sutter/Yuba	35,974	19,643	14,524	14,126	97%	8,343	8,224	99%
Tulare	114,347	77,663	46,607	44,626	96%	22,735	21,827	96%
Ventura	155,651	55,661	38,606	36,789	95%	18,521	17,936	97%
Yolo	33,724	15,424	9,920	10,124	102%	3,332	3,382	101%

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: 58 percent of California public school students did not participate in free or reduced price school meals in 2011, while 26 percent participated in school lunch alone, 11 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	58%
School lunch only	26
School breakfast only	6
Both lunch and breakfast	11

SOURCE: Authors' calculations from the 2011 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 amounts for school meals

	School breakfast		School lunch	
	Per meal	Per school year	Per meal	Per school year
Free	$1.71	$274.46	$3.18	$508.57
Reduced price	$1.41	$226.43	$2.78	$444.54
Full price	N/A	-	N/A	-

NOTES: Amounts include both federal and state reimbursements. These amounts are several cents higher for particularly disadvantaged districts (see www.cde.ca.gov/ls/nu/rs/index.asp). School year amounts shown in the table are based on an attendance factor of 92.7% and 174 days in the school year. Actual imputed amounts vary based on county-level attendance factors.

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. However, an ongoing 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 include 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 2011 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 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 this model are shown in Table C18.

TABLE C18
Regression estimates, housing subsidies participation model

	Adults	Elderly
Survey year = 2010	-0.012	0.037
	(0.007)	(0.034)
Survey year = 2011	-0.017*	0.036
	(0.007)	(0.034)
SNAP receipt	0.082***	0.177**
	(0.010)	(0.060)
Household income (ln)	-0.014**	-0.092**
	(0.004)	(0.030)
Cash welfare receipt	0.043***	-0.075
	(0.011)	(0.093)
Black	0.128***	0.093*
	(0.011)	(0.045)

	Adults	Elderly
Hispanic	-0.013	-0.062
	(0.007)	(0.042)
Asian	0.034***	0.021
	(0.010)	(0.048)
Other race/ethnicity	0.022	0.190
	(0.017)	(0.136)
Under 100% of FPL	0.017	-0.128**
	(0.011)	0.046
Between 100% and 150% of FPL	-0.053***	-0.214***
	(0.009)	(0.040)
Female	0.031***	-0.003
	(0.006)	(0.031)
Age	0.002***	-0.0005
	(0.0003)	(0.002)
High school graduate	-0.001	-0.099*
	(0.009)	(0.040)
Some college	-0.025*	-0.083
	(0.010)	(0.044)
College or postgraduate degree	-0.061***	-0.159***
	(0.011)	(0.045)
Number of adults	-0.014***	-0.097***
	(0.003)	(0.024)
Number of children	-0.003	0.008
	(0.003)	(0.039)
Separated	-0.015	-0.068
	(0.013)	(0.086)
Divorced	0.012	-0.042
	(0.010)	(0.054)
Widowed	0.015	-0.057
	(0.019)	(0.057)
Never married	0.009	-0.137*
	(0.008)	(0.066)
Married, spouse absent	-0.016	-0.137
	(0.018)	(0.066)
Constant	0.196***	1.567***
	(0.047)	(0.340)
Observations	7,748	843
Pseudo-R-squared/ R-squared	0.13	0.22

NOTE: *** p < .001; ** p < .01; * p<.05. Standard errors in parentheses.

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 1.6 million subsidy recipients in California in 2011 (or 4 percent of the total population).[29] The median housing subsidy value for this group is approximately $9,000 (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.

TABLE C19
Imputed and self-reported housing receipt and subsidy amounts for selected groups

Characteristic	ACS 2011	CPS 2011
All		
Number of recipients	1.370 million	1.347 million
Median subsidy	$8,639	$7,577
Minimum subsidy	$34	$19
Maximum subsidy	$26,520	$20,995
Children		
Number of recipients	511,804	431,379
Median subsidy	$10,601	$9,523
Minimum subsidy	$36	$456
Maximum subsidy	$26,520	$19,725
Adults		
Number of recipients	643,791	681,346
Median subsidy	$8,533	$7,577
Minimum subsidy	$36	$19
Maximum subsidy	$26,520	$20,995
Elderly		
Number of recipients	214,731	234,486
Median subsidy	$5,700	$4,389
Minimum subsidy	$34	$19
Maximum subsidy	$25,459	$20,995

SOURCES: Authors' calculations based on the 2011 public-use ACS microdata file for California and the 2012 CPS ASEC for calendar year 2011.

[29] 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 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 1.4 percentage point lower poverty rate. The role of housing subsidies is largest for older adults and for children in the CPM.

TABLE C20
CPM with and without housing subsidies

	With housing subsidy imputation	Without housing subsidies (percentage point difference)
All persons	22.0%	1.4
Children	25.1	1.9
Adults	21.4	0.9
Elderly	18.9	2.6

SOURCES: Authors' calculations based on the 2011 ACS and auxiliary data sources as described in these appendices.

Tax Liabilities and Credits

Over the past few decades, federal and state tax policy has played an increasingly important role in determining the resources available to low-income individuals and families. Refundable federal tax credits such as the EITC and the Child Tax Credit (CTC) can contribute substantially to resources among low- and moderate-income families, while payroll tax contributions to Social Security and Medicare can significantly reduce families' take-home pay. We describe below our approach to imputing tax liabilities and credits for purposes of creating the CPM.

Methodology

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.

Unfortunately, we are unable to simulate all of the detailed information often contained in individual tax returns. As discussed in the "Limitations" section below, the ACS does not contain sufficient detail on 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.

Creation of tax units and identification of filers and dependents

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. [30] Detailed information on the MetroTax Model is included in the technical appendix on the Brookings Metropolitan Policy Program's website.

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 run all resulting tax units with incomes above the 2011 tax-year income filing thresholds (minimum income amounts that require tax units to file) through the TAXSIM calculator. We are thus implicitly assuming 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 However, tax units that fall short of federal filing thresholds but that still qualify for the EITC are included as filers in our model. Table C21 shows how our CPM tax model compares to state administrative data. 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.

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

Filing status	Administrative returns filed	Administrative data (relative %)	CPM model returns filed	CPM model (relative %)
Single	6,625,890	45	7,399,615	47
Married filing joint	5,688,466	38	5,824,132	37
Married filing separate	180,560	1	included in "single"	included in "single"
Head of household	2,309,937	16	2,102,413	13

SOURCES: State tax return data from California Franchise Tax Board. Data from tax year 2010, most recent year available for filing status. CPM tax model from authors' calculations in 2011 ACS, 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.

Unauthorized immigrants

We assume that individuals identified as unauthorized immigrants in our sample use an Individual Taxpayer Identification Number (ITIN) when filing their tax returns. For more information on how we identify unauthorized immigrants in the ACS, see the "Unauthorized Immigrant" section in Appendix A.

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.

Assuming that all of the individuals whom we classify as unauthorized immigrants use an ITIN when filing their tax returns results in an over-count of the number of ITIN filers, compared to the most recent administrative data available. Taking the administrative ITIN totals as a "given," we correct our estimates by

[30] 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 do not have dependents.

randomly selecting some unauthorized filers to file with social security numbers and thus retain eligibility for the EITC until our count of ITIN filers roughly approximates available administrative data. This procedure resulted in 260,477 filers who claimed the EITC—about 7.7 percent of all EITC filers in our model. It is important to clarify that we are not claiming that 7.7 percent of California EITC filers in 2011 were in fact unauthorized immigrants—there is little evidence of unauthorized immigrants claiming the EITC at such levels. The decision to allow some individuals in our sample identified as unauthorized to claim the credit stems from the over-count of ITIN filers in our sample (when compared to the administrative data) and the underestimation of EITC benefits statewide. These under- and over-counts stem from the error inherent in our survey data and multiple imputation methods. 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 2010 administrative data	14,548,527	954,642	6.6
CPM tax model	15,806,188	954,685	6.0
CPM tax model without random selection of ITIN filers filing with SSN	15,806,188	1,450,213	9.2

SOURCE: 2010 state ITIN filers data downloaded from Brookings Metropolitan Policy Program's "EITC Interactive" website.
CPM tax model calculations from 2011 ACS.

Tax calculator and major tax credits

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 determined 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.[31]

It is important to note that several categories of income that routinely appear on a tax return were 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).

Table C23 compares the results of our CPM tax simulation to the most recent 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

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

Child Tax Credit (ACTC), which our model takes into account. Improving the CPM tax model to more accurately reflect administrative totals is an important 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	17,062,133	15,806,188	0.93
EITC amount	$7,251,211,000	$6,090,261,504	0.84
EITC filers	3,273,578	3,361,580	1.03
CTC amount	$3,193,101,000	$3,127,437,824	0.98
CTC filers	2,800,971	2,439,173	0.87
ACTC amount	$4,143,470,000	$2,523,649,280	0.61
ACTC filers	2,907,910	1,844,085	0.63
Filers with AGI between $1 and $25K	6,621,837	5,150,969	0.78
Filers with AGI between $25K and $50K	3,908,407	3,695,239	0.95

SOURCES: State returns and EITC data from IRS Statistics of Income Division for tax year 2011. CPM tax model figures from authors' calculations in the ACS.

NOTES: CPM tax model figures include individuals in group quarters. "Total state returns" includes more than 400,000 returns with Adjusted Gross Income (AGI) of $1.

In the creation of EITC-eligible tax units, we reassign "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 almost always 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, or because the filers are themselves dependents. Because all individuals eligible for the EITC do indeed file in our model, 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 better approximates the actual amount of EITC dollars paid out to filers in the state in 2011.[32]

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. 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).

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[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 children dependents, which in some cases leads to non-disabled adult dependents being claimed for EITC purposes.

The disparity between the aggregated statewide EITC benefit produced by our model and that reported by the IRS for 2011 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 One-Year SPM

Appendix F provides a comparison of the Census SPM 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 because of the EITC and CTC

Table C24 illustrates the role of other 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 2011 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)**	**Adults (65 and older)**
CPM rate	22.0	25.1	21.4	18.9
Remove payroll taxes	20.2	22.7	19.5	18.4
Remove all federal taxes (payroll plus income tax liability/refund)	22.9	28.4	21.4	18.8
All unauthorized receive the EITC (if otherwise eligible)	21.5	24.0	20.9	18.9

SOURCE: Author's calculations in 2011 ACS 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 2011 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 eleven 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.[33] 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.

[33] 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 www.census.gov/hhes/povmeas/publications/poor/RenwickShortBishawHokayemPAA.pdf.

TABLE D1
Model estimates, CPS-ASEC

A. Regression models predicting premium amounts				
	Families with nonelderly head	Elderly	Nonelderly insured unrelated individuals	
Family composition				
Single	-0.055			
	(0.0)			
Couple	-0.0914			
	(0.0)			
Number of adults in family	0.1739			
	(0.0)			
Number of persons in family	0.0543	-0.0053		
	(0.0)	(0.0)		
Household head age	-0.0093	-0.0372	-0.0042	
	(0.0)	(0.0)	(0.0)	
Household head age squared	0.0002	0.0003	0.0002	
	(0.0)	(0.0)	(0.0)	
Type of health insurance coverage				
Medicaid		-0.3256		
		(0.0002)		
Medicare		-0.1824		
		(0.0)		
Both Medicare and Medicaid		0.1286		
		(0.0002)		
Any public			-0.2428	
			(0.0)	
Private			0.2284	
			(0.0)	
Employer			0.4359	
			(0.0)	
Log of family income	0.08	0.092	0.0244	
	(0.0)	(0.0)	(0.0)	
Type of coverage for families				
Private	0.7445			
	(0.0)			
Employer	0.0231			
	(0.0)			
Constant	6.823	7.9786	7.1066	
	(0.0001)	(0.0007)	(0.0001)	
N	23,878	10,919	10,712	
AIC	88,856,606,491	33,129,701,666	30,091,704,119	
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	-0.1424			
	(0.00118)			
Number of persons in family	-0.0554	0.1575		
	(0.000478)	(0.000475)		
Household head age	-0.0142	-0.0189	-0.0634	-0.0382
	(0.000385)	(0.00225)	(0.000323)	(0.000227)
Household head age squared	-0.000000483	0.000211	0.000437	0.00026
	(0.000004453)	(0.000015)	(0.000003981)	(0.000002816)
Type of health insurance coverage				
Medicaid		-0.2518		0.0726
		(0.012)		(0.00118)
Medicare		-0.6515		-0.4359
		(0.00189)		(0.00227)
Both Medicare and Medicaid		1.2274		0.0367
		(0.0121)		(0.00322)
Any public			0.257	
			(0.00242)	
Private			0.0257	
			(0.00292)	
Employer			-0.1219	
			(0.00305)	
Log of family income	-0.1608	-0.1471	-0.0836	-0.0502
	(0.000237)	(0.000315)	(0.000279)	(0.00015)
Type of coverage for families				
Private	-0.0082			
	(0.00339)			
Employer	-0.2193			
	(0.00614)			
Any public	0.9149			
	(0.00153)			
None	1.0285			
	(0.00157)			
Constant	-0.6266	-0.3957	0.2782	0.5226
	(0.00751)	(0.084)	(0.00599)	(0.00434)
N	45,299	22,507	18,365	14,327
AIC	24,228,563	24,545,490	19,994,773	29,777,887

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	0.1217			
	(0.0)			
Number of persons in family	0.0862	-0.091		
	(0.0)	(0.0)		
Household head age	-0.0062	0.3593	0.0445	0.0321
	(0.0)	(0.0)	(0.0)	(0.0)
Household head age squared	0.0003	-0.0023	-0.0002	-0.0002
	(0.0)	(0.0)	(0.0)	(0.0)
Type of health insurance coverage				
Medicaid		-0.1903		-0.6165
		(0.0001)		(0.0)
Medicare		-0.0625		0.2297
		(0.0)		(0.0)
Both Medicare and Medicaid		-0.3805		0.0758
		(0.0001)		(0.0001)
Any public			0.1009	
			(0.0)	
Private			0.2413	
			(0.0)	
Employer			-0.0326	
			(0.0)	
Log of family income	0.1204	0.1042	0.0269	0.0179
	(0.0)	(0.0)	(0.0)	(0.0)
Type of coverage for families				
Private	0.2748			
	(0.0)			
Employer	-0.0882			
	(0.0)			
Any public	-0.375			
	(0.0)			
None	-0.0969			
	(0.0)			
Constant	5.8787	-6.9339	5.1219	5.6732
	(0.0001)	(0.0007)	(0.0001)	(0.0001)
N	43,117	20,111	16,389	10,127
AIC	201,961,442,569	125,470,058,832	51,022,220,526	32,704,598,089

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	$3,858
Elderly	$2,207
Nonelderly insured unrelated individuals	$2,125
B. Additional MOOP expense (probability)	
Families with nonelderly head	0.048
Elderly	0.094
Nonelderly insured unrelated individuals	0.093
Uninsured/Public health insurance	0.269
C. Additional MOOP expense (mean)	
Families with nonelderly head	$2,128
Elderly	$1,492
Nonelderly insured unrelated individuals	$992
Uninsured/Public health insurance	$701

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 6.8 percentage points, from 13 percent to 19.8 percent. Calculated in the ACS, MOOP increases the poverty rate for the elderly by a similar 6.9 percentage points, from 12 percent to 18.9 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 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	17.8%	-4.2	21.2%	-3.4
Children	21.1	-4.0	25.6	-2.9
Adults 18-64	17.6	-3.8	20.9	-3.1
Adults 65+	12.0	-6.9	13.0	-6.8
B. Under 50%				
All persons	4.9%	-1.2	5.8%	-1.3
Children	4.9	-0.8	5.9	-0.9
Adults 18-64	5.3	-1.2	6.3	-1.3
Adults 65+	2.5	-2.4	2.6	-2.3
C. 50 - 99%				
All persons	13.0%	-2.9	15.4%	-2.1
Children	16.2	-3.2	19.7	-2.0
Adults 18-64	12.4	-2.5	14.6	-1.8
Adults 65+	9.5	-4.5	10.3	-4.6

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

Looking at panels B and C of Table D3, about a third of the poverty rate increase for older adults due to the inclusion of MOOP occurs for those under 50 percent of the SPM threshold. In the ACS, the pattern is very similar for older adults. For working-age adults and for children, these patterns across the CPM and the SPM are not as clear.

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 (age 18 or older) earners, 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. 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 1,464 and 2,443, 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 (1)	Child care expense amount (2)	Any child care expense (3)	Child care expense amount (4)
One adult	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Two adults	0.02	1365.93	0.00019	722.49
	(0.2)	(700.14)	(0.15)	(572.78)
Three or more adults	-0.38	1132.55	-0.45	-1034.08
	(0.28	(1050.43	(0.28	(889.59
Any adult age 18-24	-0.34	-1234.4	-0.19	-862.38
	(0.21	(735.15	(0.26	(837.4
Any adult age 65 or older	-0.15	1995.29	-0.78	-3273.24
	(0.76	(3255.87	(0.63	(1242.19
One child	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Two children	0.38	2461.80	-0.32	234.87
	(0.13	(568.18	(0.13	(493.57
Three children	0.21	2875.85	-0.61	1071.15
	(0.18	(837.03	(0.19	(895.8
Four or more children	0.18	2358.66	-0.38	265.62
	(0.26	(1050.04	(0.29	(1170.22
Youngest child preschool age	0.77	1235.47		
	(0.16	(696.98		
Youngest child elementary school age	-	-	3.40	1396.78
			(0.29	(1031.35
White, non-Hispanic	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Black, non-Hispanic	0.24	-2231.83	-0.05	-2472.99
	(0.31	(1104.68	(0.27	(681.44
Asian, non-Hispanic	-0.47	-1446.52	-0.29	566.7
	(0.22	(982.7	(0.22	(892.58

	Preschool age sample (youngest child under age 6)		School age sample (youngest child age 6-17)	
	Any child care expense **(1)**	**Child care expense amount** **(2)**	**Any child care expense** **(3)**	**Child care expense amount** **(4)**
Other race, non-Hispanic	-0.31	-258.43	0.96	-1957.08
	(0.37	(1821.33	(0.36	(767.99
Hispanic, any race	-0.01	-2654.38	0.19	-1446.65
	(0.15	(687.64	(0.16	(556.88
Any member foreign born	0.12	1176.55	-0.07	-1006.19
	(0.14	(594.3	(0.14	(504.73
Highest adult education, no HS degree	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Highest adult education, HS degree	-0.19	1140.78	0.17	-500.91
	(0.25	(719.32	(0.27	(1182.23
Highest adult education, some college	0.22	1940.71	0.49	-733.5
	(0.24	(740.64	(0.26	(1171.65
Highest adult education, college	0.56	4782.00	0.97	-9.10
	(0.24	(806.03	(0.26	(1196.84
Any TANF/GA (self-reported)	-0.53	-1541.74	-0.67	4359.09
	(0.35	(869.58	(0.69	(1251.76
Any SNAP (self-reported)	-0.64	-1220.70	-0.55	-1821.21
	(0.25	(587.06	(0.36	(703.01
Bay Area /northern coastal	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Central	-0.42	-4122.75	-1.14	-760.46
	(0.29	(1105.11	(0.31	(1006.41
Los Angeles	-0.28	-2068.06	-0.27	655.52
	(0.21	(1057.23	(0.19	(701.37
Orange/San Diego	0.17	-3178.13	-0.3	595.27
	(0.22	(1054.71	(0.21	(703.2
Southern coastal	-0.63	-2301.54	-0.75	-1838.13
	(0.32	(1413.91	(0.35	(695.78
Northern inland	0.04	-4138.06	-0.42	-1188.01
	(0.24	(1089.22	(0.22	(688.9
Inland Empire	-0.09	-3400.75	-0.62	-434.51
	(0.25	(1147.08	(0.26	(1236.93
Unidentified counties (in CPS)	0.03	420.02	-0.51	603.55
	(0.23	(1249.47	(0.22	(954.73
Reference period: 2011	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Reference period: 2010	0.13	-20.36	-0.02	-752.49
	(0.15	(617.18	(0.14	(540.59
Reference period: 2009	0.07	786.75	-0.11	-458.92
	(0.15	(625.4	(0.14	(583.34
Constant	-1.21	3352.12	-4.09	4387.01
	(0.39	(1564.43	(0.43	(1560.56

	Preschool age sample (youngest child under age 6)		School age sample (youngest child age 6-17)	
	Any child care expense (1)	Child care expense amount (2)	Any child care expense (3)	Child care expense amount (4)
Observations	1,464	632	2,443	504
Pseudo-R-squared/ R-squared	0.06	0.29	0.20	0.12

SOURCES: Authors' calculations from the 2010-2012 CPS-ASEC (IPUMS) and the 2011 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 42 percent of predicted probabilities. In the case of the sample of those with a youngest child age 6-17, it is the top 19 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	1
$3,500 to $4,499	1	1
$4,500 or more	8	12
B. Mean out-of-pocket expenses, selected groups		
Any child	$1,009	$1,069
Any child, positive out-of-pocket expenditures	$5,889	$7,244
No adults with earnings, or more adults than adult earners in poverty unit	$223	$0*
All adult(s) report earnings, youngest child infant or preschool age	$3,204	$3,687
All adult(s) report earnings, youngest child elementary school age or older	$980	$1,164

SOURCE: Authors' calculations from the 2010-2012 CPS-ASEC (IPUMS) and the 2011 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 small amount ($60, or about 6%). For poverty units that have positive out-of-pocket expenses, we overstate these costs by $1,355, or 23%). 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 $483 (15%) higher than in the CPS, and for units with older children, we impute costs that are on average $184 (19%) 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. For example, the poverty threshold for a family of two adults and two children ranges between about $19,500 and $37,500, and the differences we find in child care expenses are between several hundred and about $1,400—or less than 10 percent of the lowest threshold for this family size. Final imputed, unit-level child care expenses in the ACS range between $0 and $15,379.

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 adult's earnings (or the earnings of the lower-earning adult, if there is more than one earner in the unit).[34] Table D.10 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–child care, 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.[35] 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 at an individual's earned income over the same period (so that imputed work expenses can never exceed total income derived from employment).[36] 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 2011, the median

[34] Higher earning adults in the unit have only their work expenses capped at their earnings.
[35] 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.
[36] 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*$27.16=$190.12).

value of work expenses reported in Wave 7 of the 2008 SIPP was $31.95.[37] We calculate 85 percent of this amount to obtain a base amount of weekly non-discretionary work-related expenses for the 2011 CPM: $27.16 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 2011 averaged just over 44 weeks of work, while working individuals in households below the official poverty line averaged just less than 34 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 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 ($4.89) 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 $4.89 to capture non-commute related work expenses and other miscellaneous expenses associated with those workers.

As Tables D6 and D7 illustrate, the number of individuals who work from home or who walk or bike to work represents a meaningful portion of the poor and near-poor workforce (as measured by the official poverty line). Cumulatively, these three categories of worker represented 11.4 percent of working individuals in households below the CPM poverty thresholds in 2011. 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.

[37] Amount obtained from Kathleen Short of the U.S. Census Bureau in 2012.

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	1,762,151	76.7
Bus or trolley bus	212,896	9.3
Bicycle	45,760	2.0
Walked	108,914	4.7
Worked at home	108,828	4.7

SOURCE: Authors' calculations from 2011 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 annual work expenses by commuting method for Californians age 16 and older with earnings

Poverty Status	Drivers	Bikers/Walkers/Work at Home	All
All workers	$1,280	$224	$1,185
All workers under 150% FPL	1,139	201	1,278

SOURCE: Authors' calculations in 2011 ACS.

Sensitivity Analysis and Comparison of Alternative Imputation Approaches

Other supplemental poverty measures have developed their own approaches to imputing work-related expenses. These methodological innovations are typically motivated either by the availability of localized commuting cost data or by known patterns of commuting behavior.

Marks et al. (2011) modify the Census routines with adjustments for the assumed difference in rural and non-rural commuting costs. Using data from the 2009 National Household Transportation Survey, they find that persons living outside metropolitan areas on average drive significantly farther to and from work than persons living in metropolitan areas. They then impute a proportionally higher commuting expense for rural workers than metro workers.

While rural commuters may drive more miles from home to work nationally, the evidence that non-metro commuters in California pay higher commuting costs than their metro counterparts is less clear. Our analysis of California commuters in the 2011 ACS reveal that metro drivers spend an average of 26.54 minutes driving to work, while non-metro drivers spend 22.92 minutes.38 Moreover, it is reasonable to assume that metro workers in California pay higher prices for gasoline than workers in more rural areas, as well as higher costs for parking and other expenses associated with urban and suburban environments. For these reasons, we decided against a metro/rural adjustment in the CPM.

Table D8 compares the average annual work expenses for Californians in the 2011 ACS under three separate methodologies: 1) our approach, which makes an adjustment for workers with presumably low commuting costs, 2) the Census approach, and 3) the IRP approach, which adjusts for metro and non-metro workers.

[38] This difference is statistically significant at the 5 percent level.

TABLE D8
Work expenses under alternate imputation approaches

	CPM	Census	IRP
Average individual work expenses, poor workers (OPM)	$823	$915	$908
Average annual work expenses, poor workers with 48.5+ weeks worked (OPM)	$1,214	$1,381	$1,369

SOURCE: Authors' calculations in 2011 ACS.

There are other approaches for imputing work-related expenses to the ACS as well. The NYC CEO, for example, uses several New York City data sources to impute different daily commuting fares for each different method of transport indicated in the ACS. Thus, individuals who commute via subway receive a different cost imputation than those who commute via ferry or bus. While such an attempt at differentiating between commuting options is worthwhile, it is much less feasible for a geographic area as large as California, where public transportation fares vary widely from city to city. Table D9 reviews the differences between the CPM's and other SPM approaches to imputing work expense.

TABLE D9
Comparison of SPM work expenses imputation

Approach	Weekly base expense derived from SIPP	Includes adjustment for non-commuting expenses	Adjustment for metro/rural commuters	Adjustment for commuters with presumably minimal commuting cost	Adjustment for other commuting methods
Census SPM	X	X			
IRP	X	X	X		
NY CEO				X	X
CPM	X	X		X	

Limitations

There are several limitations to our work expenses imputation model. First and foremost, 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 (Rapino et al., 2011). This systematic underestimate of commuting costs is likely compounded by our assignment of lower work-related expenditures for workers with presumably minimal commuting expenses (walkers, bikers, stay-at-home workers).

It is also worth noting that although our assignment of minimal work-related expenses ($4.89/week) for walkers, bikers, and stay-at-home workers is intended to capture the cost of uniforms, tools, and other non-commute related work expenses, we inadvertently capture some public transportation costs due to the nature of the "work-related expenditures" questionnaire developed in the SIPP. However, we believe these public transportation costs to be a relatively small component of our estimate that may in fact help compensate for non-discretionary work expenses associated with biking to work, walking to work, or working from home (such as the cost of bicycle maintenance and repair).

We can explore alternate methods of imputing non-discretionary work-related expenses in future iterations of the CPM. 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—a more than 700 percent increase from the statewide average of $1,125 produced by our methodology.

Table D10 compares the effect of work-related expenses (combining transportation and child care) in the CPM to the one-year estimates for California in the SPM. Despite the difference in methodologies, the net effect on poverty rates is similar, with the work expenses in the CPM having a slightly larger effect on child poverty than work expenses in the one-year SPM.

TABLE D10
SPM for California and CPM if work-related expenses are excluded

	CPM poverty rates absent commuting and child care expenses (%)	Percentage point difference from CPM	SPM poverty rates absent commuting and child care expenses (%)	Percentage point difference from SPM
A. Under 100%				
All persons	19.7	-2.3	22.4	-2.2
Children	21.9	-3.2	25.7	-2.8
Adults 18-64	19.0	-2.4	21.6	-2.4
Adults 65+	18.3	-0.6	19.3	-0.5
B. Under 50%				
All persons	5.6	-0.5	6.6	-0.5
Children	5.2	-0.5	6.3	-0.5
Adults 18-64	5.9	-0.6	7.1	-0.5
Adults 65+	4.8	-0.1	4.8	-0.1
C. 50%-99%				
All persons	14.1	-1.8	15.7	-1.8
Children	16.8	-2.6	19.4	-2.3
Adults 18-64	13.2	-1.7	14.5	-1.9
Adults 65+	13.5	-0.5	14.4	-0.5

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

NOTE: California sample for 2011 CPS has 19,847 observations. Negative percentage point differences shown in the table imply that the actual CPM is higher.

Appendix E: Supporting Tables

Tables E1 through E3 below provide the estimates that correspond to the figures shown in the main body of the report. In many cases the report figures do not show estimates separately for adults between the ages of 18 and 64 . The tables below provide those estimates. In addition, we systematically present the estimates for those under 50 percent of the CPM poverty threshold and those between 50 percent and 99 percent of the threshold.

The estimates presented in Table E1 correspond to Figures 1 and 2 in the report. Table E1 provides 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	22.0 [21.6-22.5]	6.1 [5.9-6.3]	15.9 [15.5-16.3]
Children	25.1 [24.4-25.8]	5.7 [5.4-6.0]	19.4 [18.7-20.1]
Adults 18-64	21.4 [21.0-21.9]	6.5 [6.2-6.7]	14.9 [14.5-15.3]
Adults 65+	18.9 [18.3-19.6]	4.9 [4.6-5.3]	14.0 [13.4-14.5]

SOURCES: Authors' calculations from the California sample of the 2011 ACS (350,673 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).

The estimates presented in Table E2 correspond to Figures 3, 4, and 5 in the report.

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 (%)
Absent CalWORKs			
All persons	23.3	6.7	16.6
Children	27.6	6.9	20.7
Adults 18-64	22.4	6.9	15.5
Adults 65+	19.2	5.1	14.1
Absent SSI			
All persons	23.4	7.3	16.1
Children	26.1	6.3	19.9
Adults 18-64	22.7	7.7	15.0
Adults 65+	21.8	7.7	14.0
Absent CalFresh			
All persons	24.2	7.2	17.0
Children	29.2	7.8	21.4
Adults 18-64	23.0	7.3	15.7
Adults 65+	19.5	5.2	14.3
Absent school meals			
All persons	22.6	6.3	16.3
Children	26.3	6.2	20.1
Adults 18-64	21.8	6.6	15.1
Adults 65+	19.0	5.0	14.0
Absent EITC/CTC			
All persons	25.3	7.3	17.9
Children	31.1	7.8	23.3
Adults 18-64	24.0	7.6	16.4
Adults 65+	19.4	5.1	14.3
Absent housing subsidies			
All persons	23.4	7.1	16.3
Children	27.0	7.3	19.7
Adults 18-64	22.3	7.2	15.1
Adults 65+	21.5	5.8	15.6
Absent all programs together			
All persons	30.4	13.7	16.8
Children	39.0	18.2	20.8
Adults 18-64	28.1	12.5	15.6
Adults 65+	24.5	10.0	14.5

SOURCES: Authors' calculations from the California sample of the 2011 ACS (350,673 observations) and auxiliary data sources as described in these technical appendices.

NOTES: Estimates in the table correspond to Figures 3-5 in the report. CalWORKs combines CalWORKs and GA. Tax assistance combines the EITC and the refundable portion of the CTC. School meals combines school breakfast and school lunch. "All programs together" simultaneously removes all the programs or program combinations listed in the earlier rows of the table. Small differences in reported percentage point program effects shown in the figure and the overall rates shown in the table are due to rounding.

The estimates presented Table E3 show the role of Social Security in CPM rates.

TABLE E3
CPM rates absent Social Security

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
Absent Social Security			
All persons	27.2	10.4	16.8
Children	26.7	6.5	20.2
Adults 18-64	24.1	8.5	15.6
Adults 65+	45.2	29.7	15.5

SOURCES: Authors' calculations from the California sample of the 2011 ACS (350,673 observations) and auxiliary data sources as described in these technical appendices.

The estimates presented in Table D3 and Table D10 (showing the role of expenses) correspond to Figure 7 in the report. The estimates presented in column 1 of Table E4, showing CPM rates if we assign the entire state the housing costs of Fresno, correspond to Figure 8 in the report. For comparison purposes, we also show CPM rates in a mid-cost county (Sacramento) and in a high-cost county (Los Angeles).

TABLE E4
CPM rates, thresholds simulation

	Fresno	Sacramento	Los Angeles
A. Under 100% of poverty threshold (%)			
All persons	15.0	18.6	23.2
Children	16.2	20.8	26.7
Adults 18-64	14.8	18.2	22.4
Adults 65+	13.3	16.1	19.6
B. Under 50% of poverty threshold (%)			
All persons	4.8	5.5	6.3
Children	4.3	5.1	6.0
Adults 18-64	5.2	5.9	6.7
Adults 65+	3.8	4.3	4.9
C. 50-99% of poverty threshold (%)			
All persons	10.2	13.1	16.8
Children	11.9	15.7	20.6
Adults 18-64	9.6	12.3	15.8
Adults 65+	9.5	11.8	14.6

SOURCES: Authors' calculations from the California sample of the 2011 ACS (350,673 observations) and auxiliary data sources as described in these technical appendices.

NOTE: Estimates in panel A of the table correspond to Figure 8 in the report. Small differences in reported percentage point program effects shown in the figure and the overall rates shown in the table are due to rounding.

Appendix F: CPS-SPM Comparison

There are some important differences between the ACS and CPS-ASEC that result in differences in their poverty estimates. One of the main differences is the purpose of these surveys. The CPS seeks to collect information on the labor force characteristics of the U.S. population. The ACS seeks to collect basic demographic characteristics and other information previously collected by the Census long-form.[39] Second, the surveys vary in when they are fielded, with the ACS a rolling survey throughout the year and the CPS-ASEC fielded in the spring only. Importantly, the sample size of the two surveys varies greatly. For the nation, 2,128,104 housing units and 148,486 individuals in group quarters were interviewed in the ACS.[40] The 2012 March supplement of the CPS included 201,398 people in its sample.[41] For California, the 2011 ACS sample included 193,822 housing units and 14,244 individuals in group quarters. The 2012 CPS sample for California included 19,738 people.

Both surveys are instrumental for measuring poverty, given their large scope and key questions about household composition and resources. However, they vary in the level of detail on both. With regard to resources, both the ACS and CPS ask about household income which can be used to calculate official poverty rates. For the broader poverty measures estimated in the SPM and CPM, differences on income questions in the two surveys become important. The ACS and the CPS both ask questions about income sources for those age 15 and older, but the data collection methods of the two surveys are different; and the questions pertaining to income are much more detailed in the CPS than in the ACS. The ACS collects information on eight different income sources, with single questions for each item:

1. Wages and salary
2. Self-employment
3. Interest, dividends, rental, and royalty
4. Social Security
5. SSI
6. Public assistance
7. Retirement
8. Other

The CPS uses a series of questions designed to identify over 50 income sources. The CPS is able to ask more questions and use a more complex question design than the ACS because the CPS uses CATI/CAPI[42] for its data collection, whereas the ACS uses a mail mode (using CATI/CAPI only to follow up on nonresponses). Because the main mode of data collection for the ACS is by mail, there are no interviewers to help respondents in interpreting the questions, so the questions that are asked need to be more straightforward to promote high response rates. Because data on the CPS are collected by interviewers, the structure of the questions can be more complex. The detailed income questions in the CPS enable more granular SPM calculations that are difficult to replicate in ACS-based estimates of the CPM. Where possible, we have

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[39] U.S. Census Bureau online fact sheet, "Differences Between CPS ASEC and ACS." Available at www.census.gov/hhes/www/poverty/about/datasources/factsheet.html.

[40] For sample size information for other years and states, see www.census.gov/acs/www/methodology/sample_size_data/.

[41] See https://cps.ipums.org/cps/sample_sizes.shtml.

[42] CATI/CAPI stands for Computer-Assisted Telephone Interviewing/Computer-Assisted Personal Interviewing. CATI is telephone interviewing with the aid of a computer for skip patterns and response entry. CAPI entails an in-person interview, with the aid of a laptop to enter responses.

created methods to obtain similar breakdowns from the ACS, for example in our algorithm for splitting GA and TANF income.

Both surveys also ask households about other, non-cash resources and expenses that are important to estimating supplemental poverty measures. In fact, questions were added to the CPS specifically to allow for estimation of the Research Supplemental Poverty Measure. These questions obtain information on the value of SNAP received, housing subsidies, and non-discretionary expenses incurred. The ACS does not contain a similar set of questions, so we impute the dollar amounts by augmenting the ACS with auxiliary data sources.

While the detailed SPM-relevant questions in the CPS are quite useful in estimating new measures of poverty, they suffer from the same sorts of reporting bias or measurement error as encountered in standard income and program participation questions. One advantage of our approach using the bigger ACS sample for California is to develop methodologies for correcting underreporting of income and program participation. This correction is another source of difference between CPM estimates generated from self-reported data in the CPS versus similar data in the ACS corrected for underreporting.

Comparison of ACS and CPS Official Poverty Rates

Table F1 compares the official poverty rates as reported in the 2012 CPS and the 2011 ACS. The samples used exclude respondents living in group quarters.

TABLE F1
Official poverty measure, CPS / ACS comparison

	CPS (%)	ACS (%)
All persons	17.0 [0.5]	16.2 [0.1]
Children	24.7 [1.1]	23.1 [0.2]
Adults 18-64	15.6 [0.5]	14.6 [0.1]
Adults 65+	8.2 [0.6]	9.6 [0.2]

SOURCES: CPS-ASEC (2012) and ACS (2011).

NOTE: Standard errors, calculated using replicate weights, in brackets (99% level). Both sets of estimates are computed excluding those in group quarters and others not in the poverty universe for purposes of the official poverty measure.

The official poverty rates reported by both the CPS and the ACS are not identical—and generally speaking they are somewhat lower calculated in the ACS as compared with the CPS. The exception is the poverty rate for older adults, which is higher. The differences seen here in poverty rates stem from the time period considered in each survey, sample size and variability differences, and survey collection differences between the ACS and CPS.

Comparison of Supplemental Poverty Measures in the ACS and the CPS

Table F2 compares CPM estimates of poverty based on the ACS with those calculated from the CPS using Census Bureau-created SPM variables for the California sample. In particular, we make the comparison between the role of cash and in-kind programs in lowering the poverty rate across the two data sources.

TABLE F2
Poverty absent social safety net programs – SPM / CPM comparison

	All persons		**Children**		**Adults**		**Elderly**	
	SPM	CPM	SPM	CPM	SPM	CPM	SPM	CPM
Under 100% of poverty	23.8%	22.0%	27.6%	25.1%	22.8%	21.4%	20.9%	18.9%
Percentage point change when:								
No EITC/CTC	3.0	3.3	5.8	6.0	2.3	2.6	0.2	0.5
No SNAP	1.0	2.2	2.0	4.1	0.7	1.6	0.2	0.6
No housing subsidies	1.2	1.4	1.5	1.9	0.8	0.9	2.9	2.6
No school meals	0.5	0.6	1.0	1.2	0.4	0.4	0.0	0.1
No TANF/GA	0.5	1.3	0.9	2.5	0.4	1.0	0.0	0.3
No SSI	1.3	1.4	0.6	1.0	1.2	1.3	2.9	2.9

SOURCE: CPS values calculated from IPUMS-CPS 2012 extract. Small differences in reported percentage point program effects and the overall rates are due to rounding.

Overall, we see that the SPM estimates of poverty in California are somewhat higher than the CPM estimates—in line with the differences across data sources in the official poverty calculation. At the same time, the role of programs is nearly always larger in the CPM than in the SPM. For example, the percentage point differences if we remove the SNAP and TANF programs from family resources is over twice as large in the CPM as compared to the SPM. This is likely due to the adjustments described in Appendix C made to correct for survey underreporting of these benefits.

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