Technical Appendices

The California Poverty Measure: 2014

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Abbreviations

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

Introduction and Changes in Methodology from Prior CPM Reports

The goal of these technical appendices is to provide detailed information on the methods, assumptions, and validation exercises undertaken by researchers at the Stanford Center on Poverty and Inequality and the Public Policy Institute of California in jointly creating the California Poverty Measure (CPM) for 2014 and developing a revised dataset for all years of the CPM (2011 through 2014). It updates two earlier appendices. The original Technical Appendix document (published with the release of 2011 CPM data) can be found on the Public Policy Institute of California web site[1], and the first revision Technical Appendix (published with the release of 2012 CPM data) can be found on the Stanford Center for Poverty and Inequality web site[2]. This Technical Appendix describes subsequent innovations to the CPM methods reflected in the 2013 and 2014 CPM and revised 2011-2014 CPM dataset using 2014 CPM methods.

The key motivation for developing the CPM is to provide a 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 or estimated using a variety of data sources and methods. This introduction provides an overview of major changes adopted for the 2014 CPM data construction, where methods differ from those described in the two prior CPM technical appendices. Appendix A provides an overview of the data sources and methodology used to construct the 2014 CPM. Appendices B through F describe in detail the CPM components for which we adopt a new imputation approach for 2014, or substantially modify the methodology described in prior technical appendices. Appendix G provides supplemental data tables including overall 2014 CPM poverty rates, poverty rates excluding specific resources and expenses, and county-level CPM thresholds and sample sizes.

Methodology Changes Implemented in CPM 2014

In general, the methodology used to construct CPM 2014 is very similar to that used to construct earlier versions of the CPM, as described in prior CPM Technical Appendices. However, we make a few corrections and improvements to the methods for the 2014 poverty measure. All changes have also been made in revised

[1] See http://www.ppic.org/main/publication.asp?i=1070.
[2] See http://inequality.stanford.edu/publications/research-reports.

data files using CPM 2014 methods for the entire time series of CPM data (2011-2014). Substantial changes to the CPM methodology reflected in CPM 2014 and the revised CPM 2011-2014 dataset include the following:

Enhanced imputation of SNAP and TANF participation. SNAP and TANF benefits are calculated using a two-step procedure (assign participation and then calculate benefit amounts) and two major sources of data (administrative records and ACS survey data). For the CPM 2014, we refine the procedure by exploiting the Current Population Survey to improve our first step of assigning participation. Although both SNAP and TANF participation are reported in the American Community Survey, the main data source for the CPM, both are underreported relative to administrative totals, so a fraction of eligible non-reporters are assigned participation. We've improved this procedure by estimating the probability of participation based on other household characteristics in 5 years of Current Population Survey data, which contains more detail overall than the ACS. This change does not affect the number of SNAP or TANF participants, but can affect the socioeconomic distribution of participating units. Details of the methodology described in Appendix B.

Inclusion of WIC (Special Supplemental Nutrition Program for Women, Infants, and Children) in CPM resources. Estimates of WIC benefits were added in the 2013 CPM for the first time and have been incorporated for all years in the revised 2011-2014 CPM dataset. WIC is not directly reported in the ACS, the main data source for the CPM, so participation and benefit amounts are imputed, with details of the methodology described in Appendix C.

Changes to imputation of school breakfast and lunch. As in prior years of the CPM, for 2014 we use administrative data on school meal claiming and school meal reimbursement amounts from the California Department of Education in combination with family size, income, age, and public school enrollment status from the ACS to impute participation in free and reduce price breakfast and lunch. However for CPM 2014, we impute school meals at the level of the school district rather than the county.

Changes to imputation of income tax liabilities and credits. As in prior CPM methodology, for CPM 2014 we use the NBER's TAXSIM tax calculator to estimate income tax liabilities and credits. In contrast to the methods described in earlier technical appendices, as of CPM 2013 we adopted a new process to identify tax filers and allocate individuals into tax units, the preliminary step required to assemble the tax-unit-level income, expense, and dependents data that are subsequently input into TAXSIM to calculate income tax credits and liabilities for each filer. This revised method of estimating taxes is used in CPM 2014 and the revised CPM 2011-2014 dataset, and is described in detail in Appendix D.

Changes to imputation of medical out-of-pocket expenses (MOOP). In contrast to the methodology for MOOP described in earlier technical appendices, as of CPM 2013 we adopted a simpler approach to estimating MOOP at the CPM unit level, aligned with the approach we continue to use for estimating child care expenses. Appendix E describes this revised MOOP methodology, used in CPM 2014 and the revised CPM 2011-2014 dataset.

CPM Estimates with Original and Revised Methodology

Table 1 shows CPM poverty estimates under the original methodology for each year and under the current revised methodology as of CPM 2014.

	Original Published Estimates	Revised Estimates Using CPM 2014 Methodology
2011		
Under 100% CPM Poverty		
All persons	22.0%	21.8%
Children	25.1%	25.1%
Adults	21.4%	21.0%
Elderly	18.9%	18.8%
Under 50% CPM Poverty		
All persons	6.1%	6.3%
Children	5.7%	6.3%
Adults	6.5%	6.6%
Elderly	4.9%	5.2%
2012		
Under 100% CPM Poverty		
All persons	21.8%	21.3%
Children	25.2%	24.4%
Adults	21.1%	20.5%
Elderly	19.8%	19.6%
Under 50% CPM Poverty		
All persons	6.0%	6.1%
Children	5.2%	5.7%
Adults	6.4%	6.4%
Elderly	5.2%	5.4%
2013		
Under 100% CPM Poverty		
All persons	21.0%	21.2%
Children	23.9%	23.6%
Adults	20.3%	20.5%

Elderly	19.1%	19.5%
Under 50% CPM Poverty		
All persons	5.9%	6.0%
Children	5.0%	5.4%
Adults	6.4%	6.4%
Elderly	5.2%	5.3%

Readers interested in further comparisons of estimates from the CPM under the original and revised 2014 CPM methodologies may contact the authors.

Appendix A: Overview of CPM Methodology

The basic formula for the CPM follows that of the Supplemental Poverty Measure (SPM). First individuals are grouped into poverty units comprised of individuals living in the same household who are assumed to share resources. For each poverty unit, an annual net resources amount is calculated which represents the cash and near-cash resources available to meet basic needs. Resources include cash income (including cash benefits like Social Security, SSI, and TANF), plus near-cash in-kind benefits (e.g. food stamps, school meals). Nondiscretionary expenses including commuting costs, child care, and medical out-of-pocket expenses are subtracted from resources. Income and payroll taxes are subtracted from resources, while tax credits (e.g. EITC) are added to resources. The resulting net resource amount for the poverty unit is then compared to a poverty threshold that is based on national contemporaneous expenditures on food, clothing, shelter, and utilities, adjusted for family size, and adjusted for the local cost of housing. All individuals in poverty units with net resources less than this adjusted poverty threshold are considered poor.

Detailed descriptions of the methods used to construct the different CPM components are available in the Technical Appendices for prior years, with updated methods for the items that are new or substantially modified in the CPM 2014 methods described in Appendices B through D here. In this section we provide an abbreviated description of the estimation approach used for each of the components of the CPM:

Poverty units: Within a given ACS household, individuals are assigned to one or more poverty units by grouping together all individuals identified in the data as related by blood, adoption, or marriage, as well as cohabiters and their blood and marriage relatives, and foster children.

Poverty thresholds: We begin with the baseline national SPM thresholds produced by the Census Bureau and Bureau of Labor Statistics, which include separate thresholds for renters, owners with mortgages, and owners without mortgages. To adjust thresholds for geographic differences, we multiply the shelter portion of the SPM threshold by the ratio of housing costs in each county or county group identified in ACS data compared to national housing costs, calculated using five-year ACS data on housing costs for two- and three-bedroom rented or owned dwellings. Unlike Census SPM procedures, we apply a “dual index” for these geographic adjustments, separately adjusting for owners without mortgages versus renters and owners with mortgages. This approach allows us to account for California’s state-specific property tax policy

(Proposition 13), which results in lower housing costs for long-term homeowners. Finally, we use the Census-developed SPM equivalency scale to adjust thresholds for family size and composition.

Unauthorized immigrants: We identify individuals who are likely unauthorized immigrants generally following the methodology outlined by Passel and Cohn (2009). Starting with the pool of noncitizen immigrants identified in ACS data, we apply a series of logical edits to remove individuals likely to be holders of valid legal authorization as indicated by country of origin with widespread amnesty or visa programs, occupations that require legal status (e.g. police officer, lawyer), or marriage to a U.S. citizen. From the remaining pool of noncitizens, we randomly assign "likely unauthorized" status to individuals matching to the DHS estimate of the total state population of unauthorized immigrants as well as estimates of the county-level distribution of the unauthorized population identified in Hill and Johnson (2011). Unauthorized immigrant status is used in the imputation of some components of family resources described below.

We turn next to CPM resource and expense components. The basic estimation approaches for each of these items are outlined in Table A1 and described in more detail below.

Table A1
CPM resource and expense components and estimation approach

CPM/SPM resource and expense components	In ACS?	Adjustments for CPM estimate
RESOURCES		
Wage and salary income	Yes	No
Self-employment income	Yes	No
Social Security income	Yes	No
"Welfare" income (TANF and GA)	Yes	Yes (underreporting adjustment for TANF)
Interest and dividend income	Yes	No
Pension income	Yes	No
SSI income	Yes	No
Alimony, child support, veteran's benefits, unemployment benefits, workers' compensation benefits, other income	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 amount imputation)
Income tax credits (EITC, ACTC)	No	Yes (imputation)
School meals	No	Yes (imputation)
WIC	No	Yes (imputation)
Housing subsidies	No	Yes (imputation)

LIHEAP (energy subsidy)	No	Not included in CPM
EXPENSES		
Income tax and payroll tax liabilities	No	Yes (imputation)
Child care expenses	No	Yes (imputation)
Other work-related expenses	No	Yes (imputation)
Medical out-of-pocket expenses	No	Yes (imputation)

Resources

Cash income: We use self-reported cash income (including cash benefits) from ACS data, adjusted for the rolling dates of data collection in the ACS. The one exception for which we do not use self-reported data is TANF income, discussed below.

SNAP and TANF: We use California state administrative data on SNAP and TANF participation to augment self-reports in the ACS. Further, we use administrative survey data to model benefit amounts which are self-reported for TANF but not for SNAP in the ACS. We assign eligibility for SNAP at the simulated program unit-level based on income less than 175% of FPL for SNAP and 125% of FPL for TANF. We take self-reported participation as given and randomly assign participation to other income-eligible units within county-race-household size cells to match administrative totals. We use a model based on unit characteristics in the administrative survey data to calculate benefits for all self-reported and imputed participants. Unit members who receive SSI or who are flagged as unauthorized are excluded from this calculation, though are assumed to share benefits within the poverty unit, as with other resources.

School meals: School meals participation is not reported in ACS data. We thus impute school meals participation and benefit amounts using ACS and administrative data. We begin by assigning school meal receipt to public school students who are categorically eligible to receive free meals based on program rules (foster children and SNAP and TANF recipients). We then randomly assign free or reduced school meal receipt to public school students with income within 133 percent of the income eligibility cutoffs (to allow for monthly income fluctuations), matching to school district-level administrative data on school meals claimed, using separate benchmarks for schools with different grade levels and adjusting for district-level attendance records.

Housing subsidies: Housing subsidy receipt is not reported in ACS data. We thus impute housing subsidy receipt by first developing a linear regression model predicting subsidy receipt in 3-year California CPS data, then applying the regression coefficients to the pool of renter household heads in our ACS data. We assign housing subsidy receipt to household heads identified as having the highest probability of subsidy receipt until we match the percentage of renters reporting subsidies in the CPS data. We disallow receipt for households where all individuals are identified as likely unauthorized immigrants. We then estimate the value of the imputed subsidy as equal to the county-specific Fair Market Rent for the housing unit size, less the tenant payment, estimated at 30 percent of household income. The housing subsidy amount plus the tenant payment is capped at the value of the shelter portion of the poverty threshold, following Census SPM procedures.

WIC: WIC receipt is not reported in the ACS. We compute eligibility using age of child (age 0-5 in the data, which covers the 12 months prior to the survey month). Women ages 16-44 who meet other criteria are deemed eligible, as are women who have infants (age 0-1 in the data). Income eligibility is defined as family income less than 1.33 times the eligibility ceiling (185 percent of FPL). All those who report Medicaid, or who are foster children, or who are imputed to get SNAP or TANF benefits are also deemed income eligible. We then randomly assign receipt to match administrative totals for women, infants, and children served by county. Months on WIC are also assigned randomly, assuming that a constant share of infants and children will age into and out of eligibility throughout the year, and that a constant proportion of women will become pregnant throughout the year. Monthly benefit amounts are based on Vericker and Zhen (2013).

LIHEAP: These near-cash energy benefits are included in resources for the Census SPM, but are not reported in ACS data and we do not impute values for them. Census calculations show that they have a generally small impact on SPM poverty rates.

Income tax liabilities and credits: Income tax credits are included in household resources for the CPM, while income tax liabilities are subtracted from resources as non-discretionary expenses. Income taxes are not self-reported in ACS data. We impute income taxes using the NBER's TAXSIM tax calculator. We first assign individuals to tax units following IRS rules and using relationship pointers in the IPUMS ACS data file. We allow for strategic claiming of EITC qualifying children within households to maximize total household EITC eligibility. We then sum income as reported in the ACS across tax units, and input these values into TAXSIM to calculate income tax liabilities and credits. Finally, we adjust the TAXSIM estimates to exclude ineligible tax filers from receiving the EITC, namely individuals we have identified as likely unauthorized immigrants. For 2014 only, we also separately calculate liability and amounts of the Affordable Care Act personal responsibility payment (the tax penalty assigned for not carrying health insurance).

Expenses

Payroll taxes: Payroll taxes are not self-reported in the ACS. We estimate payroll taxes using the TAXSIM tax calculator using self-reported wage/salary and self-employment income.

Child care expenses: Child care costs are not self-reported in the ACS. We impute child care expenses by first developing regression models predicting any expenses and the amount of expenses for SPM poverty units in 3-year California CPS data. We exclude all units without children, units without adult earners, and units with more adults than adult earners, as these households are categorically assigned zero child care expenses in Census SPM procedures. We develop separate regression models for families with a youngest child age 5 or younger versus a youngest child of school-age. We then apply the coefficients from these models to our ACS data, using parallel family categories, to predict child care expenditures at the poverty-unit level.

Other work-related expenses: We estimate commuting and other necessary work-related expenses largely following Census SPM procedures. We assign a flat weekly expense to all employed individuals used in Census SPM procedures, which is derived from national work expenses reported in the SIPP. Diverging from Census procedures, we reduce the weekly amount for individuals who report in the ACS that they work from home or walk or bike to work. We then multiply the weekly amount by the self-reported number of weeks worked. Finally, we cap the total work-related expenses plus child care for the poverty unit at the earnings of the lowest earner in the unit, following Census SPM procedures.

Medical out-of-pocket expenses: Medical expenses are not self-reported in the ACS. We impute these expenses following a procedure similar to our child care expense imputation. First we develop regression models predicting any medical out-of-pocket expenses and the amount of expenses for SPM poverty units in 3-year California CPS data. We develop separate regression models for families that include and do not include seniors. We then apply the coefficients from these models to our ACS data, using parallel family categories, to predict medical out-of-pocket expenditures at the poverty-unit level.

Appendix B: SNAP and TANF

We assign SNAP and TANF participation and model benefit amounts for each program, so that ACS aggregates to administrative totals for 2014. This year, we tested one step in that procedure: assigning participation to units that did not self-report. Previous technical appendices (2011, 2012) describe the full procedure in detail. In this appendix, we document alternative approaches to assigning participation.

In 2011-2013 CPM, we used administrative tabulations of the SNAP and TANF caseload at the county, race, household composition level to assign participation to eligible non-reporting units in the ACS. Eligible units were assigned a random number and within each demographic cell (of which there are roughly 38 count x 4 race x 8 composition = 1216 cells) were assigned receipt based on the ordering of the random number, until the participating units summed to administrative totals. In essence, we assumed that for a given county, race, and household type (say, single parents with 2 children), all eligible units had an equal probability of participation.

In 2014, we decided to explore a probabilistic approach to this procedure by assigning participation to eligible non-reporters in descending order of the probability of participation, instead of randomly, within county-race-composition cells. To estimate this probability, we use ACS self-reported participation and unit characteristics beyond those included in the administrative data. Although ACS self-reports understate true participation (which is why we undertake these corrections in the first place), research suggests that after self-reporting, household income and composition explain most of the variation in true SNAP receipt (Mittag, 2013).[3] Mittag also uncovers a U-shaped relationship between income and misreporting, with SNAP reporting most accurate for households at 50-100% of the federal poverty line. Furthermore, other work finds that underreporting of SNAP is not correlated with age or race (Li, 2013). This suggests that our original approach using administrative data at the county-race-composition level corrects for much of the underreporting in the ACS but that a method that accounts for other characteristics like age and/or income might improve the procedure. So we undertake an ACS model of participation that assumes that the correlation we estimate between self-reported participation and certain covariates in the ACS are closer to true correlations among participants than random assignments. Although most of the research evidence on underreporting pertains to SNAP, we apply the same correction to our TANF participation procedure.

[3] Mittag (2013) also finds that SNAP underreporting is worse in the CPS than the ACS, so although we explored a CPS prediction model, we opted to rely on the ACS. Also note that overreporting SNAP is highly infrequent.

We estimate participation models for SNAP and TANF separately, using the following OLS specification:

$$y_{it} = \alpha + \sum_j \beta Income_i * (PovertyRatio = j) + \phi Education_i + \gamma Age_i + \varepsilon_{it}$$

where y is either SNAP or TANF participation, i indicates unit, and t indicates year. Education and Age are categorical indicators for the highest education level in the unit or the age of the oldest member, respectively. A unit's total cash income is entered into the model continuously, for units at five (*j*) different levels of poverty status (*PovertyRatio*). Coefficients for models of both SNAP and TANF participation are shown below.

Table B1: OLS models of SNAP and TANF participation, California ACS 2014

	SNAP self-reported participation	TANF self-reported participation
Income * Poverty (<50)	7.25e-06**	3.73e-06**
	(1.53e-07)	(8.21e-08)
Income * Poverty (50-100)	1.31e-05**	2.88e-06**
	(1.19e-07)	(6.41e-08)
Income * Poverty (100-150)	3.51e-06**	2.16e-07**
	(7.17e-08)	(3.86e-08)
Income * Poverty (150-200)	4.48e-07**	-1.61e-07**
	(5.46e-08)	(2.93e-08)
Income * Poverty (>200)	-3.15e-07**	-7.66e-08**
	(6.07e-09)	(3.26e-09)
Max education less than high school	0.146**	0.0373**
	(0.00218)	(0.00117)
Max education high school graduate	0.0759**	0.0186**
	(0.00141)	(0.000756)
Max education some college	0.0225**	0.00376**
	(0.00134)	(0.000720)
Max age 26-35	-0.0847**	-0.00726**
	(0.00218)	(0.00117)
Max age 35-45	-0.114**	-0.0209**
	(0.00209)	(0.00112)
Max age 45-55	-0.144**	-0.0344**
	(0.00209)	(0.00113)
Max age 55-65	-0.159**	-0.0466**
	(0.00217)	(0.00117)
Max age 65+	-0.195**	-0.0538**

	SNAP self-reported participation	TANF self-reported participation
	(0.00210)	(0.00113)
Constant	0.215**	0.0523**
	(0.00179)	(0.000962)
Observations	357,237	357,237
R-squared	0.130	0.037

SOURCE: Author calculations from the 2014 ACS for California.

NOTES: Linear probability models. "Max" values based on all individuals in SNAP/TANF assistance units as assigned for CPM. Standard errors in parentheses, ** p<0.01, * p<0.05

Using these models we predict the probability of participation for each eligible non-reporting unit in the ACS. We then order the data based on the predicted probability within the county-race-composition cell, and assign SNAP or TANF participation to enough units until we match administrative totals. This ensures that we preserve the true distribution of participation at the county-race-composition level but also accounts for variation in participation across age, income, and education characteristics.

In the end, we assign participation in SNAP and/or TANF to almost exactly the same number of units or people in the 2014 ACS. This is because with either random assignment or our imputation-based assignment, we are matching the same administrative caseload totals. However, the characteristics of the estimated caseload may vary, especially along the dimensions identified by the participation model. The characteristics of the caseload under alternative approaches (as well as actual characteristics and self-reported) are in the following table. Because much of the variation in participation is explained by county, race, and household composition, our revised approach using probabilistic assignment conditional on administrative cells ("probabilistic conditional assignment") does not substantially alter the characteristics of the imputed caseload compared to the original approach ("conditional assignment").

The first sets of characteristics (family composition, race, and family size) are levels on which participation is matched to administrative data in both methods, so little difference is (or should be) observed in the 2 approaches. The next sets of characteristics are those explicitly accounted for in the new participation models. Note that these characteristics are correlated, in some cases, with the administrative characteristics (i.e. age is correlated with household composition) and that both approaches include a random assignment element. The probabilistic conditional assignment approach distributes SNAP participation to slightly younger individuals and both SNAP and TANF participation to slightly less educated units. For SNAP, the new approach also estimates a caseload with a lower income-to-needs ratio, and more units within 50-100%

of the federal poverty line, which is closer to the correlation reflected by self-reported participation (and supported by research evidence cited above). For TANF, the participation model imputation pushes the caseload to a slightly higher income-to-needs ratio and slightly less deeply poor distribution (relative to FPL).

Overall these shifts are quite small under the revised approach.

Table B2: Comparison of SNAP and TANF participation

	SNAP Participants				TANF Participants			
	Actual	Self-reported	Conditional assignment	Probabilistic Conditional Assignment	Actual	Self-reported	Conditional assignment	Probabilistic Conditional Assignment
Family type (% units)								
Child only	13.0%	11.5%	12.7%	12.8%	31.3%	1.7%	25.3%	24.0%
Single adult	43.8	43.4	44.6	44.7	1.6	24.5	1.9	7.8
Multiple adult, no child	4.8	6.3	5.4	5.4	0.4	7.6	0.2	1.5
Single parent	24.2	23.6	23.1	23.1	50.1	41.9	53.4	44.9
Multiple adult, children	14.2	15.2	14.1	14.1	16.6	24.2	19.1	21.8
Race (Head of unit)								
Other	17.1%	10.8%	15.9%	16.0%	13.5%	11.6%	13.3%	12.8%
White	21.9	25.4	25.8	25.7	17.9	23.2	18.4	18.4
Black	12.3	10.5	13.7	13.7	16.0	14.2	15.8	13.8
Hispanic	48.7	53.4	44.6	44.5	52.5	50.9	52.5	55.0
Number in unit (mean)		2.2	2.1	2.1		2.8	2.9	2.9
Number children in unit (mean)		1.1	1.0	1.0		1.4	1.9	1.8
Age (Head of unit)								
0-18		11.5%	12.7%	12.8%		1.7%	25.3%	23.9%
18-26		17.9	18.6	25.7		14.1	15.7	13.8
26-35		21.8	20.2	19.3		31.4	22.5	22.1
35-45		17.9	16.5	15.8		28.3	20.8	20.6
45-55		13.5	13.0	11.8		15.8	11.3	13.0
55-65		10.0	9.7	8.4		5.3	3.4	4.2
65+		7.4	9.3	6.3		3.4	1.1	2.2
Max education (Unit)								
Less than high school		15.4%	12.6%	14.1%		22.5%	12.0%	12.1%

High school		37.6	34.6	37.4		40.8	31.9	31.1
Some college		24.4	26.3	24.9		24.4	21.8	22.5
College grad		7.6	10.8	8.3		8.2	6.7	7.6
Unit's Cash Income (mean)		$13,032	$11,978	$11,857		$19,444	$10,370	$13,122
Income:Poverty, OPM (mean)		129	142	133		130	110	122
Income:Poverty, OPM (%)								
0-50 (deep poverty)		23.0%	21.4%	21.1%		28.6%	29.1%	26.3%
50-100		27.1	24.6	29.4		27.8	32.4	29.1
100-150		20.1	20.6	20.2		14.6	16.7	19.1
150-200		11.2	11.8	10.5		8.9	7.5	8.7
200+		18.6	21.5	18.8		20.1	14.2	16.9

SOURCE: "Actual" from California Department of Social Services administrative data, "Self-reported" calculated from 2014 ACS, "Conditional assignment" uses CPM 2011-2013 methodology and "Probabilistic conditional assignment" uses revised method described here.

NOTES: Participation is estimated at the CPM "SNAP unit" level, which approximates program assistance units and is distinct from the Census household or CPM poverty unit definitions (i.e. child only cases are possible, and multiple SNAP units can exist within a single household or poverty unit). Education values do not sum to 100% since education is undefined for child-only units (all under age 18).

Appendix C: The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC)

WIC is a federally funded program administered locally in California by 84 local WIC agencies and overseen by the California Department of Public Health. California's FY 2014 grant amount was more than 1.2 billion dollars.[4] The WIC program serves enrolled infants, children up to age 5, and pregnant and postpartum women by providing vouchers for specified foods and infant formula. To be eligible for WIC, women and young children must

- Have incomes under 185% of the federal poverty line (about $36,600 for a family of 3 in 2014), or currently enrolled in Medi-Cal, CalWORKs, or CalFresh; and
- Be determined to have nutritional risk.

Most women WIC participants enroll in the first trimester of pregnancy, and infants are typically enrolled at birth or very soon after; in 2012, 92.5 percent of infants nationwide were between 0 and 3 months old at time of enrollment.[5] WIC provides vouchers for specified, nutritious foods like fruits, vegetables, whole grains, and formula for infants if the mother is not breastfeeding.[6] Applicants are said to be adjunctively eligible if currently receiving benefits from Medi-Cal, CalWORKs, or CalFresh, meaning that they need not meet the income test for eligibility. WIC applicants must also be determined to be at nutritional risk by a health professional. Nutritional risk includes medical characteristics like being under- or overweight or anemia and dietary conditions such as poor diet.[7] WIC also offers nutrition education classes, provides breastfeeding promotion and support, and seeks to connect recipients with other safety net programs they may be eligible for. Participants are certified eligible for 12 months (infants and children) and for shorter periods of time (women); at the end of a recertification period, participants must show again that they meet eligibility criteria. The Healthy Hunger-Free Kids Act of 2010 lengthened the recertification period for children from 6 months to 1 year.[8]

Methodology

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[4] See http://www.fns.usda.gov/wic/wic-funding-and-program-data
[5] See page 43 for time of enrollment for women, infants, and children http://www.fns.usda.gov/sites/default/files/WICPC2012_Summary.pdf
[6] Information on WIC food package contents http://www.fns.usda.gov/sites/default/files/ops/PC2012-Summary.pdf
[7] Information on the nutritional risk requirement www.fns.usda.gov/wic/wic-eligibility-requirements
[8] See page 8 for more information on the Healthy Hunger Free kids Act http://www.fns.usda.gov/sites/default/files/PL111-296_Summary.pdf

We proceed by identifying eligible women, infants, and children in the ACS and then assigning WIC receipt to the eligible group to reach total recipients as recorded in administrative data for each county.

Defining eligible children and infants

Eligible children and infants in the ACS are defined to be those who:

- Are reported by the survey respondent to be age 1 or younger for infants, and age 0 to 5 for children and;
- Are in an economic unit (see below) with income less than 247% of the FPL (see below) or;
- Is flagged as receiving CalFresh or CalWORKs as imputed in our dataset, or is reported to be on Medicaid, or is reported to be a foster child.

Defining women eligible for WIC

Eligible women ACS are defined to be those who:

- Are reported by the survey respondent to be female and between the ages of 16 and 44 and;
- Are in an economic unit (see below) that has an income less than 247% of the FPL (see below) or;
- Is flagged as receiving CalFresh or CalWORKs as imputed in our dataset, or is reported to be on Medicaid.

Note that we are unable to determine pregnancy status and therefore only select women based on their age. Note as well that we cannot in the ACS distinguish between mothers of infants who are breastfeeding vs. formula feeding. As described below, we do assign WIC receipt first to women with infants imputed to receive WIC.

We assign adjunctive eligibility based on imputed receipt of TANF and SNAP (as described in Appendix B). We rely on self-reported family relationships to determine foster care status, implying that we undercount categorically eligible foster children. The ACS estimate of the number of foster children age 0-5 in California in 2014 is 10,910 while the actual quarterly average number of foster children age 0-5 in California in 2014 was about 10,000-22,000, depending on whether children placed with relatives, guardians, and pre-adoptive families are included or excluded.[9]

Defining economic units

We use the same definition of “economic unit” as we do when imputing school meals (see Appendix D).

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[9] See http://cssr.berkeley.edu/ucb_childwelfare/. Children under 5 in all types of foster care—including relative, guardian, and adoptive placements—are eligible for WIC. In addition, the point-in-time measure available in the ACS is an undercount of children ever in foster care during the year.

Defining income for the purposes of WIC 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 the applicable poverty guideline. However, the typical reference period used in applications to determine income eligibility for WIC is the 30 days prior to filling out the application.[10] In the ACS, the reference period is a moving 12-month window (depending on survey month, which is not a publicly available data element). Therefore, to allow for monthly fluctuations in income that may make a person eligible for part of the year, we use an income cut-off that is a third higher than the 185 percent FPL standard, or 247 percent of FPL.

Imputation approach, receipt of WIC

We obtained counts of WIC vouchers redeemed by participants by county of residence from the California Department of Public Health. These recipient counts are further disaggregated by race/ethnicity (Latino, non-Hispanic white, non-Hispanic African-American, non-Hispanic Asian, and non-Hispanic all other/not recorded) and are also disaggregated into counts of women, infants and children. Disaggregated data were not provided in the case of small cell sizes. No cells for Latino and white recipients are suppressed. We make the simplifying assumption that the share of all recipients in the race/ethnicity categories is identical across the categories of participants (women, infants and children), and calculate counts by race/ethnicity within each category in all cases where cell size restrictions permit.

We use these counts of participants by race/ethnicity and category to assign WIC receipt to the ACS sample determined to be eligible for WIC as described above. We adjust the counts upwards to reflect the number of unique individuals ever on WIC during the calendar year by making the simplifying assumption that, once certified eligible, all infant and child recipients receive WIC for 12 months, and that women recipients receive WIC for 9 months. In other words, we assume that the caseload of infants and children turns over by 1/12th each month, while the caseload of women turns over by 3/12th. This results in multiplying infant and child administrative totals by 1.92 and women administrative totals by 3.75.

To assign receipt, we randomly select eligible infants and children by race/ethnicity and county to receive WIC until we meet or exceed 95 percent of the applicable adjusted administrative recipient count. In the case of women, we first assign all mothers of infants imputed to receive WIC. Mothers and infants are linked using the IPUMS "momloc" flag. We match 706,613 mothers this way. (This number includes both mother/infant pairs that are income eligible for WIC and those that are not.) In a few instances (408) males

[10] See page 7 for income eligibility determination period http://www.fns.usda.gov/sites/default/files/2013-3-IncomeEligibilityGuidance.pdf

are identified as mothers, and some identified mothers (13,098) are not between the ages of 16 and 44. In both cases, we drop these matched mothers.

After imputing WIC to mothers of imputed infants, we then add additional eligible women (by race/ethnic group and county) to reach or exceed 95 percent of the applicable administrative total. We use 95 percent rather than 100 percent as a stopping point because ACS 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.

We then assign a number of months of WIC receipt during the calendar year. Because we have only year of birth in the ACS, infants are randomly assigned a value between 1 and 12. Children are assigned 12 months of receipt if their reported age is 2, 3, or 4, and children age 5 are randomly assigned a value between 1 and 12. Women are assigned a value between 1 and 9.

Finally, we assign a monthly dollar value to the WIC package (Table C1). We use the average amount by each participant category as determined for 2010 in a report commissioned by the U.S. Department of Agriculture, Food and Nutrition Service.[11] Weights for pregnant, breastfeeding, and postpartum women—determined from WIC caseload data—are 0.67, 0.17, and 0.17, respectively. Pre-rebate amounts are used, which increases the monthly amount for infants substantially ($126 vs. the post-rebate amount of $54). Nonetheless, we judge this a reasonable approach because in the absence of WIC, the cost of infant formula would be the retail price.[12] To arrive at final dollar amounts for 2014, we update dollar amounts for inflation using the CPI-U-RS and multiply by the number of months a recipient is imputed to be on WIC during the calendar year.

Table C1
Monthly Benefit Amounts for Women, Infants and Children

Women	$49.18
Infants	$125.87
Children	$40.71

SOURCE: FNS Fiscal Year 2010 WIC Food Cost Report. http://www.fns.usda.gov/sites/default/files/WICFoodCost2010_0.pdf

NOTES: Amounts are derived from national estimates for 2010 adjusted for inflation to 2014. We use the pre-rebate amount for infants.

Our imputation method results in assigning 70.3 percent of infants we determine to be WIC-eligible in the ACS to WIC receipt, and 71.8 percent of children.

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[11] See http://www.fns.usda.gov/sites/default/files/WICFoodCost2010_0.pdf.

[12] Of course this approach does not take into account potential incentive to switch from breastfeeding to formula feeding when the WIC program is available.

Table C2 lists imputed total WIC recipients and aggregate dollar amounts for women and children age 0-5 (infants and children) combined. Counts for infants and children are combined because an individual ACS sample member may be imputed to receive WIC as both an infant and as a child (nonetheless capped at a total of 12 months). Our imputation methods result in assigning a total of $256 million in WIC benefits to 1.05 million women and $811 million in WIC benefits to 1.44 million infants and children in California in 2014. According to the Food and Nutrition Service, U.S. Department of Agriculture, California had $764 million in food costs net of rebates from the infant formula manufacturer, and rebates totaled $236. This actual total is 94 percent of the total dollar amount assigned using our procedure statewide. In other words, we overcount the value of the WIC program by 6 percent statewide as compared to the administrative total. The mean annual value of WIC imputed is $243 for women and $555 for infants and children (combined).

Geography	Women		Infants and children	
	Recipients (thousands)	Amount (millions)	Recipients (thousands)	Amount (millions)
Statewide	**1,054**	$255.5	**1,438**	$811.1
Alameda	31	$7.9	39	$20.4
Alpine, Amador, Calaveras, Inyo, Mariposa, Mono, Tuolumne	3	$0.9	4	$2.1
Butte	6	$1.6	7	$4.3
Colusa, Glenn, Tehama, Trinity	5	$1.1	6	$3.1
Contra Costa	19	$4.4	22	$12.6
Del Norte, Lassen, Modoc, Plumas, Siskiyou	3	$0.8	4	$2.3
El Dorado	3	$0.5	3	$1.3
Fresno	46	$11.6	66	$38.4
Humboldt	3	$0.8	4	$2.2
Imperial	7	$1.9	11	$6.1
Kern	40	$9.5	56	$33.1
Kings	6	$1.8	8	$4.4
Lake, Mendocino	5	$1.1	6	$3.6
Los Angeles	314	$76.9	446	$251.5
Madera	8	$2.2	9	$6.0
Marin	3	$0.6	4	$2.4
Merced	13	$3.5	18	$10.0
Monterey, San Benito	19	$4.5	25	$13.6
Napa	3	$0.6	4	$2.1
Nevada, Sierra	1	$0.3	2	$0.8
Orange	64	$15.6	96	$54.2
Placer	3	$0.8	5	$2.7
Riverside	69	$15.9	97	$52.9
Sacramento	42	$10.4	53	$30.3

San Bernardino	70	$16.7	100	$55.7
San Diego	79	$18.9	103	$58.2
San Francisco	10	$2.6	10	$6.2
San Joaquin	26	$6.0	34	$18.4
San Luis Obispo	5	$1.0	5	$2.6
San Mateo	10	$2.4	13	$7.1
Santa Barbara	15	$3.4	18	$10.3
Santa Clara	26	$6.1	35	$19.1
Santa Cruz	7	$1.8	9	$4.8
Shasta	5	$1.3	6	$3.1
Solano	10	$2.1	11	$6.3
Sonoma	9	$2.6	10	$6.0
Stanislaus	17	$3.9	22	$12.2
Sutter, Yuba	6	$1.5	8	$4.7
Tulare	21	$4.7	30	$17.4
Ventura	18	$4.2	24	$14.7
Yolo	5	$1.1	6	$3.9

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

Limitations

We make several simplifying assumptions: that once certified eligible and participating, children and infants remain on WIC for a year and women remain recipients for 9 months. In other words, we do not allow for program drop-off or churning on and off the program. We can only determine income eligibility using annual, rather than monthly, income. We cannot determine eligibility by actual age of infants and children, and we cannot determine pregnancy or breastfeeding status for women. And we are unable to determine nutritional risk, which may be a limiting factor for a few otherwise eligible applicants. We have access to national-level dollar amounts for WIC benefits, not California-specific amounts.

Appendix D: School Breakfast and School Lunch

The approach followed for prior years of the CPM used administrative totals for county-level claiming of free and reduced price breakfast and lunch. In reality, the administrative totals are available at the school district level. For the 2014 CPM (and as revised backwards for 2011-2013), we assigned free and reduced-price school meal receipt at the level of the school district. We did this using the geographic crosswalk between Census Public-Use Microdata Area (PUMA) and school district developed by the Missouri Federal Statistical Data Center.[13] Please see the earlier CPM Technical Appendix for other details of how school meal eligibility, receipt, and values are assigned in the CPM data.

[13] See http://mcdc.missouri.edu/websas/geocorr12.html.

Appendix E: Income Tax Liabilities and Credits

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

To estimate income taxes, we first identify likely tax filers and allocate individuals into income tax filing units. We then sum income sources, expenses, and numbers of dependents by tax unit, and use these data as inputs into the TAXSIM program of the National Bureau of Economic Research (NBER), which we use to model net federal and state income taxes paid.[14] The ACS includes self-reported wages and self-employment income, which are the primary inputs determining the value of the Earned Income Tax Credit (EITC) and refundable Additional Child Tax Credit (ACTC), allowing for reasonably robust estimation of the low-income tax credits that comprise the tax policy with the largest impact on poverty as measured under SPM-like measures such as the CPM.

Creation of Tax Units

In the initial CPM methods, we used the "MetroTax Model" developed by the Brookings Metropolitan Policy Program to identify tax filers and create tax units in ACS data.[15] However, because of inconsistencies in the way this model allocates dependents, and challenges in adapting this model to explore potential changes to tax policy (e.g. changes to EITC structure), as of CPM 2013 we developed a new approach to allocating individuals in the ACS into tax units. This new approach was used for CPM 2014 and the revised 2011-2014 CPM dataset using CPM 2014 methods.

Our primary objective is to maximize accurate estimation of EITC claiming, as the EITC is the component of tax policy with the largest impact on CPM poverty rates, and we judge our success by comparing our results to IRS administrative data on EITC participation for California. We begin by using the relationship pointers included in IPUMS ACS data (imputed by IPUMS based on self-reported relationships to the household head) to identify families, subfamilies, and unrelated individuals within each ACS household and assign

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[14] We also use TAXSIM to simulate payroll taxes paid. Our methodology for payroll taxes for CPM 2013 is essentially the same as in prior years of the CPM and is described in the 2011 and 2012 CPM Technical Appendices (Bohn et al., 2013 & 2015).

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

them to separate preliminary tax units. Within each tax unit, we identify all individuals who meet the requirements to count as potential “qualifying children” for the purposes of claiming the EITC, namely children ages 0 to 18, and young adults through age 23 who are enrolled in school. IRS rules specify that children claimed for the EITC must have valid Social Security Numbers, so we exclude all children flagged as unauthorized immigrants.

We next identify all individuals (and married couples) who are not potential EITC qualifying children and who are likely to be required to file taxes due to incomes above the minimum filing threshold. Where there is more than one likely required filer within a preliminary tax unit, the additional filers are moved into their own tax units (together with their spouses and children, again using the IPUMS ACS relationship pointers), leaving the highest-income filer in the original tax unit with any remaining dependents. Foster children are assigned to the tax unit of the household head.

We then apply a procedure to strategically allocate potential EITC qualifying children across tax units within each household in order to maximize the total amount of EITC that can be claimed by the household. IRS rules allow for some strategic claiming of dependents for the EITC, as a range of relatives are allowed to claim children for the EITC, and EITC qualifying children do not have to meet the dependent “support test.” Research shows that low-income families are strategic in their claiming of children for EITC purposes (Tach & Halpern-Meekin, 2014). Allowing for strategic claiming of dependents in extended or co-habiting families, versus requiring that all children are claimed by the parent with highest income, also results in aggregate statewide EITC amounts and total EITC filers that better match IRS administrative totals.

Within each ACS household (designated by "serial" within the data), we identify all of the potentially EITC-eligible tax filers, i.e. those with earned income who are not flagged as unauthorized immigrants. We then consider each potential EITC qualifying child in sequence. We provisionally assign the child to each of the potentially EITC-eligible tax filers within the household in turn and calculate the estimated EITC amount for all tax units in the household combined under each provisional tax unit assignment. The child's final tax unit assignment is the one that produces the largest household EITC total, across all tax units in the household. We then repeat the tax unit assignment procedure with each of the other potential EITC qualifying children in the household.

In strategically allocating EITC dependents, we only assign children to tax filers who are not coded as housemates, roommates, or boarders, and who are older than the child (per EITC rules). Also, children whose original tax units (typically headed by one or both of their parents) have incomes too high to qualify for the EITC are not reassigned to other tax units. We do reassign children to relatives and cohabiting partners who do not meet the specific criteria of the EITC qualifying child "relationship test" per IRS rules. We justify this deviation from EITC rules based on the uncertainty in the relationship pointers imputed by IPUMS, and because this process reflects common EITC tax filing strategies among low-income households (Tach & Halpern-Meekin, 2014), where children are often claimed by tax filers who do not meet all EITC relationship requirements (often due to confusion about the complex IRS rules, and sometimes as a result of deliberate deviation from IRS criteria). For CPM 2014 and the revised 2011-2014 CPM dataset we make some additional improvements compared to the method used for CPM 2013, including explicitly excluding children flagged as unauthorized immigrants from being claimed for EITC; allowing citizen/legal resident children whose parents are flagged as unauthorized immigrants to be claimed for EITC by other adults in their household who are citizen/legal residents; and ensuring that additional unmarried adults living in extended family households who do not qualify as dependents are marked as tax filers, with single filing status, if they are eligible for the childless EITC.

We next allocate dependents who are not qualifying children (e.g. co-resident elderly parents) based on IRS rules for the dependent support test and maximum qualifying relative income. Last, using the final tax unit assignments after allocating qualifying children and other dependents, we identify filing status (single, married joint, head of household, or dependent filer) and we classify individuals as income tax filers if they are required to file due to incomes above the minimum filing threshold or if their incomes are below the threshold but they qualify for the EITC.

We implicitly assume that all individuals who are required to file taxes, or are eligible to claim the EITC by filing taxes, do in fact file (this assumption is partly justified to better match IRS EITC totals from administrative data, as described below). Table C21 shows how the profile of tax filers in our CPM tax model compares to IRS administrative data for California. Overall, for 2014, the total number of filers equals 92 percent of the state administrative total. We find very similar shares of single, married joint, and head of household filers compared to IRS data.

Table C1
Tax filing status: IRS administrative data vs. CPM tax model, 2014

Filing status	Administrative data returns filed	Administrative data % of returns	CPM model returns filed	CPM model % of returns
Single	8.4 M	48 %	7.9 M	49 %
Married filing joint	6.3 M	36 %	5.8 M	36 %

Head of household	2.6 M	15 %	2.4 M	15 %
TOTAL	17.4 M	100 %	16.1 M	100 %

SOURCES: Administrative tax return data from IRS Statistics of Income (SOI) for California, tax year 2014. CPM tax model from authors' calculations in 2014 ACS data and auxiliary data sources. Note that 6 percent of filers in the CPM tax model are "dependent" filers (filers claimed as dependents by another individual in the household). These filers are included in the "single" filer totals above, as IRS SOI public-use data do not report dependent filers separately. Totals may not add to 100% due to rounding.

Tax Calculator

As in the original CPM methodology, we next input tax-unit-level income and expenses into NBER's TAXSIM tax calculator to compute federal income tax liability and California state income tax liability. As part of those calculations, TAXSIM also determines a tax unit's eligibility for and amount of EITC, Child Tax Credit and refundable Additional 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.[16]

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

We also make two corrections to the calculated federal income taxes to account for a lack of precision in the EITC estimates calculated through TAXSIM.[17] Tax filers with investment income above the allowed limit for EITC claimants are excluded from receiving EITC. This change affects fewer than 100 tax filers assigned EITC by TAXSIM. Another correction is required because TAXSIM does not distinguish between dependents who count as qualifying children for the EITC versus dependents who are not EITC qualifying children (e.g. an elderly parent supported by the tax filer). For CPM 2014 and the revised 2011-2014 CPM dataset, we thus manually exclude EITC amounts for tax filers whose dependents do not meet the criteria for EITC qualifying children.

Adjustments for Unauthorized Immigrants

Federal law requires all U.S. residents, including unauthorized immigrants, to file income taxes. All unauthorized immigrants do not in fact file taxes, but a substantial proportion do. Estimates of the

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

[17] In the original CPM methodology, we also corrected TAXSIM estimates for age limits on EITC eligibility for tax filers with no dependents. (Tax filers without child dependents may only claim the EITC if they are between the ages of 25 and 64.) However, in 2016 the TAXSIM program was revised to account for the age of tax filers in determining EITC eligibility, so this manual correction to the TAXSIM estimates is no longer needed.

proportion of unauthorized immigrants who file federal income taxes range from about half up to more than 80 percent (Hill & Johnson, 2011).

For the CPM tax model, we assume that all individuals identified as unauthorized immigrants in our sample file federal and state income taxes using an Individual Taxpayer Identification Number (ITIN) if they have taxable income above the required filing threshold. This assumption likely overestimates of the proportion of unauthorized immigrants actually filing income taxes. Implicitly we assume that families (immigrant or not) cannot be considered nonpoor unless their incomes are high enough to cover their income tax liabilities, even if some families "save" on these expenses by not filing required income tax returns.

The TAXSIM calculator does not account for immigration status of tax filers. However, the federal tax code prohibits individuals who lack a valid Social Security Number from claiming the EITC. Thus we adjust the TAXSIM output to eliminate EITC eligibility for those tax units in which we identify the tax filer to be a likely unauthorized immigrant. All other portions of the tax model remain the same for likely unauthorized individuals. Our method here differs from the method used in the initial methodology for the CPM, in which some unauthorized individuals were randomly assigned to file taxes with a Social Security Number and retain eligibility for the EITC, as a strategy to better match IRS administrative data on EITC claims and thereby correct for the error inherent in our survey data and imputations in order to approximate the impact of tax policy at the statewide level. With our revised tax unit assignment procedure, our EITC totals match administrative totals reasonably well, allowing us to avoid introducing this additional adjustment.

Comparison to IRS Tax Totals

Table C23 compares the results of our CPM tax simulation to IRS data publicly available for California. The results suggest that we fairly closely approximate the population of total filers across the state. Though we somewhat underestimate the total amount of refundable tax credit dollars flowing to Californians, our aggregate statewide totals equal 81 percent of total from administrative data for the EITC and 87 percent for the ACTC. Our calculated total number of filers eligible for these credits equals 91 percent of the IRS total for the EITC and 70 percent of the total for the ACTC. By comparison, the Census tax calculator in the CPS, used with data for California for 2014, produces an aggregate EITC amount equal to 75 percent of the IRS-reported total for the state, and a statewide number of EITC filers equal to 82 percent of the IRS total. (CPS estimates for the ACTC are not available separately.) Our CPM model thus produces less underestimation of EITC receipt for California than the Census CPS tax calculator, even after we adjust our estimates downward to account for ineligibility of unauthorized immigrants, a factor which is not accounted for in Census CPS tax data.

Table C2
Major tax credits: Administrative data vs. CPM tax model, 2014

Return figure	IRS data	CPM tax model	Ratio
Total state returns	17.4 M	16.1 M	0.92
EITC amount	$ 7,748.3 M	$ 6,238.4 M	0.81
EITC filers	3.3 M	3.0 M	0.91
CTC amount	$ 3,084.7 M	$ 3,128.0 M	1.01
CTC filers	2.7 M	2.5 M	0.93
ACTC amount	$ 3,592.6 M	$ 3,128.0 M	0.87
ACTC filers	2.6 M	1.8 M	0.70
Filers with AGI between $1 and $25K	6.3 M	5.3 M	0.83
Filers with AGI between $25K and $50K	4.0 M	3.9 M	0.97

SOURCES: Administrative tax return data from IRS Statistics of Income (SOI) for California, tax year 2014. CPM tax model from authors' calculations in 2014 ACS data and auxiliary data sources.

Limitations

As mentioned earlier and as reflected in the above comparison to administrative tax records, our tax simulation procedures are limited by the assumptions required to assign individuals to tax units, as well as the limited information about some types of income in the ACS. We also assume that every individual and family eligible to claim the EITC files a return and claims the credit, when in fact some eligible individuals fail to claim the credit, while others claim the credit in error. The disparity between the aggregated statewide EITC and ACTC benefits produced by our model and those reported by the IRS for 2014 may be attributable to several factors. These include errors in the identification and claiming of qualifying children compared to actual tax filer behavior, incomplete income information, uncertainty in the identification of unauthorized immigrant filers, and the inability to identify tax filers who claim children not living within their household of residence at the time of the ACS survey.

Sensitivity Analysis and Comparison to Census SPM

Table C24 illustrates the role of various components of the tax code on CPM poverty rates. Excluding all refundable tax credits from family resources results in a 3.2 percentage point increase in the CPM poverty rate overall and a 6.2 percentage point increase for children. The EITC alone results in a 2.2 percentage point reduction in overall CPM poverty and a 3.9 percentage point reduction of child poverty. Comparable figures for the Census SPM in CPS data for 2014 are similar, with a 2.1 percentage point reduction in overall SPM poverty attributable to the inclusion of EITC and a 4.2 percentage point reduction in SPM child poverty.

Excluding net income taxes (federal and state income tax liabilities net of credits) also results in an increase in the CPM poverty rate, indicating that on net, the role of refundable tax credits in reducing CPM poverty is larger than the role of net tax liabilities in increasing poverty.

Table C3
Effect on CPM poverty rates of excluding income tax credits and liabilities from family resources, 2014

	Poverty rates (%)			
	All persons	**Children**	**Adults (18-64)**	**Seniors (65 and older)**
CPM rate	20.6	23.1	20.1	18.7
Excluding EITC	22.8	27.0	21.9	19.2
Excluding ACTC	21.7	25.4	20.8	18.8
Excluding EITC + ACTC	23.8	29.3	22.7	19.3
Excluding net income tax liability/refund	23.4	29.1	22.0	19.2

SOURCE: Authors' calculations using 2014 ACS data and auxiliary data sources.

Affordable Care Act Personal Responsibility Payments

The personal income tax system is also used to administer federal penalties adopted under the "individual insurance mandate" of the Patient Protection and Affordable Care Act (ACA) for individuals who do not carry health insurance. These "shared responsibility payments" were first implemented in 2014. We identify individuals liable for these penalties following the criteria outlined in IRS tax filing guidelines, using self-reported ACS data on insurance status, calculated tax unit income, and assigned unauthorized immigrant status (as unauthorized immigrants are not liable for the penalty). Limitations of these ACS data for the purpose of identifying individuals who owe the ACA penalty include insurance status reported for a time period that differs from that used for the ACA penalty[18], and lack of information in the ACS about available

[18] ACS respondents report whether they lack insurance at the time of the survey, while the ACA penalty applies to individuals who have been uninsured for more than three months of the calendar year.

but unaffordable insurance offered by employers[19]. Initial results show a significantly larger share of tax units owing the ACA penalty than found in IRS administrative data for California, likely due to imprecision in the insurance data available through the ACS, as noted above. To address this issue, we randomly select tax units from among those initially identified as owing the penalty to match the share of tax units reported as paying the penalty in IRS data for California for 2014, and assign the ACA penalty to these tax units only. This results in 5.7 percent of tax units owing the ACA penalty.

Penalty amounts are calculated following IRS guidelines. Among tax filers owing the penalty, the average penalty amount is $323 and the median is $190. Like income tax liabilities, the ACA "shared responsibility payments" are considered a nondiscretionary expense subtracted from family resources when calculating CPM poverty status.

Tax credits created by the Affordable Care Act to subsidize health insurance costs are also administered through the personal income tax system. However, nearly all individuals eligible for these credits utilize the available "advance credit" option, which reduce insurance costs at the point of purchase rather than as a retroactive reimbursement. Because the advance credits thus reduce out-of-pocket costs, these subsidies are incorporated into reduced medical out-of-pocket expenses (as reported in the CPS, used to impute medical out-of-pocket expenses in the CPM ACS data) and do not need to be estimated separately.

[19] Individuals are exempt from the ACA penalty if they have been offered employer-sponsored insurance that is unaffordable to them according to specified criteria.

Appendix F: Medical Out-of-Pocket Expenses

To assign values for medical out-of-pocket expenses (MOOP) to ACS respondents, as of CPM 2013 we have followed a procedure similar to the method we use for estimating child care expenses, as described in the prior CPM Technical Appendices. This new MOOP method replaces the more complex procedure used to estimate MOOP expenses in the initial CPM methodology, as this simpler approach produces comparable results while allowing us to streamline production of the estimates. For CPM 2014, we begin by estimating two sets of regression models to predict medical expenses for the California CPS-ASEC sample for 2014 (as reported in the spmmedxpns variable), and we do this at the level of the SPM unit by selecting one individual from each SPM unit and applying household weights in all analyses.

We use a one-year 2014 CPS sample for the CPM 2014 MOOP estimates because the Affordable Care Act's individual mandate, health insurance subsidies, and Medicaid expansion were all fully implemented together for the first time in 2014, creating a substantially different health insurance policy context versus prior years. In addition, the health insurance questions in the CPS were changed beginning with the data for 2014, creating another discontinuity in the data. In estimating MOOP expenses for earlier years in the revised 2011-2014 CPM dataset, we used three-year CPS samples instead in order to take advantage of greater precision from a larger sample.

We stratify the sample into two groups: poverty units that include one or more individuals age 65 or older, and those that do not include any seniors. The first group is our senior families sample (n=1,738) and the second is our non-senior families sample (n=5,604).

We estimate two models for each sample. The first (logistic regression) models (Columns 1 and 3) predict whether an SPM unit has any MOOP expenses. The second (linear regression) models (Columns 2 and 4) predict, for those who have any expenses, the amount of those expenses. Note that the spmmedxpns variable in the CPS-ASEC comprises self-reported medical out-of-pocket expenses with an adjustment to account for Medicare Part B premiums for Medicare recipients.[20] We include in the models a set of family demographic, economic, and health insurance characteristics.

Type of health insurance is a key predictor in the model. As the implementation of the ACA in 2014 significantly affected prices and subsidies for health insurance purchased directly on the private market

[20] See https://cps.ipums.org/cps-action/variables/SPMMEDXPNS#description_section for details.

(primarily through the ACA marketplace), we explicitly account for this type of insurance in categorizing insurance type for CPM 2014. Thus the insurance categories for CPM 2014 include private – privately purchased, other private – not privately purchased (generally employer-provided), public, or uninsured. When imputing MOOP for years prior to 2014 in the revised 2011-2014 CPM dataset, we collapsed the two private insurance categories into a single private insurance category. Other predictors included for all years are family size, log of family income, race/ethnicity, immigrant in the family, and highest educational attainment within the family. The included variables are identical across the participation and amount models.

Table D1 provides the estimation results. Columns 1 and 3 include all observations for SPM units in the CPS-ASEC 2014 California with the sample characteristics described above. Columns 2 and 4 include only observations for units with positive MOOP expenses.

Table D1
Model estimates, medical out-of-pocket (MOOP) expenses

	Senior household sample (1+ individuals age 65+ in SPM unit)		Non-senior household sample (0 individuals age 65+ in SPM unit)	
	Any MOOP expense	MOOP expense amount	Any MOOP expense	MOOP expense amount
	(1)	(2)	(3)	(4)
Private insurance, privately purchased	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Other private insurance	-0.11	1898.73	0.44	1516.62
	(0.65)	(1050.47)	(0.23)	(252.27)
Public insurance	-1.62	-1820.59	-1.63	-2686.98
	(0.47)	(703.58)	(0.15)	(152.40)
Uninsured	-3.04	-2850.90	-1.90	-2377.72
	(0.92)	(1467.10)	(0.17)	(150.04)
1 person	(omitted category)	(omitted category)	(omitted category)	(omitted category)
2 people	0.02	2820.82	0.45	1353.01
	(0.37)	(749.14)	(0.16)	(194.97)
3 people	-1.16	1718.06	-0.66	2586.07
	(0.43)	(642.21)	(0.18)	(261.67)
4 people	-0.43	2625.51	-0.85	2815.48
	(0.85)	(680.11)	(0.18)	(238.61)
5 or more people	-1.24	3626.57	-0.62	3002.35
	(0.58)	(759.46)	(0.18)	(264.19)
Log of family income	0.29	463.36	0.09	239.59
	(0.05)	(110.88)	(0.02)	(35.13)
White, non-Hispanic	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Black, non-Hispanic	0.01	-1114.18	-0.08	-1505.98
	(0.57)	(555.61)	(0.21)	(210.76)
Asian, non-Hispanic	0.05	-546.53	-0.10	-926.76
	(0.47)	(556.80)	(0.22)	(277.54)
Other race, non-Hispanic	0.22	-1246.65	0.33	-392.40
	(1.13)	(933.36)	(0.35)	(471.15)
Hispanic, any race	0.33	-912.06	-0.15	-1466.72
	(0.44)	(439.94)	(0.15)	(226.10)
Any member foreign born	-0.39	-1186.25	-0.22	193.75
	(0.38)	(513.15)	(0.14)	(217.81)
Highest adult education, no HS degree	(omitted category)	(omitted category)	(omitted category)	(omitted category)
Highest adult education, HS degree	0.69	-64.22	0.32	-467.57
	(0.41)	(458.79)	(0.17)	(251.67)

Highest adult education, some college	1.96	-0.78	0.51	-34.47
	(0.56)	(538.55)	(0.18)	(231.44)
Highest adult education, college	1.02	2382.69	0.76	530.40
	(0.42)	(517.76)	(0.20)	(249.91)
Constant	1.01	-703.58	1.51	449.16
	(0.70)	(1641.61)	(0.29)	(384.59)
Observations	1,738	1672	5,604	5125
Pseudo-R-squared/ R-squared		0.08		0.15

SOURCES: Authors' calculations from the 2014 CPS-ASEC (IPUMS) and the 2014 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 household weights.

We then impute values for the California ACS sample using the model parameters developed in the CPS. We first predict the probability of any expenses, then rank the predicted probabilities and select the weighted fraction that corresponds to the weighted CPS fraction of respondents with any expenses in each of the two samples. In the case of senior households, it is the top 97 percent of predicted probabilities. In the case of non-senior households, it is the top 91 percent. After predicting expense amounts using the second set of models, we recode any predicted negative amounts to zero.

Table D5 provides the mean and median values of non-zero MOOP expenses by SPM unit reported in the 2014 California CPS-ASEC sample and compares it to the values we calculated in the ACS by CPM unit using the procedure described above. We present the values for all poverty units, and for poverty units with and without seniors. By design, we match the share of poverty units with no MOOP expenses. For poverty units with non-zero expenses, our estimated mean expenses in ACS data are relatively similar to but somewhat larger than mean expenses in the CPS, while our median expenses are larger by a greater magnitude.

Table D2
Mean and median values for medical out-of-pocket (MOOP) expenses, by SPM/CPM poverty unit, in California samples of CPS and ACS for 2014

	By SPM unit in CPS	By CPM unit in ACS
A. All SPM/CPM poverty units		
No expenses	7%	7%
Mean non-zero expenses	$ 4,408	$ 4,644
Median non-zero expenses	$ 2,500	$ 4,591
B. SPM/CPM poverty units with one or more seniors		
No expenses	3%	3%
Mean non-zero expenses	$ 5,891	$ 6,332
Median non-zero expenses	$ 3,660	$ 6,396
C. SPM/CPM poverty units with no seniors		
No expenses	9%	9%
Mean non-zero expenses	$ 3,855	$ 4,041
Median non-zero expenses	$ 1,900	$ 4,243

SOURCE: Authors' calculations from the 2014 CPS-ASEC (IPUMS) and the 2014 ACS (IPUMS).

Table D3 provides a comparison of the impact of subtracting MOOP from family resources on poverty status as calculated in the CPS for SPM poverty versus our calculations in the ACS for CPM poverty for year 2014. Calculated in the 2014 data from the CPS-ASEC for the California sample, MOOP increases the SPM poverty rate for senior individuals by 6.8 percentage points, from about 14 percent to about 21 percent. Per our calculations in the ACS, MOOP increases the CPM poverty rate for senior individuals by 6.3 percentage points, from 12.4 percent to about 19 percent. For children and working-age adults in California, the increase in the SPM poverty rate due to the inclusion of MOOP is about 3.5 to 4 percentage points in the CPS, while the increase in CPM poverty in the ACS is about 4 to 4.5 percentage points. Thus our calculations in the ACS for CPM 2014 somewhat overstate the effect of MOOP on the poverty rate for children and working-age adults, and somewhat understate the effect of MOOP for seniors, relative to the SPM in the CPS.

Table D3
Influence of medical out-of-pocket (MOOP) expenses on CPM (in ACS) and SPM (in CPS) poverty rates for California for 2014

	SPM (CPS) without subtracting medical expenses	Percentage point difference from baseline SPM	CPM (ACS) without subtracting medical expenses	Percentage point difference from baseline CPM
A. Under 100%				
All persons	17.9%	-4.0%	16.3%	-4.3%
Children	21.3	-4.1	18.5	-4.6
Adults 18-64	17.4	-3.3	16.2	-3.9
Adults 65+	14.2	-6.8	12.4	-6.3
B. Under 50%				
All persons	5.1%	-1.2%	4.5%	-1.4%
Children	4.6	-1.5	4.1	-1.1
Adults 18-64	5.5	-1.4	5.0	-1.2
Adults 65+	4.0	-2.7	3.0	-2.6

SOURCE: Authors' calculations from ACS and CPS-ASEC/IPUMS 2014 data as described in the text.

Overall, the MOOP estimation method we use for CPM 2014 (which we began using with CPM 2013) and for the revised CPM 2011-2014 dataset using CPM 2014 methods provides a better match to the distribution of MOOP values in the CPS and the effect of MOOP on SPM poverty rates in the CPS than the method used in the initial CPM methodology. Nonetheless, further improving the method for estimating MOOP values is an area for future work.

Appendix G: Supplemental Tables

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

Table G1 presents CPM poverty rates by age group with 99% confidence intervals, using the replicate weights created by Census and included on the public-use file. The standard errors presented in Table G1 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 G1
Californians in CPM poverty and deep poverty

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
All persons	20.6 [20.2, 21.1]	5.9 [5.7, 6.1]	14.7 [14.3, 15.1]
Children	23.1 [22.4, 23.8]	5.2 [4.8, 5.6]	17.9 [17.2, 18.6]
Adults 18-64	20.1 [19.6, 20.5]	6.2 [5.9, 6.5]	13.9 [13.5, 14.2]
Adults 65+	18.7 [18.1, 19.3]	5.6 [5.3, 6.0]	13.1 [12.6, 13.6]

SOURCES: Authors' calculations from the California sample of the 2014 ACS and auxiliary data sources.

NOTE: Confidence intervals, calculated using replicate weights, in brackets (99% level).

Table G2 presents CPM poverty rates by age group with resources from individual safety net programs excluded.

Table F2
CPM rates in the absence of social safety net programs

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
CPM with all resources included			
All persons	20.6%	5.9%	14.7%
Children	23.1	5.2	17.9
Adults 18-64	20.1	6.2	13.9
Adults 65+	18.7	5.6	13.1

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
Excluding CalWORKs (TANF) + GA			
All persons	21.7	6.4	15.3
Children	25.3	6.4	18.9
Adults 18-64	20.9	6.6	14.3
Adults 65+	19.1	5.7	13.4
Excluding SSI			
All persons	21.9	7.1	14.7
Children	24.1	5.8	18.2
Adults 18-64	21.3	7.4	13.9
Adults 65+	20.9	8.3	12.6
Excluding CalFresh (SNAP)			
All persons	22.8	7.2	14.7
Children	27.2	7.7	19.5
Adults 18-64	21.9	7.2	14.7
Adults 65+	19.4	5.9	13.5
Excluding school meals			
All persons	21.2	6.1	15.0
Children	24.2	5.8	18.5
Adults 18-64	20.5	6.4	14.1
Adults 65+	18.8	5.7	13.2
Excluding WIC			
All persons	21.0	6.0	14.7
Children	23.8	5.5	18.3
Adults 18-64	20.3	6.3	14.0
Adults 65+	18.8	5.6	13.2
Excluding EITC + refundable ACTC			
All persons	23.8	7.0	16.9
Children	29.3	7.2	22.2
Adults 18-64	22.7	7.2	15.5
Adults 65+	19.3	5.7	13.6
Excluding housing subsidies			
All persons	21.7	6.7	14.9
Children	24.4	6.5	17.9
Adults 18-64	20.9	6.9	14.0
Adults 65+	20.3	6.3	14.0

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
Excluding all programs above combined			
All persons	28.8	13.3	15.5
Children	37.1	17.8	19.3
Adults 18-64	26.8	12.2	14.5
Adults 65+	23.3	10.1	13.1
Excluding Social Security			
All persons	25.9	10.6	15.3
Children	24.7	6.2	18.5
Adults 18-64	22.9	8.4	14.4
Adults 65+	43.1	29.5	13.6
Excluding all programs above including Social Security			
All persons	33.5	18.3	15.2
Children	38.3	19.2	19.1
Adults 18-64	29.2	14.8	14.5
Adults 65+	45.5	33.9	11.6

SOURCES: Authors' calculations from the California sample of the 2014 ACS and auxiliary data sources.

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

Table G3
CPM rates without subtracting expenses from family resources

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
CPM with all components			
All persons	20.6%	5.9%	14.7%
Children	23.1	5.2	17.9
Adults 18-64	20.1	6.2	13.9
Adults 65+	18.7	5.6	13.1
Without subtracting payroll tax and income tax liabilities (before credits)			
All persons	20.8	6.2	14.6
Children	25.6	6.2	19.4
Adults 18-64	19.5	6.3	13.1
Adults 65+	18.4	5.6	12.8

	Under 100% of poverty threshold (%)	Under 50% of poverty threshold (%)	50%-99% of poverty threshold (%)
Without subtracting child care and other work-related expenses			
All persons	18.2	5.2	13.0
Children	19.8	4.4	15.4
Adults 18-64	17.6	5.4	12.1
Adults 65+	18.1	5.4	12.7
Without subtracting medical out-of-pocket expenses			
All persons	16.3	4.5	11.8
Children	18.5	4.1	14.4
Adults 18-64	16.2	5.0	11.2
Adults 65+	12.4	3.0	9.4

SOURCES: Authors' calculations from the California sample of the 2014 ACS and auxiliary data sources.

NOTES: Tax liabilities include federal payroll tax (FICA), federal income tax before credits, and state income tax before credits. Child care plus other work-related expenses are capped at the earnings of the lowest wage-earner in the CPM unit.

Table G4
CPM analysis sample, American Community Survey

County	Sampled individuals	Weighted children	Weighted adults 18-64	Weighted seniors 65+	Weighted population
California total	356,373	9.120 M	23.887 M	4.870 M	37.877 M

SOURCE: ACS 2014, accessed via the Integrated Public Use Microdata Series (IPUMS).

Table G5
CPM thresholds for a family of four (two adults, two children)

County	Renters		Owners with mortgage		Owners without mortgage	
	Threshold	Difference from official threshold	Threshold	Difference from official threshold	Threshold	Difference from official threshold
Alameda	$31,993	33%	$33,398	39%	$25,038	4%
Alpine	$26,356	10%	$27,000	12%	$22,011	-8%
Amador	$26,356	10%	$27,000	12%	$22,011	-8%
Butte	$25,523	6%	$26,962	12%	$20,808	-13%
Calaveras	$26,356	10%	$27,000	12%	$22,011	-8%
Colusa	$24,438	2%	$24,792	3%	$19,802	-18%
Contra Costa	$32,116	34%	$33,072	38%	$23,795	-1%
Del Norte	$24,375	2%	$24,892	4%	$20,552	-14%
El Dorado	$27,088	13%	$28,198	17%	$25,140	5%
Fresno	$24,792	3%	$25,464	6%	$21,466	-11%
Glenn	$24,438	2%	$24,792	3%	$19,802	-18%
Humboldt	$25,283	5%	$25,662	7%	$20,374	-15%
Imperial	$24,286	1%	$23,846	-1%	$20,788	-13%
Inyo	$26,356	10%	$27,000	12%	$22,011	-8%
Kern	$24,514	2%	$25,156	5%	$20,990	-13%
Kings	$23,807	-1%	$25,213	5%	$25,142	5%
Lake	$26,154	9%	$26,558	11%	$26,233	9%
Lassen	$24,375	2%	$24,892	4%	$20,552	-14%
Los Angeles	$30,841	28%	$32,287	34%	$23,511	-2%
Madera	$24,851	4%	$25,013	4%	$25,913	8%
Marin	$34,910	45%	$35,571	48%	$28,352	18%
Mariposa	$26,356	10%	$27,000	12%	$22,011	-8%
Mendocino	$26,154	9%	$26,558	11%	$26,233	9%
Merced	$24,202	1%	$24,788	3%	$23,571	-2%
Modoc	$24,375	2%	$24,892	4%	$20,552	-14%
Mono	$26,356	10%	$27,000	12%	$22,011	-8%
Monterey	$29,586	23%	$30,365	26%	$21,380	-11%
Napa	$32,306	35%	$32,584	36%	$23,963	0%
Nevada	$28,728	20%	$29,207	22%	$23,628	-2%
Orange	$34,034	42%	$35,009	46%	$23,707	-1%
Placer	$30,040	25%	$30,651	28%	$23,608	-2%
Plumas	$24,375	2%	$24,892	4%	$20,552	-14%
Riverside	$28,566	19%	$29,552	23%	$22,446	-7%
Sacramento	$27,611	15%	$27,883	16%	$21,926	-9%
San Benito	$29,586	23%	$30,365	26%	$21,380	-11%
San Bernardino	$27,304	14%	$28,170	17%	$21,533	-10%
San Diego	$31,355	31%	$32,265	34%	$23,476	-2%
San Francisco	$39,437	64%	$38,661	61%	$23,687	-1%

San Joaquin	$26,929	12%	$26,996	12%	$21,511	-10%
San Luis Obispo	$29,809	24%	$30,654	28%	$22,346	-7%
San Mateo	$37,061	54%	$38,736	61%	$26,879	12%
Santa Barbara	$32,398	35%	$33,353	39%	$22,859	-5%
Santa Clara	$35,344	47%	$36,585	52%	$25,863	8%
Santa Cruz	$33,661	40%	$33,960	41%	$23,687	-1%
Shasta	$26,485	10%	$27,079	13%	$25,643	7%
Sierra	$28,728	20%	$29,207	22%	$23,628	-2%
Siskiyou	$24,375	2%	$24,892	4%	$20,552	-14%
Solano	$29,516	23%	$30,284	26%	$21,084	-12%
Sonoma	$31,268	30%	$31,780	32%	$23,626	-2%
Stanislaus	$26,303	10%	$27,998	17%	$21,587	-10%
Sutter	$25,082	4%	$25,454	6%	$20,848	-13%
Tehama	$24,438	2%	$24,792	3%	$19,802	-18%
Trinity	$24,438	2%	$24,792	3%	$19,802	-18%
Tuolumne	$26,356	10%	$27,000	12%	$22,011	-8%
Tulare	$24,007	0%	$24,637	3%	$20,130	-16%
Ventura	$32,797	37%	$33,953	41%	$23,857	-1%
Yolo	$28,805	20%	$29,294	22%	$22,050	-8%
Yuba	$25,082	4%	$25,454	6%	$20,848	-13%

SOURCES: Authors' calculations from the California sample of the 2014 ACS and auxiliary data sources.

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