Reducing Child Poverty in California

A Look at Housing Costs, Wages, and the Safety Net

Technical Appendices

CONTENTS

Sarah Bohn and Caroline Danielson

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Appendix A. Background on the California Poverty Measure and Scenario Development

This appendix:

1. Briefly reviews the data and methodology used to create the California Poverty Measure (CPM);
2. Describes adjustments made to actual poverty estimates to create baseline poverty; and
3. Gives background relevant to all scenarios.

Succeeding Appendices B–F give additional background on each scenario and Appendix G presents margins of error for child poverty rates under each scenario and provides estimates for other populations.

California Poverty Measure Data

This report relies on 2012–2015 estimates from the CPM, a joint effort of researchers at PPIC and the Stanford Center on Poverty and Inequality (Bohn et al. 2013; Wimer et al. 2015). The CPM is a research effort to create a detailed, California-specific version of the Census Bureau's Supplemental Poverty Measure (Renwick and Fox 2016), which is itself a more up-to-date and comprehensive picture of poverty. To do so, CPM researchers augment single-year American Community Survey (ACS) public-use micro data with additional data sources, including the Current Population Survey (CPS), administrative records from the Department of Social Services, and 3-year ACS datasets. This report pools four years of CPM micro-data (i.e. we do not use multi-year ACS datasets). The 2012–2015 ACS data is pooled and reweighted to give an average value over the period.

The primary goal of the CPM is to describe poverty based on updated methodologies that make improvements in the following general areas: (1) allow poverty thresholds to vary across regions according to housing cost, (2) count key categories of resources that families have on hand to meet basic needs, rather than just pre-tax cash income, (3) update the definition of family units to include foster children, cohabiting adults, and other family types. For details on each of these improvements, see Bohn et al. (2013) and Wimer et al. (2015). In summary, updated poverty thresholds that vary according to housing cost result in CPM thresholds across the state that range from about $20,083 to $39,115 in 2012–2015 (for a family of four with two children) and average (weighted) $31,209—compared to a single federal poverty threshold of $24,250 in 2015. CPM poverty thresholds are based on representative amounts spent on food, clothing, shelter, and utilities and are adjusted county-by-county for variation in housing costs. On the family resource estimates, we count both cash and near-cash resources in family budgets and subtract non-discretionary expenses that reduce a family's disposable income. Specifically, we estimate all cash income (from work, retirement savings, unemployment insurances, business, etc.), any cash welfare payments received (SSI, General Assistance, and TANF), and net out taxes paid or tax credits received (federal Earned Income Tax Credit and Child Tax Credit). We then include the cash value of major safety net programs including SNAP, the school breakfast and lunch program, WIC, and federal housing subsidies. Two types of necessary expenses are deducted from the resulting "gross resource" calculation: out-of-pocket medical expenses and work-related expenses (principally child care and commuting).

California Poverty Measure estimates result in poverty rates for the state that are substantially higher than those from official poverty measure estimates, but not markedly different from Supplemental Poverty Measure estimates for California. Over 2012–2015, the CPM estimates 20.6 percent in poverty, the same rate Census Bureau SPM estimate for the 2013–2015 period (Renwick and Fox 2016) and compared to 16.3 percent from official poverty measure estimates (2011–2015 ACS 5-year estimate). The higher poverty rate compared to official poverty estimates results principally from the inclusion of variable housing cost in the CPM as well as out-of-pocket expenses that reduce family disposable income. However, counting safety net resources mitigates poverty in the state; without the additional resources counted in the CPM, we estimate that the poverty rate would be 28.8 percent, 8.2 points higher.

Creating Baseline CPM Poverty

We make a number of adjustments to the 2012–2015 CPM data in order to build the scenarios presented in the report and to facilitate comparability. First, we create an updated baseline poverty status for all individuals to account for changes in policy that have occurred since 2012–2015. This includes incorporating the following adjustments:

1. Cost of living adjustments in the CalWORKs program, estimated at 11% for 2012 and 2013 observations, 10% for 2014 observations, and 4% for 2015 observations (California Department of Social Services 2016).
2. Cost of living adjustment in the SSI program, estimated at 0.8% for all recipients (Martin and Warren 2016).
3. California EITC passed June 2017, which augments the 2015 California EITC (see Appendix D below for details)
4. Minimum wage as of January 2017; we use the $10.50 minimum for large employers and assume no change in employment (see Appendix C for details)

The resulting baseline represents the economic standing for Californians if the above policy changes had been enacted by 2012–2015. We also adjust all dollar values to year-end 2016 levels using the CPI-U-RS series. Any changes in economic standing resulting from the scenarios in Table A1 below should thus be interpreted as if such policies had been implemented in 2012–2015, after changes 1–4 above. While this approximates the 2017 policy landscape, the approach does not account for other factors that have affected economic standing since 2012–2015, such as improvement in the labor market, migration, and family dynamics. However, the baseline data used here are the most up-to-date and comprehensive for assessing potential changes in poverty (and other outcomes) in detail within and across California.

Table A1 summarizes the CPM poverty rate for 2012–2015 under actual and baseline assumptions. Because of the variability in survey data and imputations in the CPM underlying methodology, please note that these estimates are subject to margin of error.

TABLE A1

CPM poverty rates

	Actual 2012–2015			Baseline			Baseline, excluding all safety net resources		
	Poverty Rate	Deep Poverty Rate	Near Poverty Rate	Poverty Rate	Deep Poverty Rate	Near Poverty Rate	Poverty Rate	Deep Poverty Rate	Near Poverty Rate
Age 0–5	24.1%	5.4%	49.1%	23.0%	5.0%	48.5%	38.5%	18.4%	54.4%
Age 6–17	22.7%	5.2%	47.1%	21.7%	4.8%	46.5%	36.0%	17.0%	51.7%
Adult with Children 0–5	21.0%	4.1%	46.1%	19.9%	3.8%	45.4%	34.1%	14.1%	52.1%
Adult with Children 6–17	18.9%	4.0%	41.2%	18.1%	3.7%	40.6%	27.8%	11.2%	44.6%
Adult with no Children	20.0%	7.9%	34.2%	19.4%	7.8%	33.7%	22.1%	11.3%	35.0%
Older Adult	19.2%	5.6%	33.6%	19.1%	5.6%	33.5%	22.6%	10.1%	34.8%
All	20.6%	5.9%	40.2%	19.9%	5.6%	39.7%	28.3%	13.0%	43.1%

SOURCES: CPM 2012–2015

NOTES: "Adult" refers to age 18–64, and does not count parents only, but rather any person age 18–64 in a poverty unit with children of specified age (or no children). Deep poverty is defined as having net resources below 50% of the CPM threshold, poverty 100% of threshold and near poverty 150% of threshold.

Building Counterfactual Scenarios using CPM Data

In this report, we put the CPM data to use for the purpose of policy simulations, exploiting the richness of the underlying sources of data and of the policy simulation method created for the CPM. Table A2 summarizes the counterfactual scenarios we build using the CPM data; each approach is detailed in Appendix B through Appendix F.

TABLE A2

Overview of scenarios

Policy	Scenario 1	Scenario 2
Housing supply	Housing portion of CPM threshold adjusted to be at the lower of actual or the 90th percentile of metropolitan areas outside of California	Housing portion of CPM threshold adjusted to be at the lower of actual or the 75th percentile of metropolitan areas outside of California
Minimum wage	$13/hour	$15/hour
State EITC	Maximum federal EITC in phase-in range for eligible filers, then $0	Federal EITC plateau extended by 85% of distance between current max credit income and max Adjusted Gross Income (AGI) for receiving federal EITC; plateau and maximum AGI extended 30% in Region 1
Child credit	Maximum federal EITC in phase-in range for all families with children, then $0	Child allowance of $1,700 for first child, smaller amounts for additional children, phasing out and ending with federal EITC in Region 2; plateau extended 30% in Region 1
Renter's credit	For those with the lesser of Fair Market Rent (FMR) or actual rent above 50% of income, credit excess rent up to $3,900, phasing out with the federal EITC	For those with the lesser of FMR or actual rent above 50% of income, refundable $3,900 credit, out to max AGI for current credit in Region 2, max AGI increased by 30% in Region 1

NOTE: See text and table below for definitions of Region 1 and Region 2.

Tax filers and non-filers

Tax units are constructed using the Brookings Metropolitan Policy Program's "MetroTax Model" and adjusted to reflect EITC actual claims (for a complete discussion of the construction of tax units, see the Technical Appendix to Bohn, et al. 2013). For purposes of this research we also identify potential filers in the units where no members are required to file, or are likely claim the federal EITC, in order to simulate scenarios in which all low-income families can potentially qualify for assistance. The total number of tax filers added under the assumption that all potential residents file, even if not required to, is 2.8 million, and includes families in which 8.5 percent of all children 0 to 5 years old live.

We identify the potential filers in these units using an abbreviated version of our method for identifying those who are required to file (or who could claim the federal EITC). In tax units where no one is considered a likely filer, we mark as filer the oldest non-dependent person with the highest income. As we construct them, units that do not file taxes are substantially smaller than units that file taxes: 60.5 percent are single person units, compared with 37.9 percent among units that do file.

In the scenarios that broaden eligibility to include the largest number of the lowest-income families, we use this method of identifying filers only for units with no assigned filers. Sorting tax units by relevant personal characteristics lacks some of the detail of our primary approach. However, we consider the approach to be adequate for the purposes of the scenarios developed for this research.

Regional adjustment factor

A number of the policy scenarios presented in the report and described in detail in Appendices D–F include an adjustment factor to account for the higher cost of living in some parts of the state. These appendices also report the impact on total cost and poverty rate change of excluding the adjustment factor. The counties we categorize as "higher cost" are those listed as Region 1 counties by the California Department of Social Services for purposes of determining the Maximum Aid Payment (MAP) in the CalWORKs program. Because Census combines smaller counties to protect respondents' confidentiality in the ACS, it is not possible to separately identify Monterey (Region 1) and San Benito (Region 2) in the data we use. Both are classified as Region 1 counties; San Benito's population is under 15 percent of Monterey's population. Finally, when we classify counties by tercile of CPM threshold, all Region 1 counties are in the top third of counties, while Region 2 counties are in the middle and lowest third of counties. The sole exception is Placer County, which is in the top third of counties according to the CPM methodology, but is classified as a Region 2 county for CalWORKs purposes. Table A3 provides the breakdown across these two classification schemes.

TABLE A3
County Cost Tercile Definitions

County cost tercile	Average CPM threshold for a family of two adults and two children	Percent of children 0–5	CDSS Region 1	CDSS Region 2
High	$32,916	65.8%	Alameda, Contra Costa, Los Angeles, Marin, Monterey, Napa, Orange, San Diego, San Francisco San Luis Obispo, San Mateo, Santa Barbara, Santa Clara, Santa Cruz, Solano, Sonoma, Ventura	Placer, San Benito
Mid-range	$28,179	22.7%	–	Alpine, Amador, Butte, Calaveras, El Dorado, Inyo, Lake, Mariposa, Mendocino, Mono, Nevada, Riverside, Sacramento, San Bernardino, San Joaquin, Shasta, Sierra, Stanislaus, Tuolumne, Yolo
Low	$25,131	11.5%	–	Colusa, Del Norte, Fresno, Glenn, Humboldt, Imperial, Kern, Kings, Lassen, Madera, Merced, Modoc, Plumas, Siskiyou, Sutter, Tehama, Trinity, Tulare, Yuba

SOURCE: Author calculations from the 2012–2015 CPM.

NOTE: Averages for 2012–2015 shown. Dollar amounts are inflation adjusted to 2016. Statewide average threshold for a family of four is $31,209. San Benito cannot be identified separately from Monterey County in the ACS and so it is included in the Region 1 grouping.

While the MAP is about 5 percent higher in Region 1 counties, we use a larger, 30 percent, adjustment factor drawn from comparing the population-weighted housing cost adjustment factor developed for the CPM in the highest cost tier of counties to the middle tier counties. Note that the U.S. average SPM poverty threshold for a family with two adults and two children was $26,623 (author calculation from the 2012–2016 CPS), implying that most counties in California fall above the national average cost of living.[1]

County Cost Tiers

CPM thresholds—the dollar amount of resources needed to be above the poverty line—vary by family size, housing tenure (owned with a mortgage, owned and paid off, rented), and county of residence. For purposes of discussing differences across the state, we divide counties into three roughly equally sized tiers (based on county unit, not population size) based on their poverty threshold (two adults and two children). See Table A3 for a listing of counties by cost tier and average CPM poverty thresholds across these three groups of counties.

[1] Data used are from the IPUMS CPS. See Flood, King, Ruggles, and J. Robert Warren (2015).

Appendix B. Analysis for the Housing Cost Reduction Scenarios

In this appendix we describe the methodology for the housing cost scenarios considered in the body of the report.

Policy context

California's high cost of housing is a longstanding matter of concern. Recent reports on the topic include Legislative Analyst (2015, 2016, and 2017) and Woetzel, et al. (2016). There is a consensus that housing is undersupplied in California, even relative to other large, diverse states, and that key driving factors include a lack of adequate local financial incentives to build housing given that local governments control property taxes only indirectly, as well as the interests of local residents in maintaining the character of their neighborhoods and towns or cities.

The Legislative Analyst's Office (2015) has modeled the extent of the housing shortage in California using data from counties of at least 850,000 in population in California and elsewhere in the U.S. This report finds that substantially more housing would have been needed to be built in California between 1980 and 2015 to keep housing cost growth more in line with the rest of the United States. The decade of worst shortfall was the 2000s, and the most severe shortfalls were in the coastal counties of Alameda, Los Angeles, San Francisco, San Mateo, and Santa Clara. The report suggests that building an additional 100,000 units per year primarily in coastal areas could keep housing cost *growth* in California more in line with growth in the rest of the U.S.—albeit still relatively high.

Policy designs presented in the report

We recalibrate housing costs also using national information about housing costs. Our approach is cross-sectional and relies on leveraging a core aspect of the shared CPM and Census Supplemental Poverty Measure (SPM) approach to calculating poverty thresholds. Renwick (2011) discusses the Metropolitan Statistical Area (MSA)-level geographic adjustments developed for the SPM thresholds.

The CPM and SPM are well-suited to examine the role of housing costs because poverty thresholds in these measures depend in part on reported cost of renting or owning one's place of residence. Both poverty thresholds are determined using nationally reported family expenditures on food, clothing, shelter, and utilities. For the CPM, the shelter portion of the threshold is further adjusted by California county to take account of reported costs of rental housing, housing owned with a mortgage, and housing owned free and clear. The shelter portion of the threshold ranges between 40.2 percent and 50.5 percent for the 2012–2015 CPM, and the geographic adjustment ranges across counties between 0.83 and 1.88 for rental and mortgaged housing and between 0.75 and 1.67 for housing owned without a mortgage. For additional detail about the construction of the thresholds see the Technical Appendix B to Bohn, et al. (2013).

To adjust the housing cost portion of the CPM threshold in the scenarios presented in the report, we use the SPM variables provided in the IPUMS Annual Social and Economic Supplement to the Current Population Survey (CPS-ASEC) for the years 2013–2016 (Flood, King, Ruggles, and Warren 2017). We calculate percentiles of the Metro area (MSA) housing cost adjustment factor within the three housing tenure types (renter, mortgaged owners, and non-mortgaged owners) for all non-California MSAs, by population size. Sizes are categorized into: nonmetropolitan, 100,000–249,999, 250,000–499,999, 500,000–999,999, 1,000,000–2,499,999, 2,500,000–4,999,999, 5,000,000 and up.

We consider two main policy scenarios, both of which make implicit assumptions about substantially higher housing supply without assuming any particular mechanism:

1. California housing costs adjusted to the 90th percentile in US outside of California by MSA size and tenure status (rented, owned with a mortgage, or owned free and clear). For context, an MSA outside of California with over 5 million in population in the 90th percentile for renters is New York-Northern New Jersey-Long Island, while a small, non-California MSA (100,000–249,999 in population) at the 90th percentile is Santa Fe, New Mexico.
2. The same approach, but costs adjusted to the 75th percentile of housing outside of California. For context, an MSA outside of California with over 5 million in population in the 75th percentile for renters is Miami-Fort Lauderdale-Miami Beach, Florida, while a small, non-California MSA (100,000–249,999 in population) at the 75th percentile is Champaign-Urbana, Illinois.

In cases where the housing geographic adjustment factor is below the specified percentile, the adjustment factor is unchanged in the scenario. We then import these calculations into the CPM by crosswalking MSAs with counties and adjust the housing factor in the CPM threshold downwards for affected counties.

The 90th percentile scenario represents an 8.1 percent reduction in the housing cost portion of the threshold statewide. This translates into a $1,141 or 3.7 percent reduction in the statewide threshold for a family of four. The reductions are concentrated in the most expensive tier of counties, which see on average an 11.3 percent reduction in the housing cost portion of the threshold. The 75th percentile scenario reduces the housing cost portion of the threshold across the state by 12.8 percent on average (and 17.4 percent in the highest cost counties). Statewide, this represents an average reduction in the threshold for a family of four of $1,760 (5.6%).

Table B1 summarizes the actual and hypothesized geographic adjustments for both scenarios. The adjustments we make are county- and housing tenure-specific, but for the sake of brevity we show averages statewide and by lowest, middle, and highest cost county tiers. See Appendix Table A3 for a list of counties in each cost tier.

TABLE B1

Mean geographic housing cost adjustments and CPM thresholds, by tercile of county cost

		Scenario 1: 90th percentile housing cost factor		Scenario 2: 75th percentile housing cost factor	
County cost tercile	Actual threshold, family of 4	Change in housing cost adjustment (%)	Recalculated threshold, family of 4	Change in housing cost adjustment (%)	Recalculated threshold, family of 4
Statewide	$31,210	8.1	$30,069	12.8	$29,450
Highest	$32,919	11.3	$31,292	17.4	$30,483
Middle	$28,165	0.2	$28,142	1.8	$27,937
Lowest	$25,122	0.0	$25,122	1.0	$25,002

SOURCES: CPM 2012–2015 and author calculations.

NOTES: CPM poverty thresholds vary by county, housing tenure, and family size. Estimates shown are weighted mean values.

See Appendix G for detailed estimates of number of Californians affected by these scenarios, the change in the poverty rate, and related estimates.

Methodology

The analyses presented rely on the CPM datasets described in Technical Appendix A. Both scenarios assume that the housing portion of the CPM poverty threshold is adjusted downwards by assumed amounts while family resources and expenses are held unchanged. Poverty rates and related metrics are then recalculated under the assumed lower thresholds. These scenarios are quite straightforward in that they simply assume a reduction in aggregate housing costs such that the poverty threshold is lowered by a specified amount. Neither scenario considers specifically the production of affordable housing units vs. other types of units, or limits the reduction to certain types of families (e.g., those with children).

Limitations

The goal of the housing supply section of the report is to frame the housing cost issue in California in terms of poverty. It is outside the scope of this research to provide assessments of specific policies. This exercise also takes no position on change in the size of the state's population or where people live, their preferences for housing, and assumes no other changes that could increase/decrease costs—for example, an increase in the size of units built, or amenities or safety features that increased costs.

Appendix C. Analysis for the Minimum Wage Increases

In this appendix we describe the methodology for simulating increases in the minimum wage in our 2012–2015 California Poverty Measure data and assess the sensitivity of outcomes to a wide range of plausible parameters.

Policy context

Using minimum wage law to reduce poverty is often proposed as a powerful policy tool, especially among those focused on the struggle of the working poor in California. For example, a full-time job at the 2015 state minimum wage level would provide insufficient income to keep a worker out of poverty in almost any county in the state, according to our California Poverty Measure housing cost-adjusted thresholds; it would certainly be insufficient if the individual had children ($9/hour for 2,080 hours, and ignoring for the moment expenses or safety net resources). Indeed, in recent years a number of minimum wage increases have been implemented in California cities and in June 2016, California policymakers set forth a timetable for increasing the statewide minimum wage to $15. The minimum is set to increase to $10.50 in January 2017, $13.00 in 2020 and $15.00 in 2022 (for covered employees at firms larger than 26; all size firms to be covered by 2023). The 43% increase by 2022 is a slightly faster-paced increase than changes in the California minimum wage schedule dating back to 2000 (on a nominal, per year basis). At the same time, a number of localities in California already have minimum wage levels set higher than the statewide minimum, up to a high of $14.82 in Emeryville as of July 2016 (for large employers).

Increasing the minimum wage is often motivated by concerns that stagnating wage levels at the low end of the distribution are not keeping up with changes in the cost of living or in living standards. As a tool for addressing this aspect of poverty, the minimum wage is attractive because it requires no direct outlay of government resources unlike many of the other policy approaches considered in this report. However, because government services in some domains are carried out by workers affected by the minimum wage, increases are not "free" in terms of government budgets.[2] Nonetheless, a policy that increases wages does have the potential to also increase tax revenue and decrease safety net outlays, which could offset some of these costs and/or be a net benefit to government budgets.

Whether, or the extent to which, increasing the minimum wage is an effective tool for reducing poverty is dependent on a number of other factors. First, the impacts clearly depend on who is working in minimum wage jobs or in low-wage jobs that would be affected. For this report, it is particularly relevant to know how many parents of young children are working in affected jobs. In terms of targeting poverty overall, the minimum wage is often critiqued as applying mostly to teenage workers, not working-age or parents whose work contributes most to family budgets. However, in California, the age distribution of low-wage work has shifted toward older adults in the last few decades,[3] making the minimum wage potentially a relevant policy tool for addressing poverty broadly. Regardless, we examine the distribution of low-wage and minimum wage work in our data as one important facet to understanding the broader poverty impacts of the minimum wage.

Second, whether or how much minimum wage increases contribute to poverty alleviation is dependent on whether higher wages produce countervailing decreases in employment or hours. This possibility is the most prominent feature of the debate, both in policy and academic circles. While simple economic theory suggests that a mandated minimum higher than prevailing wage rates would yield a loss in employment, there are a number of complications in applying theory in real world markets. Our intent is not to explore all such complications here,

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[2] This is especially the case in sectors such as child care and health care, where a sizeable share of the workforce is low wage.

[3] Bernhardt, Perry, and Cattell, 2015.

but in sum, factors such as the variation in workers' skills and their substitutability, the market power of firms, and the interplay between wage levels and worker productivity all play a role.[4] Further complicating the picture is the fact that effects could vary across time, across markets, or across industries, depending on both fixed features and/or contemporaneous trends in the economy. Indeed, the empirical research literature bears out the complexity, finding a range of estimates on how much, or whether, minimum wage increases result in employment decline. Again, we do not aim to summarize that vast literature here, but rather understand the range of plausible outcomes that our simulations should reflect. Surveying high-quality studies, the bulk characterize employment effects as small, finding a 1% to 7% decrease in employment after a 10% increase in minimum wage.[5] Some estimates lay outside that range as well, from no detectable effects to as high as 30%. There remains a vigorous debate on how to isolate the causal impacts of minimum wage on employment from the multitude of factors at play in the real world. In addition, generalizing from even the best causal study could be misleading because of contextual factors such as the geography, industry, or time period where a study is conducted. For example, a city-wide minimum wage may induce larger employment effects than a state-wide minimum in a place as large as California, because, statewide, employers cannot as easily relocate. Or, a study that perfectly isolates the employment effect for teenage workers in the restaurant industry may not apply broadly to other sectors of the low-wage labor market.

The scale of the increase is also a factor that varies considerably across studies. California's increase to $13 by 2020 would be a 24% hike and the further increase to $15 by 2023 would be another 15%. This schedule reflects a bit larger increase (even on per-year terms) than prior increases in California, and is roughly the same percentage increase as the recent Seattle wage hike. The evidence coming out of Seattle's increase is compelling for that reason, and because researchers have been able to assess how hours might change in addition to employment on the extensive margin (typically such data are either not collected or difficult to obtain).[6] The evidence from the Seattle minimum wage evaluation suggests negative effects on employment (a 10% to 30% decrease in employment for a 10% increase in wage) and detects an 8% to 11% decrease in hours for the increase to $13 minimum. Although there are limitations to applying Seattle's results to California, as noted above, we include this in our range of possible outcomes as a point of comparison.

The concerns about low-wage workers losing employment or hours as a result of minimum wage increases are heavily debated and studied because it is central to the question of how well it would work as a poverty reduction lever. However, employment or hours declines do not need to be zero to judge an increase in the minimum wage worthwhile for poverty alleviation. Even with the loss of some jobs or some hours, if enough workers earn enough more in annual wages, on an aggregate level we could observe improvements in poverty. As with all policy choices, there are tradeoffs to consider in who benefits or who might be harmed. It is worth noting that there are broader economic consequences to minimum wage law to consider, though we do not empirically test any in this report. For example, minimum wage levels may be a factor in business or family location decisions, labor force participation, productivity, capital vs. labor investments, fiscal policy, and the like.

The objective of the present simulation is to assess how the minimum wage could affect families with young children relative to other policy alternatives. All of the parameters discussed above are relevant because the range of possible outcomes is potentially quite wide. However, we aim to help quantify just how different likely outcomes might be using some of the best available data to do so. Central questions for this study include how an increase in the minimum wage—compared to other policy options—fills the gap that families still have in their

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[4] For example, Lordan and Neumark (2017).

[5] A number of useful meta-analyses and surveys of the literature are instructive. Belman and Wolfson (2014), Neumark and Wascher (2008), Neumark (2014), Acs, Wheaton, Enchuategui, and Nichols (2014) are just a few.

[6] Jardim, Long, Plotnick, Inwegen, Vigdor, and Wething (2017). One complicating factor examined closely in the aforementioned study is separating Seattle's low wage labor market trend of decreasing employment (underway before the new minimum was instituted) from the effects of the increase in the minimum wage.

resources even after social safety benefits are accounted for and after considering the high cost of living in much of the state. The scope of our research is limited by the data available and by our willingness to extrapolate future outcomes. On the former, Appendix A describes our baseline estimates built from 2012–2015 American Community Survey data. On the latter, we are notably modest in that we aim to simulate what an increase in wages would look like for families in our baseline data rather than what the poverty landscape will look like when minimum wages actually reach $13 or $15 in 2020 and beyond.

Simulation methods

We draw on the vast body of research to present a range of plausible estimates for how family resources and poverty status might change were the scheduled increases to be implemented in our 2012–2015 baseline sample. To implement this research-based simulation in California using California Poverty Measure (CPM)/American Community Survey (ACS) data, we largely follow the approach taken in Giannarelli, Wheaton, and Morton (2015) and Acs, Wheaton, Enchautegui, and Nichols (2014) but also incorporate some alternative modeling decisions similar to Neumark, Thompson, Brindisi, Koyle, and Reck (2013).

Specifically, we simulate raising the minimum wage to $10.50 (which becomes the baseline), $13 and $15, if these were implemented in the 2012–2015 CPM sample. In each case, we assume that the minimum applies to *all* minimum wage workers regardless of firm size, in essence the fully implemented version of each increase.[7] As discussed above, our focus is rather narrow, simply aiming to quantify who is affected and how, in terms of their hourly and annual wages. We abstract from broader economic consequences that could also filter down to the family and from adjustments to behavior at the firm or individual level that might occur over time as a result of minimum wage increases. We think of the estimates as relatively short-run and static.

There are a number of challenges to simulating increases in minimum wage, some arising from the range of plausible outcomes estimated in the research literature as described above and some from data limitations. For both reasons, we have undertaken a number of sensitivity checks, discussed below. The main results presented in the report aim to reflect a middle ground among the plausible effects. The main challenges that we are able to address are summarized as follows:

1. Accurately estimating **hourly wage rates** in ACS data
2. Determining **which workers are likely to receive wage increases**—both those employed at exactly the minimum, and those employed just above or below prevailing minimum wage levels who might also be affected, **and to what extent**
3. Determining whether and to what extent **employment or hours declines** might result from higher minimum wage levels
4. Consequences for **taxes and other means-tested program benefits**.

Taking these challenges one at a time, we next summarize the range of approaches taken in our modeling procedure. All of our simulations rely on the CPM datasets described in Technical Appendix A. We consider only individuals who report income from wages and salary, report working at least 1 week and at least 1 hour per week, are not self-employed, and are at least 16. Our overall estimates reflect the wage and income levels of individuals who live and work in California (that is, those who live outside but work inside California are not considered).

[7] California's minimum wage law applies to almost all workers, with few exceptions. The state also does not distinguish between a minimum for "tipped" (e.g. restaurant workers) vs not tipped workers. This simplifies our analysis in some ways, since ACS self-reported wage and salary data is supposed to include tips. Of course, such information could be underreported, contributing to the measurement error in our analysis.

Hourly wages

Individuals surveyed in the ACS report annual earnings from wages and salary, weeks worked, and hours worked. Throughout this analysis, we take these self-reported items as given. In general these three pieces of information would be sufficient to estimate an hourly wage rate, however in the public-use ACS data weeks worked are reported as a categorical variable (1–13 weeks, 14–26 weeks, etc.), which means it is impossible to calculate hourly wages exactly. Research based on the ACS often assigns the midpoint of each weeks worked range to estimate hourly wage rates. We take a slightly more data-driven approach, which is to estimate the distribution of weeks worked within each range from the California sample of the Current Population Survey from 2011–2014, where the data is reported non-categorically. We apply the CPS-estimated median hours of work within each ACS range. This works particularly well at the high end of the weeks work spectrum, where the median weeks worked is also the weeks worked for the majority of workers in the given range. Approximately 68% of California wage and salary workers in our survey period were employed 48 weeks or more. For the remaining share of workers, at the lower end of the weeks-worked spectrum, there is much more variation in weeks worked within each ACS range. To test the sensitivity of our results to this approach, we re-estimate all of our results using a "maximum" hourly wage and "minimum" hourly wage for each individual. To obtain the "maximum", we apply the minimum weeks worked within each ACS categorical range (if 1–13 weeks worked, we assign 1 week, and so forth). To obtain the "minimum" hourly wage we do the opposite. These estimates give us bounds on the possible hourly wage rates in our dataset and thus also helps bound the poverty effects with respect to this issue of estimating hourly wages accurately. [8]

FIGURE C1

Distribution of hourly wage rates in California's low wage workforce under alternative definitions

SOURCE: Author calculations from CPM 2012–2015.

NOTE: Only workers estimated to earn between $6–20/hour are included in this calculation. See text for "Base, "Minimum", and "Maximum" calculations.

We use these hourly wage calculations to summarize wage levels across California and to identify workers impacted by minimum wage increases (described below). To summarize low-wage work, we include anyone with

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[8] Since individuals report only total hours, earnings, and weeks worked in a year, it is not possible to separate multiple jobs that an individual might hold in a calendar year in ACS data. For this reason, the hourly wage calculated as described is actually an average hourly wage, and we assume that it reflects the wage level a worker is subject to uniformly across jobs.

wages below two-thirds the median hourly wage.[9] Figure C1 shows the wage distribution according to the three definitions described above, for wage & salary workers earning between $6 and $20/hour. Under the "minimum" definition of hourly wages, the distribution is more concentrated at lower wage levels and the opposite for the "maximum" definition, as we expect. In general, the base definition that underlies our main estimates appears to be an appropriate middle ground between the two extremes. Note that about one-fifth of workers earn below the $9 minimum wage level in these data.

In the first two columns of Table C1, we present additional summary statistics on the characteristics of California workers and low-wage workers, including their occupation, industry of employment, age, poverty status, household composition, and participation in safety net programs. The latter columns of the table present the same statistics for workers affected by minimum wage increases under the assumptions of our model, which is described in detail later. Columns 3–5 allows us to look at whether there are meaningful differences in the characteristics of workers according to the hourly wage definition we employ.

The first takeaway from Table C1 is that characteristics of low-wage or minimum wage workers do not differ much, if at all, across the three possible ways to calculate hourly wages (columns 3–5). Nonetheless, we provide final poverty results for these alternative definitions to ensure that there are no additional meaningful differences.

Second, the characteristics of low-wage or minimum wage workers in our sample are similar to those described in other related work, which takes various approaches to measuring wage rates. For example, low-wage or minimum wage workers are more likely to be working part-time compared to the workforce overall, are more likely to be poor, and are younger. In addition, low-wage and minimum wage workers are over-represented in occupations like food preparation/serving, building and ground maintenance, and personal care and are over-represented in food & accommodations and retail service industries.

TABLE C1

Characteristics of low wage workers in California sample of ACS

			Affected by Minimum Wage Increase				
	Wage and Salary Employed	Low Wage Workers	$10.50 (base hourly wage definition)	$10.50 ("minimum" hourly wage definition)	$10.50 ("maximum" hourly wage definition)	$13	$15
Percent of Employed	100%	35%	15%	15%	13%	20%	27%
Number	16,871,736	5,877,088	2,484,105	2,512,599	2,184,096	3,407,554	4,484,559
Full-time (%)	76%	61%	64%	64%	64%	68%	70%
Part-time (%)	24%	39%	36%	36%	36%	32%	30%
Weekly hours (mean)	37.9	34.5	35.2	35.1	35.4	35.9	36.3
Full-time year-round (%)	63%	45%	50%	49%	53%	54%	57%
Poverty (%)	14%	32%	28%	27%	29%	23%	20%
Occupation Distribution							
Other	55%	37%	37%	38%	36%	40%	41%
Food Prep and Serving	6%	12%	12%	12%	12%	10%	10%

[9] Bernhardt et al, 2015.

	Wage and Salary Employed	Low Wage Workers	Affected by Minimum Wage Increase				
			$10.50 (base hourly wage definition)	$10.50 (“minimum” hourly wage definition)	$10.50 (“maximum” hourly wage definition)	$13	$15
Building and Grounds Maintenance	4%	6%	7%	7%	7%	6%	6%
Personal Care	4%	8%	8%	8%	8%	7%	6%
Sales and related	11%	14%	13%	13%	13%	12%	12%
Office and administrative support	14%	14%	14%	14%	14%	16%	17%
Transportation and Moving	6%	9%	9%	9%	9%	9%	9%
Industry Distribution							
Other	46%	38%	38%	38%	37%	39%	40%
Food and Accommodation	8%	15%	15%	15%	15%	13%	12%
Health and Social Services	13%	11%	12%	12%	12%	12%	12%
Retail Trade	12%	17%	17%	16%	17%	16%	15%
Manufacturing	10%	9%	9%	9%	9%	9%	10%
Education Services	9%	6%	6%	6%	6%	7%	7%
Personal Services	2%	4%	4%	4%	4%	4%	3%
Age Distribution							
16–19	3%	7%	5%	4%	4%	4%	3%
20–24	11%	23%	21%	21%	22%	19%	17%
25–29	13%	15%	16%	16%	16%	17%	17%
30–39	23%	19%	20%	20%	20%	21%	22%
40–49	21%	16%	17%	17%	17%	17%	18%
50+	28%	19%	21%	22%	21%	22%	23%
Weeks Worked Distribution							
1–13 weeks	6%	10%	6%	6%	1%	6%	5%
14–26	5%	9%	7%	6%	5%	6%	5%
27–39	6%	8%	8%	8%	7%	7%	7%
40–47	6%	6%	6%	7%	7%	6%	6%
48–49	2%	2%	2%	3%	3%	2%	2%
50–52	75%	64%	71%	70%	77%	72%	74%
Poverty Distribution							
>400% threshold	18%	4%	4%	4%	4%	4%	5%
Deep Poverty (<50%)	3%	8%	5%	4%	5%	3%	3%
50–100%	11%	24%	23%	23%	24%	19%	17%
100–150%	17%	28%	31%	31%	31%	32%	31%
150–200%	15%	16%	17%	17%	17%	19%	20%
200–300%	22%	14%	15%	15%	14%	16%	18%

	Wage and Salary Employed	Low Wage Workers	Affected by Minimum Wage Increase $10.50 (base hourly wage definition)	$10.50 ("minimum" hourly wage definition)	$10.50 ("maximum" hourly wage definition)	$13	$15
300–400%	13%	5%	5%	6%	5%	6%	6%
Weekly hours worked Distribution							
<20 hours	7%	11%	9%	9%	8%	8%	7%
20–34 hours	17%	28%	27%	27%	28%	24%	22%
>35 hours	76%	61%	64%	64%	64%	68%	70%
Household Type Distribution							
Other	21%	15%	16%	16%	15%	16%	17%
Single	17%	15%	16%	16%	16%	16%	16%
Single Adult with Children	3%	3%	3%	3%	3%	3%	3%
Multiple Adults with Children	59%	67%	66%	66%	66%	65%	64%
Family receives resources from:							
CalFresh	16%	30%	28%	27%	29%	25%	23%
CalWORKs	5%	10%	9%	9%	9%	8%	7%
WIC	14%	24%	24%	23%	24%	22%	21%
Social Security	13%	15%	14%	15%	14%	14%	14%
SSI	4%	6%	5%	5%	5%	5%	5%
GA	1%	1%	1%	1%	1%	1%	1%
School lunch	11%	19%	19%	18%	19%	18%	17%
School breakfast	7%	13%	13%	13%	13%	12%	12%
Housing Subsidy	1%	3%	2%	2%	3%	2%	2%
EITC	24%	43%	40%	39%	41%	38%	36%
CTC	17%	29%	30%	30%	31%	29%	28%

SOURCES: CPM 2012–2015 and author calculations.

NOTES: Only workers age 16+ with non-zero earnings, non-zero weeks worked, non-zero usual hours worked, and employed in wage and salary (non-self-employed) work are included in this table. See text for definition of each column. Full-time is defined as working 35 or more hours per week; part-time includes all other workers. Year-round refers to working at least 50 weeks. Poverty status and breakdowns are determined by the California Poverty Measure definitions.

Identifying workers affected by minimum wage increases

With an estimate of each worker's hourly wage rate, we can then simulate who might be subject to an increase in the statewide minimum. As mentioned previously, our estimates pertain to individuals who live and work in California, so those who live outside but work inside California are not considered. In practice using ACS data, a small share of low-wage workers have exactly the prevailing minimum wage level. That is in part because the calculation of hourly wages described above is not exact. Regardless, even taking a 5 cent range around the statewide minimum of $9 in 2014–2015, we find only 0.3% of the wage & salary workforce or 1.2% of the low-wage workforce earns "exactly" the minimum wage. We also find a sizeable share of workers well below the statewide minimum (see Figure C1), and in keeping with the research literature, we assume these very low wage workers are not employed in work covered by minimum wage law or are working under the table.[10]

An additional complication to identifying minimum wage workers is that some localities have set minimum wage levels above the statewide mandate. ACS data allows us to determine where workers live and where they work, so that we can take into account that some workers will already be earning higher minimum wages than the $13 statewide minimum set for 2020 because of the county where they work. For this reason, our county or regional estimates of poverty (and other outcome metrics) are somewhat more nuanced than statewide ones: if a county has a minimum wage higher than statewide (or if many of a county's residents work outside of the county in a place with a higher minimum wage), the effect increasing the statewide minimum may be attenuated. We rely on a database of minimum wage laws maintained by the UC Berkeley Labor Center[11] to determine which local areas have higher than statewide minimums as of January 2017 and include these in our baseline simulation. Many localities with higher minimum wages are cities, not counties, but unfortunately our ACS data only provides an individual's county of work. So we only presume that a worker in the county is subject to a higher minimum if the localities with higher minimums cover a majority of the workforce of the county, and in that case we use the median minimum rate across the county.

To identify which workers would receive wage increases due to higher minimums, we identify three sets of workers: one group at the minimum, a second group below the minimum but within a range that they would be affected, and a third group above the minimum but also within a range that could be affected. Identifying this spillover range has some nice features given our data constraints. For one, it helps assuage concerns with measurement error in our hourly wage rate, so that the hourly wage estimate only needs to be within the spillover range for the appropriate set of workers to be identified. Second, it allows us to preserve the ranking of workers by shifting the wage distribution within the spillover range upward. For example, rather than giving all workers exactly the new minimum wage, we give workers just below the minimum a proportional increase but keep them below the new minimum, and likewise for workers above. This prevents a minimum wage worker at $10.50 to suddenly be earning the same wage rate as another worker who was $2.50 above the old minimum (earning $13 before the increase to $13). Lastly, this procedure also reflects findings from the research literature that minimum wage increases affect not just minimum wage workers but other low wage employees.

To identify workers who receive wage increases, we first presume that anyone with hourly wages within 5 cents of the prevailing minimum wage—either the state minimum or the city or county minimum—is deemed a minimum wage worker. These workers are simulated to receive the new minimum hourly wage. For example, for the increase from $10.50 to $13 minimum, we deem those earning $10.45–10.55/hour to be minimum wage workers and assign them a new wage of $13.

Following Giannarelli et al (2015) and Acs et al (2014), we assume that the other two groups of "spillover" workers must be within $1—either $1 below the prevailing minimum or $1 above the new minimum. These workers are simulated to receive a boost in hourly wage rate inversely proportional to how far they are from the minimum (we later test this assumption by narrowing the range to 50 cents). For example, for the increase from $10.50 to $13, workers with wages as low as $9.50 and as high as $14 are affected. So a worker earning $9.51/hour sees a very tiny bump in hourly wage, but someone earning $10.30/hour would receive almost the entire increase to $13. On the other hand, if you were earning $13.99/hour before the $13 minimum wage, afterwards your wages will be essentially the same. But if you were earning $13/hour beforehand, after the

[10] Measurement error in the survey data is also a plausible explanation for some of these very low wage rates.
[11]See http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/, we use version last updated 5/8/2017.

minimum wage is instituted, your new wage will be proportionally higher, the proportion related to the size of the minimum wage increase. The specific formulas we use are as follows:

$$NW = (NMW - CMW + 1) * (CW - CMW) + NMW \text{ if below the current minimum, but within \$1}$$

$$NW = \frac{CW - CMW}{(NMW - CMW + 1)} + NMW \text{ if above the current minimum, but within \$1 of the new minimum}$$

where *NW*=individual's new wage, *CW*=individual's current wage, *CMW*=current minimum wage, and *NMW*=new minimum wage.

The workers affected by each minimum wage increase simulation are not cumulative. We first simulate the increase from 2012–2015 actual to $10.50. The next two minimum wage increases—to $13 and $15—each build separately on the $10.50 scenario. In that sense the methodology for determining the spillover range and for calculating wage increases is of particular consequence for workers close to the minimum wage levels who are simulated multiple wage bumps. We test the sensitivity of our results to this $1 spillover range by cutting it in half, however, the formula for linearly increasing wages remains similar. This alternative is labeled "narrow spillover range" in the tables that follow. We also simulate each increase under the assumption that only workers below the new minimum wage level receive increases (following Neumark et al. 2013). This alternative is labeled "no spillover above minimum" in the tables that follow.

Table C1 shows the size and characteristics of the workers determined affected according to these assumptions. 15%, 20%, and 27% of the wage & salary workforce would be affected by the successive increases in minimum wage. Recall that these simulations rely on 2012–2015 data that is adjusted to 2017 only by inflation. Because the labor market has also improved since 2012–2015, the affected workforce today could be slightly different. Similarly, when the minimum wage level increases to $13 in 2020 (and so on), the labor force situation and resulting low-wage workforce could be different. It is important to keep these limitations in mind when evaluating the effects on poverty and other outcomes.

The workers identified as affected by this methodology are not that different from low-wage workers overall in terms of age, industry, occupation, and other central tendencies. One exception is poverty status, where it is clear that successively higher minimum wage levels affect more of the non-poor population. However, the poverty rate among workers estimated to be affected by the $15 minimum wage are still more likely to be poor than average for the overall workforce.

Before summarizing the effect of the minimum wage under these assumptions, we describe our approach to simulating how employment and safety net resources may also change.

Employment declines

The most controversial aspect of minimum wage policy—in terms of public debate as well as in the economic research literature—is the extent to which a higher minimum wage causes employers to reduce labor demand. We attempt to simulate a range of possible outcomes that reflect the range of quasi-experimental causal estimates in the literature, as summarized earlier.

Our baseline estimates present a world in which new minimums cause no change in hours or weeks of work, or in employment on the extensive margin. Additionally, we undertake a number of simulations that presume some affected workers will lose their job and some will lose hours of work. In each case, we assume that the individual would not compensate for the loss of employment or loss of hours by finding alternative work or by seeking cash support from unemployment insurance or other sources. Though unlikely, this gives perhaps a lower bound on the results and prevents us from introducing additional assumptions and subjective decisions about longer-term, dynamic consequences of the minimum wage. Also, our ACS/CPM data does not separately estimate unemployment insurance among the other safety net programs that are included, which is a key data limitation.

We estimate the following employment change scenarios:

1. Workers below the new minimum wage have a chance of losing their job—and those with the largest increase have the highest odds; odds are calculated as 10% of the change in wages (for a worker at the minimum, going from $10.50 to $13 these odds translate to a 1.2% chance of losing their job, for $10.50 to $15, a 2.1% chance).[12] In our data, this scenario simulates the low end of wage elasticities in the literature, roughly 0.5.
2. Same as (1) but the odds are higher: calculated as 20% of the change in wages (for a worker at the minimum, going from $10.50 to $13 that translates to a 2.4% chance of losing their job, for $10.50 to $15, a 4.3% chance). Translates to a wage elasticity of roughly 1.
3. Same as (1) but the odds are much higher, to simulate the upper end of the range of wage elasticity estimates: odds of job loss are 100% of the change in wages, equivalent to a 13% chance of losing your job (for the $10.50 to $13 increase) or 24% chance (for the increase to $15). In our data, this reflects a wage elasticity of roughly 6.
4. Same as (1) but odds are higher yet: calculated as 120% of the change in wages, which is equivalent to a 24% chance (at the $13 minimum) or 43% chance (at the $15 minimum). Translates in our data to a wage elasticity of roughly 10.
5. Affected workers receive higher hourly wage rates, but see a reduction in hours on the order of 4% annually.
6. Same as (5) but a larger reduction: 9% annually.[13]

The first four calculations attempt to simulate job loss on the order estimated in the literature. We remain agnostic as to the exact scale and seek to provide a range of possible outcomes. We use a random number generator to select the unlucky individuals from among the workers in the spillover range of the minimum wage, and zero out their income from wages and salary.

The last two calculations attempt to simulate recent results on hours worked from Seattle's minimum wage increase (Jardim et al. 2017). Although there is debate on whether the negative hours worked results they detect are applicable to California, the supposition that employers might cut hours is a common one, so we include a simulation here.[14] In these simulations, there is no random component, rather, we cut hours across the board for affected workers. The effect could differ if hours declines occurred more or less for certain affected workers.

Tax and other consequences

In the CPM methodology, individuals are presumed to share resources within family/cohabitating units, so a minimum wage worker's increase (or job loss) affects family-level resources and poverty status. In our estimates, an increase in earnings may affect tax burden (or tax credit) at the state and federal level, as well as eligibility for CalFresh, CalWORKs, WIC, and school meals program benefits.

For every poverty unit with an increase in wages, we re-estimate federal and state income tax, FICA, and federal and state earned income tax credits. These calculations operate at the tax filing unit level, which may or may not be the same as the poverty unit. Tax implications of changes in wages could be a net positive, negative, or neutral result for families, and depends on the size of the wage increase (or decrease in the case of job loss) relative to tax rules and tax filing unit characteristics.

[12] This calculation again follows Giannarelli et al (2015) and Acs et al (2014)
[13] These two hours reduction parameters specifically derived from Jardim et al (2017).
[14] Also, workers may attempt to adjust their hours so as to maintain eligibility for certain means-tested programs.

We also simulate changes in eligibility for CalFresh, CalWORKs, WIC, and school meals programs. Our CPM model for these programs is not detailed enough to estimate changes in benefit amounts but does allow us to estimate whether a family would lose eligibility completely as a result of higher earnings. Units whose income now exceeds 175% of the federal poverty line would lose CalFresh eligibility and those above 125% would lose CalWORKs eligibility. Units whose income is above 247% of the federal poverty line would lose WIC and free and reduced-price school meals eligibility.[15] Such units would then receive $0 in cash or cash-equivalent benefits. Our methodology is limited in the sense that we only determine eligibility cliffs rather than changes in benefit levels for families whose income changes but they remain eligible.

Results

We first describe the overall impact of minimum wages—under a variety of assumptions—on overall earnings and employment. Table C2 shows that aggregate earnings increase by about $100–700 million for each increase, compared to the 2012–2015 actual earnings level (all in 2016 dollars). Under scenarios where some share of affected workers loses employment, we see that earnings and employment are much lower. When only hours decline, the impact on total earnings can be larger than for employment changes alone. Of course, these relative effects depend on the scale of job loss and hours loss that one simulates. We chose these levels to be consistent with prior research and to show the multiple dimensions that matter for understanding the effects of the minimum wage.

TABLE C2

Aggregate earnings and employment for workers affected by the minimum wage

	2017 Minimum ($10.50 or local area minimum)	$13	$15
Total earnings (dollars)			
Actual 2012–2015 for workers affected by scenario	1,384,410,000	2,220,790,000	3,259,890,000
No employment changes (base scenario)	1,506,810,000	2,603,050,000	4,049,360,000
Job loss scenario 1	1,494,210,000	2,572,560,000	3,960,900,000
Job loss scenario 2	1,481,390,000	2,542,820,000	3,881,730,000
Job loss scenario 3	1,379,420,000	2,297,000,000	3,182,870,000
Job loss scenario 4	1,351,700,000	2,236,000,000	3,018,950,000
Narrow spillover range	1,497,940,000	2,595,290,000	4,036,670,000
No spillover above minimum	1,496,650,000	2,593,040,000	4,035,350,000
Hours loss at 4%	1,462,300,000	2,518,970,000	3,908,710,000
Hours loss at 9%	1,406,650,000	2,413,870,000	3,732,900,000
Total employment (number of individuals)			
Actual 2012–2015 for workers affected by scenario	2,480,000	3,410,000	4,480,000
No employment changes (base scenario)	2,480,000	3,410,000	4,480,000
Job loss scenario 1	2,460,000	3,370,000	4,380,000
Job loss scenario 2	2,440,000	3,330,000	4,290,000
Job loss scenario 3	2,280,000	3,000,000	3,500,000
Job loss scenario 4	2,230,000	2,920,000	3,310,000

[15] These cutoffs are the same used for our main CPM safety net imputations. The cutoffs are higher than the actual rules for each program because of the limitations of modeling eligibility for each program in ACS data. In particular, the CPM allows for intra-year income volatility vis a vis certification windows for each program. See Bohn et al (2013) for more details.

	2017 Minimum ($10.50 or local area minimum)	$13	$15
Narrow spillover range	2,480,000	3,410,000	4,480,000
No spillover above minimum	2,480,000	3,410,000	4,480,000
Hours loss at 4%	2,480,000	3,410,000	4,480,000
Hours loss at 9%	2,480,000	3,410,000	4,480,000

SOURCES: Author's calculations from CPM 2012–2015 data.

NOTES: Only income and employment for workers affected by each minimum wage increase are used to calculate these aggregate amounts. Dollars amounts adjusted for inflation.

Next, we look more closely at the wage and income levels for workers affected by minimum wage increases in our simulation (Table C3). In the baseline simulation, the median impacted worker sees a 8.5% increase in their wage rate from the 2012–2015 original data to the 2017 minimum level of $10.50 (or the local area higher minimum level for that period). The percent increases are a bit larger for the subsequent minimum wage levels of $13 or $15; note that these increases are measured relative to the 2017 minimum and are not cumulative. Average income rises accordingly, and because the majority of affected workers work full time and all year long, the percent increase in income mirrors the percent increase in wage rates.

When we simulate a share of workers losing employment, the average wage and income increases are lower by design. If instead we simulate a loss in hours, we obtain a similar net effect on income, with increases at the average but to a lower level than in the baseline scenario.

TABLE C3

Wages and income for workers affected by the minimum wage

	2017 Minimum ($10.50 or local area minimum)	$13	$15
Median hourly wages			
Actual 2012–2015 for workers impacted by scenario	9.95	11.15	12.12
No employment changes (base scenario)	10.91	13.25	15.26
Job loss scenario 1	10.90	13.25	15.24
Job loss scenario 2	10.90	13.25	15.24
Job loss scenario 3	10.82	13.22	15.18
Job loss scenario 4	10.82	13.22	15.16
Narrow spillover range	10.91	13.25	15.26
No spillover above minimum	10.82	13.22	15.23
Hours loss at 4%	10.91	13.25	15.26
Hours loss at 9%	10.91	13.25	15.26
Median percent change in hourly wages			
No employment changes (base scenario)	8.5	11.8	21.9
Job loss scenario 1	8.2	11.6	21.1
Job loss scenario 2	8.2	11.1	20.3
Job loss scenario 3	7.1	9.4	12.6
Job loss scenario 4	6.9	8.9	10.4
Narrow spillover range	8.2	11.8	22.0

	2017 Minimum ($10.50 or local area minimum)	$13	$15
No spillover above minimum	8.5	12.3	22.4
Hours loss at 4%	8.5	11.8	21.9
Hours loss at 9%	8.5	11.8	21.9
Mean annual income			
Actual 2012–2015 for workers impacted by scenario	$16,276	$18,879	$20,988
No employment changes (base scenario)	$17,716	$22,128	$26,071
Job loss scenario 1	$17,567	$21,869	$25,501
Job loss scenario 2	$17,417	$21,616	$24,991
Job loss scenario 3	$16,218	$19,526	$20,492
Job loss scenario 4	$15,892	$19,008	$19,437
Narrow spillover range	$17,611	$22,062	$25,989
No spillover above minimum	$17,596	$22,043	$25,980
Hours loss at 4%	$17,192	$21,413	$25,165
Hours loss at 9%	$16,538	$20,520	$24,033
Percent workers who lose job under scenario			
No employment changes (base scenario)	0.0%	0.0%	0.0%
Job loss scenario 1	0.8%	1.2%	2.2%
Job loss scenario 2	1.7%	2.4%	4.3%
Job loss scenario 3	8.4%	11.9%	22.0%
Job loss scenario 4	10.1%	14.2%	26.2%

SOURCES: Author's calculations from CPM 2012–2015 data.

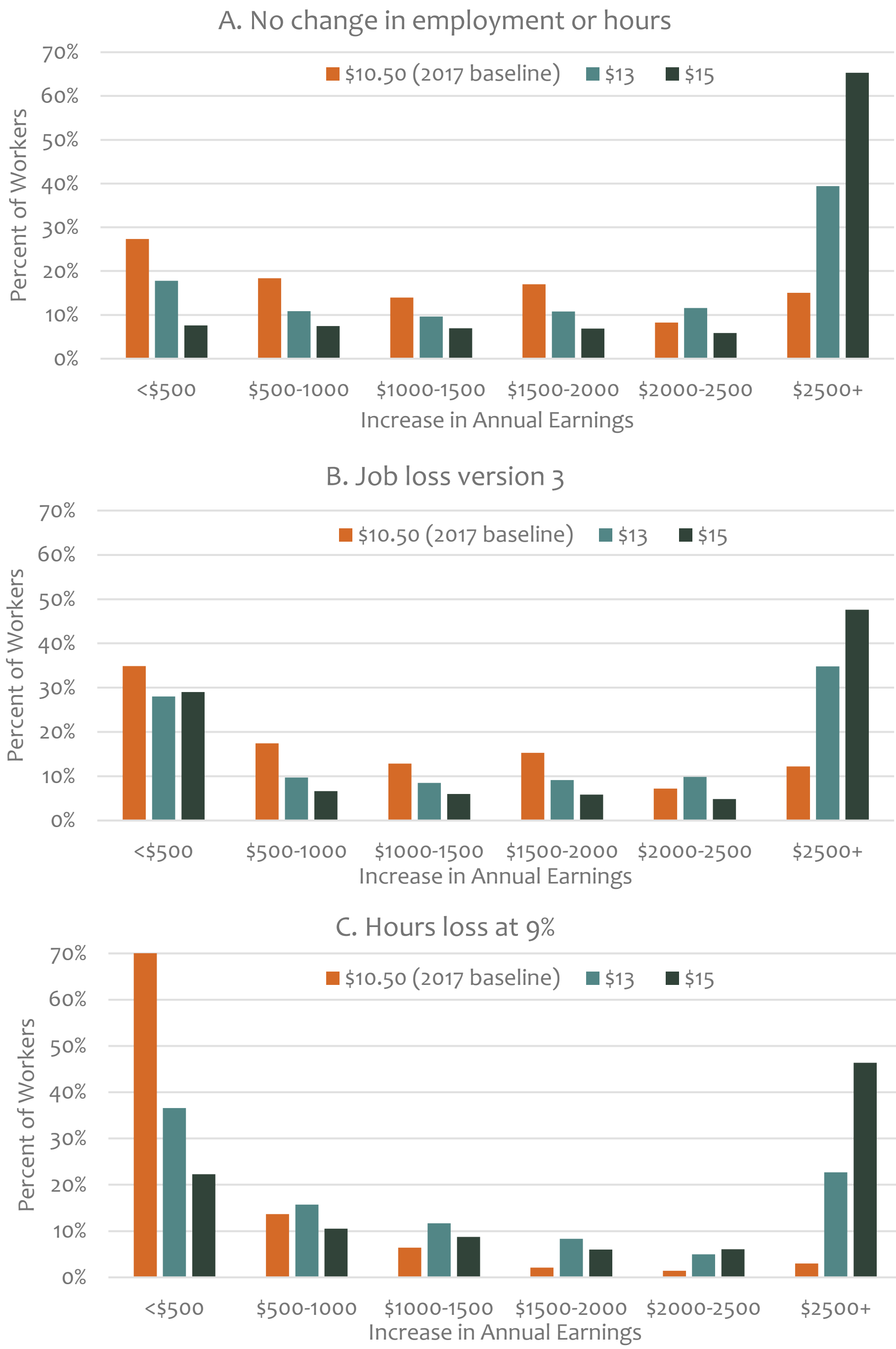
NOTES: Only workers affected by minimum wage increases are included, see text for definitions of each row. "Job loss 1–4" refers to the itemized list in the text, corresponding to 10%, 20%, 100%, and 120% odds. "Narrow spillover" reduces the spillover range from $1 to $0.50 and "No spillover above minimum" calculates no increase in wages for those above the new minimum wage. "4% hours loss" and "9% hours loss" refer to simulations where all affected workers lose 4 or 9% of hours, respectively. See text for additional explanation.

Figures C2 show the distribution of increases in wages across a few of the scenarios implemented here. To calculate the difference in earnings, the 2017 minimum wage scenario is compared to 2012–2015 earnings. Then both the $13 and $15 minimum wage scenarios are compared to the 2017 baseline.[16] As panel A shows, the distribution of annual earnings increases shifts toward the right with each increase. For the increase from $10.50 to $15, the majority of affected workers have an increase of over $2,500, whereas only 40% have as large an increase for the $13 minimum. If we simulate job loss, the distribution of effects are quite similar for low-elasticity scenarios. We start to see some differences in the distribution for higher rates of job loss, as panel B shows. A much smaller share of workers have the largest increase in earnings, though still there are many workers with substantial earnings increases. This reiterates the fact that the distributional consequences of minimum wage increases (who is harmed, who is assisted) are important tradeoffs to consider. Last, if we simulate an across-the-board reduction in hours the distribution of effect sizes is not too dissimilar for a 4% reduction (not shown), but a 9% reduction does yield a substantial shift left of the distribution. Over 70% of workers affected by the increase to $10.50 see an increase in annual earnings less than $500 compared to 30% such workers in the baseline simulation.

[16] This decision allows us to compare each minimum wage increase individually to the other array of policy changes simulated in the report.

FIGURE C2

Distribution of increase in earnings for $10.50, $13, and $15 simulations



SOURCE: Author calculations from 2012–2015 CPM.

NOTE: Only workers affected by the minimum wage increase at each level are included (number of workers varies across steps).

Table C4 and Figure C3 summarize how these earnings differences impact poverty status. Recall that while minimum wages are simulated at the individual level, poverty status is determined by family-level characteristics. So not only the change in wages for a worker, but also the number of affected workers in a family and subsequent changes in taxes and safety net program benefits, factor into these calculations. For some families, the net change in their total resources could be negative as a result of higher taxes or lower safety net benefits. For others, the increase in minimum wage is small proportion of their earnings, as in the case where the minimum wage worker is a teenage child of working parents. As Table C1 showed, roughly two-thirds of the workers in our sample who are simulated to have increased wages are not in poverty to begin with, which attenuates the impact of increasing wages on poverty.

We find that the poverty rate statewide is estimated to drop 0.8 points for the increase from 2012–2015 minimum wage levels ($9 from 2014–2015 and $8 in 2012–2013) to 2017 levels ($10.50 or higher in some localities), drop 1.0 points from 2017 levels to $13 minimum, and another 1.2 points for the last increase from $13 to $15 minimum. The poverty impacts for young children are slightly larger—1.1, 1.3, and 1.5 points respectively. The changes tend to be also a bit larger in high cost parts of the state, though the patterns are not entirely consistent.

When we simulate job loss resulting from higher minimums, the poverty effects are attenuated, as expected. The poverty reduction is still positive, however, for the smaller two job loss scenarios. In both of the two largest job loss scenarios, for the increase from 2012–2015 to $10.50, the effect on poverty is still favorable, though much smaller. However, for the larger minimum wage increases and these two largest job loss scenarios, the overall impact on poverty is not favorable. We estimate increases in the poverty rate by 0.5 to 1.3 points across these simulations. That is, once the odds of an individual worker losing his or her job exceed roughly 12%, we find that the aggregate impact of a higher minimum wage on poverty is 0 or negative (increasing poverty). Note that even though poverty rates increase, there are nonetheless many workers and families who are better off in these scenarios. It is also important to remember that these simulations randomly assign job loss to minimum wage workers; in the real world, which workers benefit and which are harmed could be more distinct and that would affect changes in poverty as well.

Narrowing the spillover range by 50% yields very small differences in the poverty effect. The change is poverty is at most 0.1 percentage points smaller. This check assumed that only workers within $0.50 of the current minimum or new minimum would be affected, rather than within $1.00. Recall that the change in wage we simulate is also proportional to the difference between a workers wage and the minimum, so the workers who are now excluded from benefiting from the increase were already receiving a smaller increase than other affected workers in the baseline model. Differences are similar if we restrict workers above the new minimum from receiving any increase as well.

Simulating a loss in hours across the board also reduces changes in estimated poverty rates. Poverty is estimated to drop 0.6 points from 2012–2015 to 2017, another 0.7 points for the increase to $13, and 1.1 points for the increase to $15 if in addition to increased wages workers also work fewer hours, at the rate of 4%.[17] Declines are roughly half as large for the 9% reduction in hours simulation. The scale of the difference is certainly in part driven by the scale of the hours reduction modeled here. These parameters are taken from the most recent study on Seattle's experience after introducing a $13 minimum (Jardim et al. 2017). While we do not presume these would apply exactly to the California context, using these parameters helps to quantify how changes in hours affect aggregate statistics like the poverty rate. In our data, even a 4–9% reduction in hours still yields a drop in poverty, although the changes in poverty narrow substantially. That is, hours would need to drop by larger amounts or differentially across important subgroups in order to completely nullify the poverty-reducing effect of the minimum wage.

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[17] Note that these latter two changes compare the 9% hours loss estimate to the "no job loss" scenario in the prior year, since all simulations use the "no job loss" scenario as the baseline.

TABLE C4

Poverty rates under various minimum wage assumptions

	Among all			Among young children			Low-cost counties			Mid-cost counties			High-cost counties		
	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty
2012–2015 original data															
	18.9%	4.0%	41.2%	24.1%	5.4%	49.1%	16.5%	3.9%	40.7%	16.1%	3.4%	40.2%	20.2%	4.2%	41.6%
$10.50 minimum (baseline)															
No employment changes	18.1%	3.7%	40.6%	23.0%	5.0%	48.5%	15.7%	3.7%	39.7%	15.4%	3.2%	39.6%	19.4%	3.9%	41.1%
Job loss scenario 1	18.2%	3.8%	40.7%	23.0%	5.1%	48.6%	15.7%	3.7%	39.8%	15.4%	3.2%	39.6%	19.5%	4.0%	41.1%
Job loss scenario 2	18.2%	3.8%	40.7%	23.1%	5.1%	48.6%	15.8%	3.7%	39.9%	15.5%	3.2%	39.6%	19.5%	4.0%	41.1%
Job loss scenario 3	18.9%	4.2%	41.0%	23.7%	5.6%	48.8%	16.4%	4.1%	40.5%	15.9%	3.4%	39.9%	20.1%	4.5%	41.5%
Job loss scenario 4	19.0%	4.3%	41.1%	23.9%	5.7%	49.0%	16.5%	4.4%	40.2%	16.1%	3.5%	39.9%	20.2%	4.6%	41.5%
Narrow spillover range	18.2%	3.8%	40.7%	23.0%	5.1%	48.6%	15.7%	3.7%	39.7%	15.4%	3.2%	39.6%	19.4%	4.0%	41.1%
No spillover above minimum	18.2%	3.7%	40.7%	23.0%	5.1%	48.6%	15.7%	3.7%	39.7%	15.4%	3.2%	39.7%	19.4%	3.9%	41.1%
Hours loss at 4%	18.3%	3.8%	40.8%	23.2%	5.1%	48.7%	16.0%	3.7%	39.9%	15.5%	3.2%	39.8%	19.6%	4.0%	41.2%
Hours loss at 9%	18.6%	3.9%	41.0%	23.6%	5.1%	48.9%	16.2%	3.8%	40.4%	15.8%	3.2%	40.0%	19.8%	4.1%	41.4%
$13 minimum															
No employment changes	17.1%	3.6%	39.6%	21.7%	4.9%	47.4%	15.0%	3.6%	38.0%	14.3%	3.1%	38.5%	18.3%	3.8%	40.2%
Job loss scenario 1	17.3%	3.7%	39.7%	21.8%	5.0%	47.6%	15.2%	3.7%	38.1%	14.5%	3.2%	38.7%	18.5%	3.9%	40.2%
Job loss scenario 2	17.5%	3.8%	39.8%	22.0%	5.2%	47.6%	15.3%	3.9%	38.2%	14.7%	3.2%	38.7%	18.7%	4.0%	40.3%
Job loss scenario 3	18.6%	4.6%	40.7%	23.4%	6.2%	48.4%	17.1%	4.8%	40.1%	15.8%	4.0%	39.9%	19.7%	4.7%	41.1%
Job loss scenario 4	19.1%	4.8%	40.9%	23.8%	6.5%	48.6%	17.7%	5.1%	40.6%	16.2%	4.1%	40.1%	20.2%	5.0%	41.2%
Narrow spillover range	17.2%	3.6%	39.6%	21.7%	4.9%	47.5%	15.0%	3.6%	38.0%	14.4%	3.1%	38.5%	18.3%	3.8%	40.2%
No spillover above minimum	17.1%	3.6%	39.6%	21.7%	4.9%	47.5%	15.0%	3.6%	38.1%	14.4%	3.1%	38.5%	18.3%	3.8%	40.2%
Hours loss at 4%	17.4%	3.6%	39.9%	22.0%	4.9%	47.8%	15.2%	3.6%	38.6%	14.6%	3.1%	38.9%	18.6%	3.8%	40.5%

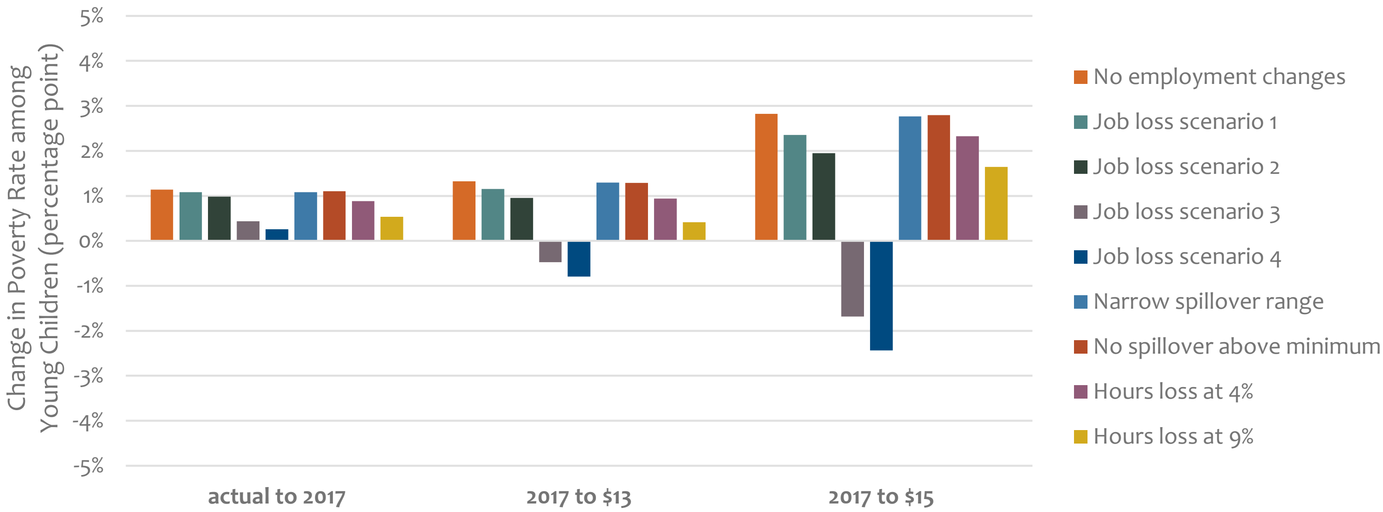
	Among all			Among young children			Low-cost counties			Mid-cost counties			High-cost counties		
	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty
Hours loss at 9%	17.8%	3.7%	40.3%	22.6%	5.0%	48.2%	15.5%	3.7%	39.2%	15.1%	3.1%	39.3%	19.1%	3.9%	40.8%
$15 minimum															
No employment changes	15.9%	3.5%	38.1%	20.1%	4.8%	45.9%	14.0%	3.6%	36.1%	13.4%	3.0%	36.9%	17.0%	3.7%	38.8%
Job loss scenario 1	16.3%	3.7%	38.5%	20.6%	5.1%	46.2%	14.6%	4.0%	36.7%	13.7%	3.2%	37.2%	17.3%	3.9%	39.2%
Job loss scenario 2	16.7%	3.9%	38.7%	21.0%	5.3%	46.5%	15.0%	4.1%	37.1%	14.2%	3.4%	37.6%	17.7%	4.1%	39.3%
Job loss scenario 3	19.9%	5.8%	41.1%	24.7%	7.9%	48.8%	18.9%	6.3%	41.2%	17.8%	5.2%	40.6%	20.7%	6.0%	41.3%
Job loss scenario 4	20.8%	6.5%	41.8%	25.4%	8.4%	49.2%	20.6%	7.3%	42.6%	18.4%	5.8%	41.0%	21.6%	6.5%	41.9%
Narrow spillover range	16.0%	3.5%	38.2%	20.2%	4.8%	46.0%	14.1%	3.6%	36.1%	13.4%	3.0%	36.9%	17.0%	3.7%	38.9%
No spillover above minimum	15.9%	3.5%	38.2%	20.2%	4.8%	46.0%	14.0%	3.6%	36.1%	13.4%	3.0%	36.9%	17.0%	3.7%	38.8%
Hours loss at 4%	16.3%	3.5%	38.7%	20.6%	4.8%	46.5%	14.3%	3.6%	36.6%	13.7%	3.0%	37.3%	17.4%	3.7%	39.4%
Hours loss at 9%	16.9%	3.6%	39.3%	21.3%	4.9%	47.1%	14.9%	3.6%	37.7%	14.2%	3.0%	38.0%	18.0%	3.7%	40.0%

SOURCES: CPM 2012–2015 and author calculations

NOTES: "Job loss 1–4" refers to the itemized list in the text, corresponding to 10%, 20%, 100%, and 120% odds. "Narrow spillover" reduces the spillover range from $1 to $0.50 and "No spillover above minimum" calculates no increase in wages for those above the new minimum wage. "4% hours loss" and "9% hours loss" refer to simulations where all affected workers lose 4 or 9% of hours, respectively. See text for additional explanation.

FIGURE C3

Change in California young child poverty rates across minimum wage robustness checks



SOURCE: CPM 2012–2015 and author calculations.

NOTE: Positive changes indicate reduction in poverty. "Job loss 1–4" refers to the itemized list in the text, corresponding to 10%, 20%, 100%, and 120% odds. "Narrow spillover" reduces the spillover range from $1 to $0.50 and "No spillover above minimum" calculates no increase in wages for those above the new minimum wage. "4% hours loss" and "9% hours loss" refer to simulations where all affected workers lose 4 or 9% of hours, respectively. See text for additional explanation.

Appendix D. Analysis for the EITC Policy Scenarios

Policy context

The federal EITC, in place since 1975, is one of the largest safety net programs for Californians. The 3 million Californians who filed for the federal EITC in 2015 received an average of $2,400.[18] The credit primarily assists low- and moderate-income families, increasing to a plateau amount and then phasing out. The EITC is most generous for families with dependent children, and the majority of those who claim it are single filers. For an introduction to the research literature that finds a range of positive effects of the EITC—including increased employment, but also beneficial health and education effects—see Hoynes (2014).

The 2015 and 2017 CalEITC

In 2015, California became one of now 27 states that offered state-level EITCs that augment the federal credit. Most of these programs directly shadow the federal EITC by multiplying the federal credit by a state-specific factor. Washington DC, for example, has the highest factor, setting its EITC at 40% of the federal credit, while Louisiana has the lowest factor of 3.5%.[19]

The 2015 CalEITC was unique among state-level programs in that it complemented the federal EITC by targeting very low-income families and providing up to 80% of the federal credit (multiplied by an 85% adjustment factor), instead of augmenting all federal EITC beneficiaries by matching a percentage of the credit.[20] The CalEITC essentially matched the federal credit for the lowest-income workers (those who earn up to $3,429 or $7,229 depending on number of dependents, and in 2016 dollars). It also matched a smaller, declining percentage of the federal credit for families earning up to $6,717 to $14,161 (again depending on the number of dependents).[21] For these workers, the 2015 CalEITC brought their total federal plus state credits up to the maximum available (roughly $5,500). The Franchise Tax Board reports that 400,000 filers claimed the CalEITC for tax year 2015, in families that we estimate contained a total of 1.3 million Californians.[22]

Recent legislation (SB 106) retains the original structure of the 2015 CalEITC, but increases the maximum income at which filers can receive the CalEITC in light of the 2017 increase in California's minimum wage. Filers who earn up to between $15,030 and $22,305 (roughly speaking full-time, minimum-wage workers) can now receive a small credit.[23] Thus the current structure of the CalEITC still extends the maximum value of the federal EITC to filers at very low incomes, but also now gives filers at slightly higher income levels an extra boost. The bill also brings the CalEITC in line with the federal credit by including self-employment income in the definition of earned income. The CalEITC remains different from the federal EITC in that it does not distinguish between single and joint filers. The state budget for 2017–18 anticipates that a total of 1.4 million filers will claim the CalEITC for tax year 2017.[24] In our baseline dataset, these credits benefit about 5.4 million family members of those filers.

Table D1 shows differences in effects between the CalEITC original design (2015), and its design as of 2017. Note that the first column of the table (Total/Actual) is directly comparable with the second column (2015 CalEITC) in the sense that these two columns rely on the 2015 CPM data. The final column of the table (2017 CalEITC) uses instead the baseline data for this report, which is further documented in Appendix A. In short, the percentage point

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[18] Danielson, C. April 2017. Just the Facts: Earned Income Tax Credits in California.

[19] Internal Revenue Service. December 7, 2016. State and Local Governments with Earned Income Tax Credit.

[20] For additional discussion of the CalEITC in relationship to other state EITCs, see Rueben, Sammartino, and Stark (2017).

[21] For additional detail on CalEITC eligibility, see State of California Franchise Tax Board, 2017, California Earned Income Tax Credit (CalEITC).

[22] California Franchise Tax Board. April 7, 2017. Personal Income Tax Statistics 2014–2015 Tax Years.

[23] Senate Bill 106 (Committee on Budget and Fiscal Review, Chapter 96 of 2017).

[24] California Department of Finance, June 27, 2017. 2017–18 State Budget.

differences in poverty shown in column 2 can be directly added to the poverty rates shown in column 1. The direct comparison for column 3 is to the poverty rates for the baseline CPM shown in Appendix G (Table G2). These percentage point changes are small. For example, looking at the overall deep poverty rate (5.5%), subtracting the resources from the 2015 CalEITC increases it by 0.05 percentage points to 5.55%.

TABLE D1

Effects of the 2015 and 2017 CalEITCs

	Total/Actual	2015 CalEITC	2017 CalEITC
Californians assisted:			
Number	38,220,000	1,290,000	5,350,000
Percent	100.0%	3.4%	14.2%
Young children assisted:			
Number	2,990,000	160,000	550,000
Percent	100.0%	5.2%	18.3%
Increase in poverty without program dollars (percentage point):			
Overall population			
Deep poverty	5.5%	0.05	0.10
Poverty	19.5%	0.06	0.14
Children 0–5			
Deep poverty	4.7%	0.10	0.20
Poverty	22.4%	0.14	0.31
Children 6–17			
Deep poverty	4.6%	0.12	0.17
Poverty	21.2%	0.13	0.23
Adults 18–64			
Deep poverty	5.9%	0.04	0.08
Poverty	19.0%	0.05	0.11
Seniors 65+			
Deep poverty	5.0%	0.00	0.01
Poverty	18.1%	0.01	0.04

SOURCE: Authors' calculations using California Poverty Measure data for 2015 (total/actual and 2015 CalEITC columns) and 2012–2015 baseline CPM data for the *Reducing Child Poverty* report.

NOTE: Numbers rounded to the nearest 10,000. Number assisted includes all family members of those who could file for the CalEITC. All filers who could file are assumed to claim the CalEITC. FTB reports that 390,000 filers claimed the CalEITC for tax year 2015; the state budget anticipates 1.4 million filers claiming the CalEITC for tax year 2017.

Policy designs presented in the report

We show the CalEITC in conjunction with the federal EITC throughout the Technical Appendices because it is specifically designed to supplement that program. The graphs below therefore show both programs, highlighting the total EITC resources that the CalEITC program design assumes are available to eligible filers.

This report models three expansions to the CalEITC:

- The 2017 expansion of the CalEITC
- An additional expansion targeting the lowest income families

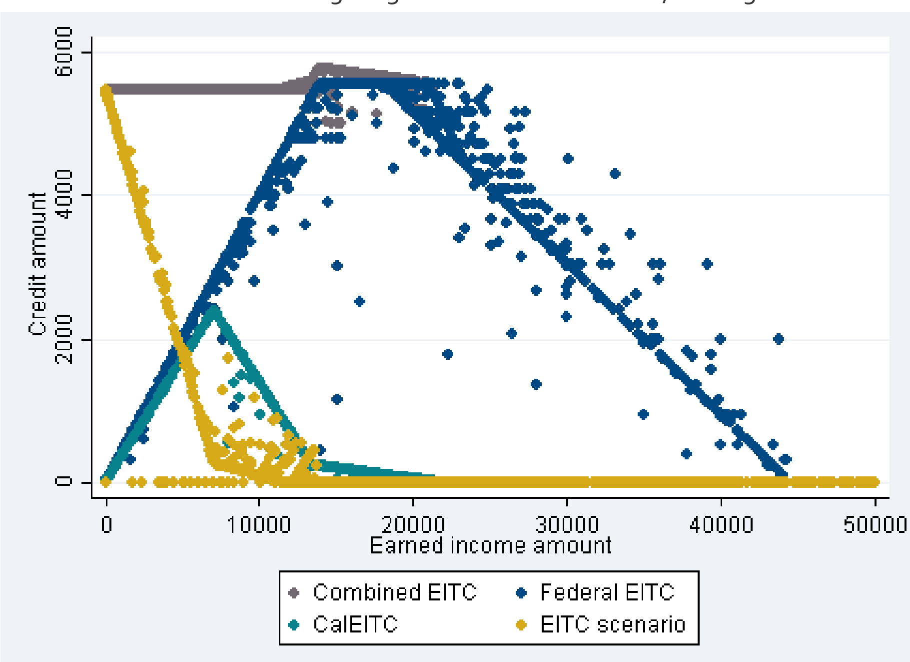
- An additional expansion targeting low- to moderate-income families, with a goal of reaching a larger share of low income workers in high cost areas

The methodologies for implementing these expansions in CPM are detailed in the next section. Here, we describe the general policy approaches. Because our data pertain to 2012–2015, we must first simulate the 2017 CalEITC so that any additional policy expansions can be understood from a baseline landscape that reflects (to the extent possible) the state of policy today. Simulating the 2017 CalEITC is straightforward because, of course, the parameters are already established in law. To quantify the possible effects of additional expansions, we proceed as follows.

First, we consider further targeting very low-income families. This scenario essentially ensures that all lowest-income workers eligible for some EITC receive the maximum amount (roughly $5,500, but depending on family size); the new credit makes up the difference between the maximum amount and the federal EITC and 2017 CalEITC combined. This new credit would be available for all filers who earn up to $13,700 (for filers with two or more dependent children (or $6,500 for filers with no dependent children). Note that EITC-qualifying children are under 19, or up to 24 if they are enrolled in school full-time and have valid social security numbers. In other words, in this scenario all filers who are in the phase-in range of the federal EITC receive a state supplemental EITC that fills the gap between the state EITC and the federal maximum benefit. Figure D1 provides an illustration from our data for single filers with two children. The 2017 CalEITC is shown in green, the existing federal EITC is shown in blue, and the scenario described here is shown in gold. The grey dots show the combined EITC amounts from both existing credits and the scenario credit, and illustrate the fill-the-gap nature of this first EITC scenario.

FIGURE D1

Amounts for EITC scenario targeting lowest-income workers, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2015.

NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

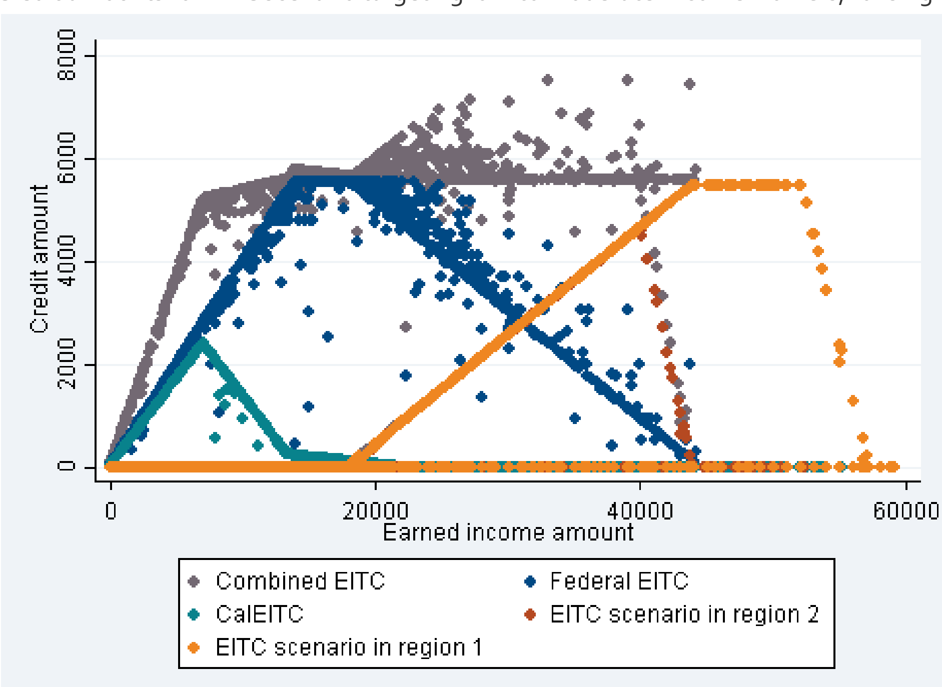
These changes direct the largest credit increases to the lowest-income filers, with small credits going to filers without children, and progressively larger ones going to filers with one or more children. One benefit of this particular scenario is that it simply applies the logic underlying the CalEITC on a larger scale. The CalEITC already offers larger credits to families with children, and it already seeks to extend access to the maximum federal EITC amount to filers with lower incomes. In this way, the scenario modeled here quantifies the effects of taking the current CalEITC to its maximum. It is not, however, pegged to a specific policy rationale beyond that used in developing the current CalEITC.

In the second scenario, we target filers at the other end of the EITC schedule. We increase the maximum income a filer can earn and still qualify for the EITC. This credit affects more of the spectrum of low-income workers in California, providing a useful point of contrast to the first scenario. Also, because we adjust the maximum allowable income according to regional cost of living, this scenario directly aims to address an important gap in the social safety net. In Region 1, we increase the maximum income by the 30 percent adjustment factor for higher cost counties described in Appendix A. In order to prevent these increases from creating a sudden benefit cliff, we also increase the income at which filers become completely ineligible for this expansion by the same factor of 30 percent.

One strength of this scenario is that it implements a version of the 2017 increase in the CalEITC that is consistent with the CalEITC's original intention to work in concert with the federal EITC. The 2017 increase includes minimum-wage workers in the CalEITC, raising the total amount of EITC resources those filers can receive above the maximum federal credit. This scenario instead mirrors the original CalEITC for near-minimum wage workers. This second EITC scenario is illustrated in Figure D2. As in Figure D1, the existing state and federal credits are shown in green and blue, while the scenario credits are shown in orange (Region 1) and in red (Region 2). The figure makes clear that this scenario provides substantial credits to higher income workers who are in or beyond the phase out range of the federal EITC.

FIGURE D2

Credit amounts for EITC scenario targeting low-to moderate-income workers, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2015.

NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

See Technical Appendix G for detailed results from both EITC scenarios for all populations.

Methodology

2017 CalEITC

The baseline for this report assumes that eligible filers receive the most current version of the California EITC, as outlined in SB 106. Because this version of the policy has not yet been implemented, and because the ACS does not gather data on taxes owed or credits received, we impute CalEITC credit values by modeling the current credit schedule. Dollar values in that legislation for the incomes at which the maximum credit can be received, however, reflect the earlier design of the CalEITC. We adjust them for inflation to 2017 using a rate of 2.1%, based on guidance from the Legislative Analyst's Office.[25] As with other dollar values in this analysis, this schedule was deflated to current-year values throughout, and then re-adjusted to reflect a December 2016 baseline scenario using the CPI-U-RS.

The Franchise Tax Board has not yet set total earned income and AGI eligibility caps that reflect the latest addition to the CalEITC. In our model, we follow the example of the CalEITC's original design, and set the new total AGI caps at the earned incomes where filers no longer receive the CalEITC. With the first expansion scenario, which includes lower-income filers, we keep those caps. The second scenario includes higher incomes, and as such, we move the income and AGI caps to match the earned incomes at which filers no longer receive the expanded CalEITC. We also keep expansion scenarios consistent with the original CalEITC design by making the value of the credit a percentage of AGI rather than earned income as it phases out, if AGI is greater than earned income.

Finally, for both the CalEITC and the expansion scenarios, we assume that EITC increases have no impact on family expenses, participation in safety net programs, wages offered, and/or labor supplied.[26]

Our model for the CalEITC closely relates to the model used to impute values of the federal EITC in the annual CPM datasets, because legislation directly links the California credit schedule to the federal EITC. The rates at which the CalEITC phases in and out across a range of incomes are set to be a percentage—determined annually by the state legislature—of the rates at which the federal EITC phases in and out. We assume throughout this analysis that this adjustment factor will continue to be 85%, as it has been for the first two years of the CalEITC.

The state and federal policies also share most eligibility requirements. Eligibility for the CalEITC derives from earned income (including both wages and self-employment), adjusted gross income (AGI), investment income, filing status, number of dependents, length of California residency, and age (if filing without dependents).[27] With the exception of California residency, these same factors determine the federal EITC.

We ensure consistency between the two models by using shared variables for shared eligibility factors. This means that the CalEITC and scenarios for its expansion are calculated using modified ACS income variables. The federal EITC values used in the CPM are the product of ACS variables prepared for the CPM, processed by TAXSIM, the National Bureau of Economic Research's program for tax modeling. TAXSIM does not allow values for income to be negative. Since earned income for both federal and state EITCs includes self-employment income, which can be negative, the earned income variable for TAXSIM includes just wage and positive self-employment income. Investment income instead incorporates negative values for self-employment income.

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[25] Personal communication with Legislative Analyst's Office, July 10, 2017.
[26] For the CalEITC, this caveat applies both to the 2015 original credit and to the 2017 expansion.
[27] State of California Franchise Tax Board. 2017. California Earned Income Tax Credit (CalEITC).

For additional detail on the construction of the federal EITC for the CPM, and that model's limitations, see Technical Appendix C to Bohn, et al. (2013).

CalEITC Expansions

For the scenario that targets the lowest-income workers, we determine expansion credit amounts by simply finding the difference between the maximum federal EITC amount and the projected amount of CalEITC a filer would receive. The second, rightward expansion scenario also provides filers with the maximum federal EITC amount, but because filers eligible for the expansion have incomes too high to receive the current CalEITC, we determine their expansion credit amounts differently. The second scenario's credit phases in for the expansion at the same rate that it phases out for the federal EITC. In lower cost counties, the credit phases out again at the designated income, so that filers receive zero credit at the same income for federal EITC and the CalEITC expansion. In higher cost regions, where the designated income is increased by the regional adjustment factor, the credit is capped at the maximum federal EITC amount, and filers receive zero credit at 1.30 times the maximum income for federal EITC eligibility. The schedule for the expansion is shown in Table D2.

TABLE D2

Schedule for EITC expansion targeting low- to moderate-income workers

			Lower cost counties (Region 2)					Higher cost counties (Region 1)				
Filing status	**Min income**	**Phase in rate**	**Income for max credit**	**Max credit**	**Phase out income**	**Phase out rate**	**Max income**	**Income for max credit**	**Max credit**	**Phase out income**	**Phase out rate**	**Max income**
Single or Head of Household												
0 qualifying dependents	$ 8,139	7.65%	$ 13,672	$ 423	$ 13,672	43.35%	$ 14,648	$ 14,244	$ 498	$17,882	38.93%	$ 19,095
1 dependent	$ 17,898	15.98%	$ 35,547	$ 2,820	$ 35,547	90.55%	$ 38,662	$ 37,479	$ 3,318	$46,338	81.32%	$ 50,399
2 dependents	$ 17,898	21.06%	$ 40,019	$ 4,659	$ 40,019	119.34%	$ 43,922	$ 42,617	$ 5,481	$52,167	107.17%	$ 57,256
3 + dependents	$ 17,898	21.06%	$ 42,783	$ 5,241	$ 42,783	119.34%	$ 47,175	$ 45,964	$ 6,166	$55,771	107.17%	$ 61,459
Married, filing jointly												
0 qualifying dependents	$ 13,594	7.65%	$ 19,127	$ 423	$ 19,127	43.35%	$ 20,103	$ 14,244	$ 498	$ 24,934	38.93%	$ 26,206
1 dependent	$ 23,353	15.98%	$ 41,003	$ 2,820	$ 41,003	90.55%	$ 44,117	$ 37,479	$ 3,318	$ 53,450	81.32%	$ 57,510
2 dependents	$ 23,353	21.06%	$ 45,474	$ 4,659	$ 45,474	119.34%	$ 49,377	$ 42,617	$ 5,481	$ 59,298	107.17%	$ 64,367
3 + dependents	$ 23,353	21.06%	$ 48,239	$ 5,241	$ 48,239	119.34%	$ 52,630	$ 45,964	$ 6,166	$ 62,882	107.17%	$ 68,607

NOTES: Dashes indicate that the value is the same as that of the cell or set of cells above. Dollar amounts are presented in 2015 values, as in the graphs above.

Additional policy designs

We estimate results from these EITC expansion scenarios based on the assumption that all income-eligible filers with qualifying children and valid social security numbers claim their credits. By means of comparison, however, we also model the expansions under circumstances in which income-eligible filers with qualifying children claim the credits regardless of their documentation status. For the expansion scenario that includes a regional adjustment for cost of living, we model a version without the adjustment. Table D3 shows the impacts of these changes on number of young children assisted and reductions in poverty.

TABLE D3

EITC expansion additional designs

	Number	Percent	Deep poverty	Poverty
Baseline	–	–	*4.9%*	*21.9%*
	Young children assisted		Decrease in young child poverty (percentage point)	
1. Lowest-income workers	**210,000**	**7.1%**	**0.27**	**0.30**
Include unauthorized	220,000	7.3%	0.29	0.31
2. Low- to moderate-income workers	**820,000**	**27.2%**	**0.03**	**1.17**
Include unauthorized	1,040,000	34.6%	0.05	1.68
No regional adjustment	680,000	22.6%	0.02	1.05
A. Low-cost counties	**90,000**	**26.1%**	**0.00**	**0.30**
Include unauthorized	110,000	32.1%	0.00	0.44
No regional adjustment	90,000	26.1%	0.00	0.30
B. Mid-cost counties	**170,000**	**25.5%**	**0.01**	**0.69**
Include unauthorized	200,000	30.0%	0.01	0.88
No regional adjustment	170,000	25.5%	0.01	0.69
C. High-cost counties	**550,000**	**27.9%**	**0.03**	**1.49**
Include unauthorized	730,000	36.6%	0.07	2.18
No regional adjustment	420,000	21.0%	0.02	1.31

SOURCE: Author's calculations from 2012–2015 CPM.

NOTES: Numbers rounded to the nearest 10,000. County groups defined in Appendix A. See text for details on each alternative scenario.

Limitations

As discussed in the Technical Appendix to Bohn, et al. (2013), the level of detail available in the ACS limits the precision possible from state and federal EITC estimates. We use the TAXSIM estimate of federal AGI to calculate CalEITC, for example, because the ACS includes neither AGI, California AGI, nor enough information to calculate California AGI; the language defining the CalEITC also does not specifically state that AGI refers to California AGI (Cal. Rev. & Tax. Code § 17052). Using federal AGI in place of state AGI is not likely a major limitation. State and federal AGIs might differ substantially for people who move into California in the middle of the tax year, but CPM data show that in 2014, only about 1 percent of federal EITC recipients had moved to California in the last year, and less than half that number had incomes eligible for the CalEITC. Federal AGI is likely quite similar to California AGI for filers with incomes low enough to be eligible for the CalEITC, or scenarios for its expansion.

Both federal and state EITC models rely on the assumption that all eligible people claim the EITC. The minimum income at which California required filing income taxes for 2016, however, far exceeds the maximum income at which the CalEITC is available. Research shows that federal EITC claims vary by ethnicity (Short, Donohue, & Lynch 2012), and a recent survey by the California Budget and Policy Center found that only half of the population eligible for the CalEITC in 2015 filed taxes that year. Our estimates for the total resources directed to eligible filers by the baseline and expanded CalEITCs therefore best simulate the impacts of the tax credits if they were fully implemented. This assumption is consistent with the intent of this report to frame policy responses to California's high cost of living, rather than to design specific programs.

Appendix E. Analysis for the Child Credit Policy Scenarios

Policy context

The federal Child Tax Credit (CTC) is the existing federal policy that is most closely related to the child credit policy scenarios discussed in this report. The CTC provides up to $1,000 per eligible child to families with more than $3,000 in earned income and children under age 17. The program loosely follows the structure of the EITC: the amount of the credit increases with earned income until it reaches its maximum value for the number of dependents, and progressively decreases once income passes a certain threshold. Like the EITC, the maximum CTC credit is available to married filers at higher incomes than it is to single filers. Unlike the EITC, the CTC was introduced in 1997 as a non-refundable credit. The Additional Child Tax Credit (ACTC), as adopted in 2001 and amended in 2009, allows filers eligible for CTC amounts larger than their tax liabilities to receive refunds of 15 percent of their earned income that exceeds $3,000, up to their CTC amounts.[28] The ACTC significantly expands the impacts of the CTC for low-income filers with low or no tax liabilities.

Filers can claim the CTC within a much wider range of incomes (earned and AGI) than they can the EITC. Single filers with two eligible children, for example, are eligible for the maximum CTC credit if their earned income falls between about $16,000 and $75,000, while only those earning between $14,000 and $18,000 could potentially be eligible for the maximum EITC credit. As a result, the CTC reaches a larger number of filers with children than the EITC does, but a greater share of its resources goes to middle- and moderate-income filers.[29] The CTC nonetheless plays a critical role in resources for low-income families with children. Almost 2.6 million Californians claimed the ACTC in 2014, directing almost $3.6 billion to low-income families.[30]

California does not have a state-level version of the CTC. Its most closely related credit is the Dependent Exemption, a non-refundable credit of $344 (in 2016) per dependent.[31] Only four other states offer any version of the CTC. These credits differ in whether or not they are refundable, between being flat amounts and being percentages of the federal credit, and in the ages at which children are eligible dependents.[32]

Whitehurst (2017) provides a recent, national-level examination of tax and other safety net programs that serve families with children. This report proposes a substantially streamlined and more progressive structure for tax expenditures on families with children, including the CTC. See Hammond and Orr (2016) and Shaefer et al. (2016) for standalone child credit proposals.

Policy designs presented in the report

The scenarios in this analysis for a California refundable child credit in part frame those credits in the context of the EITC, rather than the CTC. We do this to leverage the existing CalEITC infrastructure, and to make the policy more easily comparable to other scenarios in this analysis. Doing so increases the size of the average credit per child (for up to six children) and the age range of eligible dependents, relative to the CTC, and ensures that the credit is available to the lowest-income families.

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[28] Crandall-Hollick, M.L. January 19, 2016. The Child Tax Credit: Current Law and Legislative History. Congressional Research Service.

[29] CPM CTC and EITC imputations show that in 2015, 3.47 million Californians could likely claim either CTC or ACTC, while only 1.85 million Californians with children under age 18 could claim the federal EITC. We estimate the median income for CTC/ACTC filers to be $44,056, compared with $20,525 for EITC filers with children under 18.

[30] Internal Revenue Service. 2017. SOI Tax Stats - Individual Income Tax Return (Form 1040) Statistics.

[31] State of California Franchise Tax Board. 2017. 2016 California Tax Rates and Exemptions.

[32] Tax Credits for Workers and Their Families. 2016. State Tax Credits.

We simulate two child credit scenarios in this report:

- A child credit that directs the largest benefits, up to the maximum EITC amount, to the lowest-income families with children
- A child credit that provides a flat credit for families with children, up to maximum income cap that depends on regional cost of living

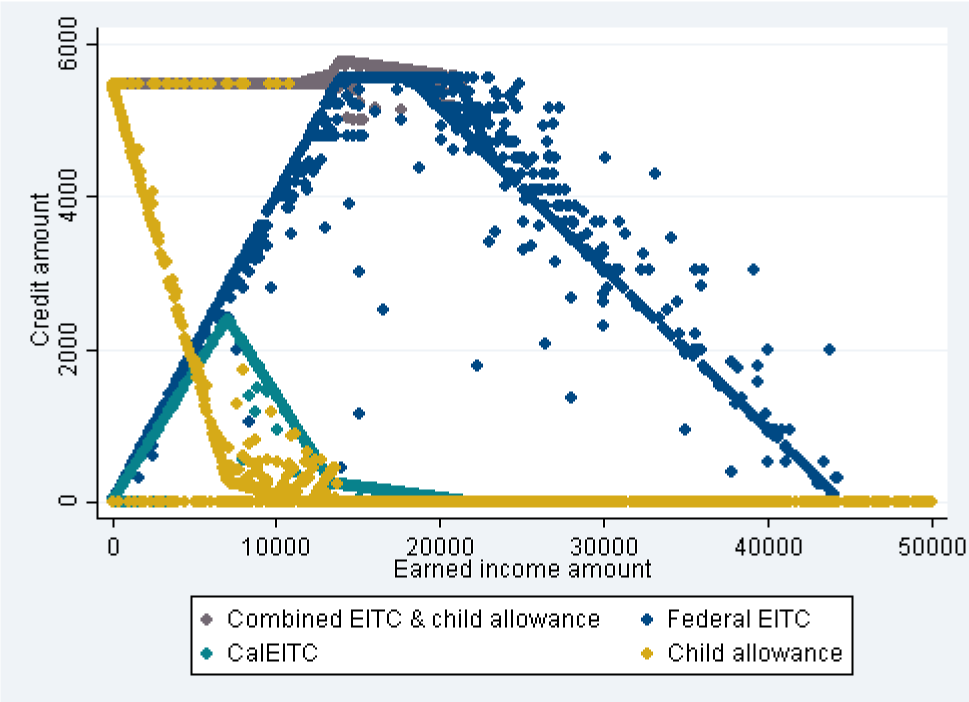
The first scenario is similar in concept to the first CalEITC expansion in Appendix D, which, for the lowest-income families, fills the gap between existing tax credits and the maximum federal EITC amount. However, the child credit considered here includes families who do not file taxes or are not eligible for the EITC and CalEITC as well as those who are. In that way, the first EITC expansion in Appendix D is a subset of this scenario. Setting the maximum California child credit value equal to the maximum EITC value has the effect of capping program expenses at a lower level. Filling the gap created by the federal CTC for low-income families would be significantly more costly, because of that program's emphasis on middle- and moderate-income families. Because this California child credit schedule operates independently from the federal CTC, however, the two overlap briefly. This means that CTC-eligible families get an additional boost at $3,000 in earned income.

This version of the California child credit explicitly targets California families in deep poverty, by including people without earned income and by directing the largest credits to the lowest income families with children. This California child credit would be available to filers with two dependents only if they had less than $14,040 in earned income.

Figure E1 illustrates the result in the CPM data for a single filer with two children. As in earlier figures, the existing state and federal credits are shown in green and blue; here, the scenario credits are shown in gold, and the sum total of the credits is shown in gray. This figure differs from D1, which shows the comparable EITC expansion scenario, in the flat line at the maximum credit level for filers who receive no CalEITC because of their immigration status or because they are not required to file.

FIGURE E1

Amounts for child credit scenario targeting lowest-income families, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2012–2015.

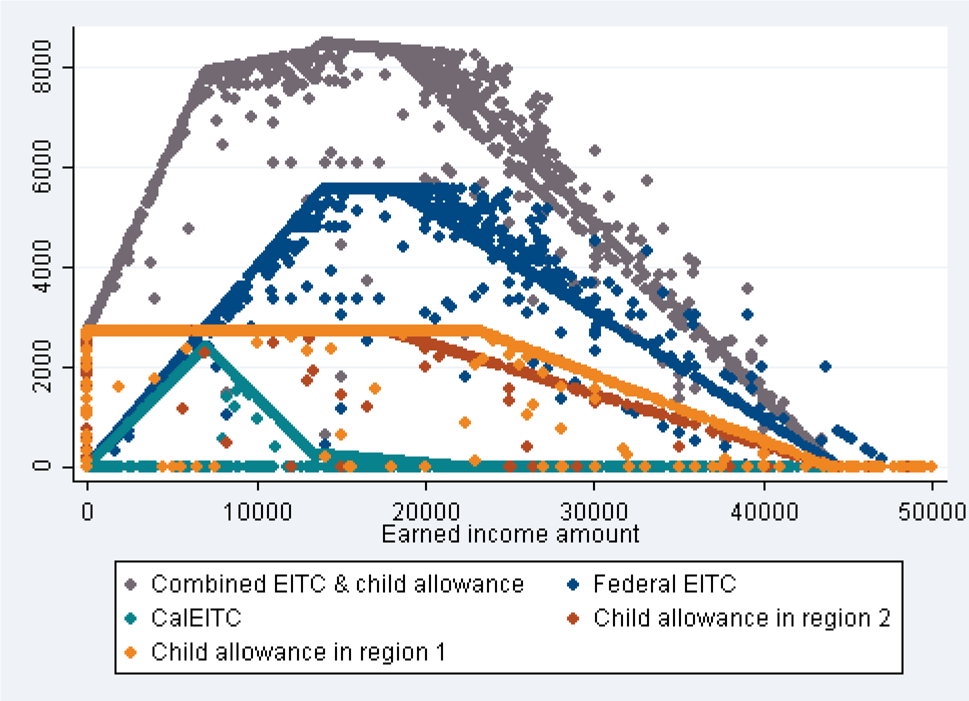
NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

The second child credit we consider takes the form of a flat child allowance. In other words, every eligible family receives a flat amount that depends only on the number of children in the family. Families are eligible if their AGI fits within the federal EITC schedule, but remain eligible for the full credit amount at 1.30 times the income in higher cost counties that they do in lower cost counties. The credit modeled is $1,700 for the first dependent child in the family, and is scaled thereafter by the number of children raised to the power of 0.7, which is related to the adjustment factor used in creating the Supplemental Poverty Measure equivalence scale. For example, this yields a credit of $2,762 for family with two children (1.62*1,700) and a credit of $4,486 for a family with four children (2.64*1,700). All dependent children for tax filing purposes are made eligible for this credit, including children who are not eligible for the EITC due to immigration status.

Figure E2 illustrates the result in the CPM data for a single filer with two children. As in earlier figures, the existing state and federal credits are shown in green and blue; here, the scenario credits are shown in orange (Region 1) and red (Region 2), and the sum total of the credits is shown in gray.

FIGURE E2

Amounts for child credit scenario targeting low- and moderate-income families, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2012–2015.

NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

See Technical Appendix G for detailed results from both child credit scenarios for all populations.

Methodology

The first child allowance scenario, which fills the EITC gap, is constructed by almost the same methods as the first EITC expansion scenario in Appendix D. In this scenario, too, the credit is the difference between the maximum federal EITC amount a filer could receive and their projected amount of CalEITC. See Appendix D for a complete discussion of data, methods, and limitations related to the federal and CalEITC. The child allowance scenarios differ from the EITC expansions in that they use the same broad baseline population as the renter's credits. They are only available, however, to filers with children, where children are under 19 or up to 24 years old and full-time students. See Appendix A for additional information about non-filers included in these scenarios.

The child allowance scenario that targets low- and moderate-income families is designed to give credit amounts based on income, filing status, and number of children alone. Table E1 shows the complete schedule for this credit.

TABLE E1

Schedule for child credit scenario targeting low- and moderate-income families

	Lower cost counties				Higher cost counties			
Number of children	Max credit amount	Phase out income	Phase out rate	Max income	Max credit amount	Phase out income	Phase out rate	Max income
Single or head of household								
1	$1,700	$17,898	7.99%	$38,662	$1,700	$23,446	12.13%	$38,662
2	$2,762	$17,898	10.36%	$43,922	$2,762	$23,446	14.23%	$43,922
3	$3,668	$17,898	12.23%	$47,175	$3,668	$23,446	16.16%	$47,175
4	$4,486	$17,898	15.00%	$47,175	$4,486	$23,446	19.73%	$47,175
Married filing jointly								
1	$1,700	$23,353	7.99%	$44,117	$1,700	$30,593	10.82%	$44,117
2	$2,762	$23,353	10.36%	$49,377	$2,762	$30,593	13.10%	$49,377
3	$3,668	$23,353	12.23%	$52,630	$3,668	$30,593	15.01%	$52,630
4	$4,486	$23,353	15.00%	$52,630	$4,486	$30,593	18.36%	$52,630

NOTES: Dashes indicate no change in the value from the cell above. Credit amounts for families with more than four children have been omitted. Dollar amounts are shown in 2015 values, as in the graphs above.

Additional policy designs

We also model variations of the scenarios that exclude units where no one is required to file and unauthorized immigrants, and, in the flat child allowance scenario, remove the adjustment for higher cost regions. Table E2 shows the impacts of these changes on key metrics.

Restricting the eligible population to required filers significantly decreases the number of young children assisted and the credit's impact on young child poverty. This is in part a function of the fact that the non-required filers receive zero federal or CalEITC, and therefore all receive the maximum child allowance amount. Not surprisingly, the result of restricting the eligible population to required filers for the first child credit scenario is to make it comparable in size and impact to the first EITC expansion for this report.

For the credit that includes moderate-income families, the sensitivity analysis demonstrates that the design used in the report has the greatest capacity to reduce young child poverty and deep poverty. Removing regional adjustment for cost of living seems to have only a small impact on young child poverty, but this is in part because its impact is dwarfed by the scale of poverty reductions in this scenario. In other scenarios, a 0.29 percentage point decrease in the reduction of young child poverty is a relatively large change.

TABLE E2

Child allowance additional designs

Baseline	Number –	Percent –	Deep poverty *4.9%*	Poverty *21.9%*
	Young children assisted		**Decrease in young child poverty (percentage point)**	
1. Lowest-income families	**390,000**	**12.8%**	**1.46**	**1.42**
Exclude unauthorized	310,000	10.2%	0.79	1.14
Exclude non-filing population	180,000	6.0%	0.29	0.28
2. Low- and moderate-income families	**1,590,000**	**52.7%**	**1.57**	**4.43**
Exclude unauthorized	1,230,000	40.8%	0.83	3.14
Exclude non-filing population	1,330,000	44.1%	0.64	3.69
No regional adjustment	1,590,000	52.7%	1.56	4.14
A. Low-cost counties	**230,000**	**68.1%**	**2.04**	**4.77**
Exclude unauthorized	190,000	55.2%	1.21	3.48
Exclude non-filing population	190,000	54.6%	0.61	3.36
No regional adjustment	230,000	68.1%	2.04	4.77
B. Mid-cost counties	**390,000**	**57.0%**	**1.41**	**4.73**
Exclude unauthorized	330,000	48.0%	0.95	3.62
Exclude non-filing population	330,000	47.8%	0.63	3.71
No regional adjustment	390,000	57.0%	1.41	4.73
C. High-cost counties	**960,000**	**48.5%**	**1.53**	**4.26**
Exclude unauthorized	710,000	35.8%	0.72	2.92
Exclude non-filing population	810,000	40.9%	0.65	3.73
No regional adjustment	960,000	48.5%	1.52	3.83

SOURCE: Author's calculations from 2012–2015 CPM.

NOTES: Numbers rounded to the nearest 10,000. County groups defined in Appendix A. See text for details on each alternative scenario.

Appendix F. Analysis for the Renter's Credit Policy Scenarios

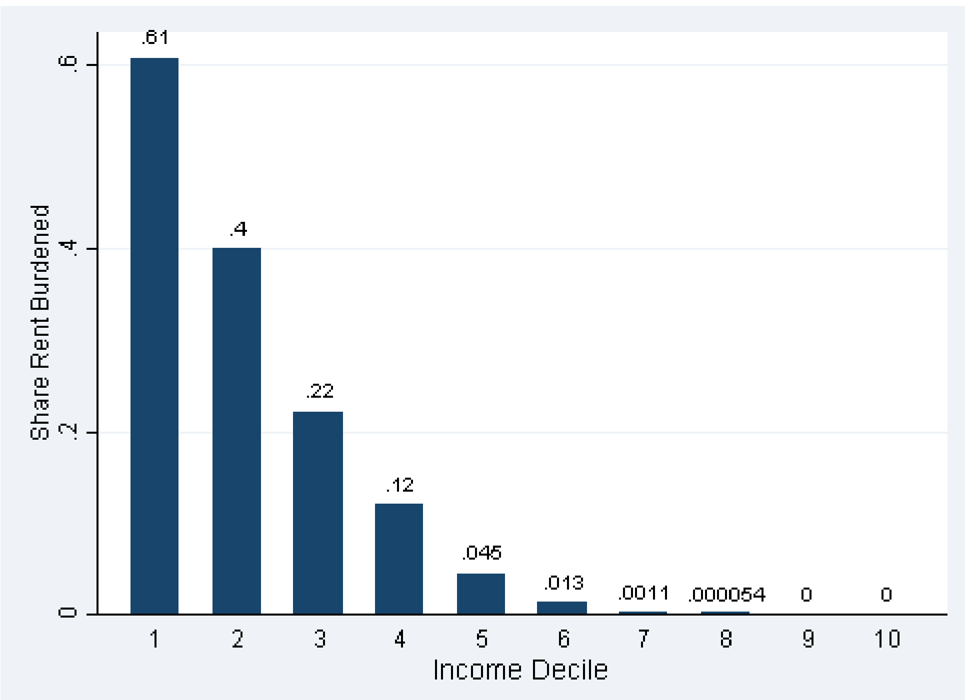
Policy context

As the report discusses, the high cost of housing in California is often described as having reached crisis levels. Home prices and rental costs are much higher in California than in other large states; only Hawaii has higher average home prices (Legislative Analyst 2015). Even within California, most of the least expensive areas are still more expensive than the national average. These trends of increasing home prices, lack of affordable housing supply, and stagnating wages for lower income individuals contribute to disproportionately high housing cost burdens (Sard and Fischer 2013).

In California from 2012–2015, renters in lower deciles of the income distribution had consistently larger "rent burdens," or proportion of rent to income, than those in higher deciles. Figure F1 documents the median share of gross income (defined as the sum of earnings, income from retirement and investments, and payments from the state and federal EITC and the CTC) devoted to rent, by decile of income using data from the 2012–2015 ACS.[33]

FIGURE F1

Median fraction of income paid in rent by income decile



SOURCE: Author's calculations from the 2012–2015 ACS.

California's current nonrefundable renter's credit provides tax credits of $60 for single or married filers filing separately with adjusted gross incomes of $39,062 or less, and $120 for heads of household, widowers, and joint filers with adjusted gross incomes of less than $78,125 (in 2016). The credit is estimated to have cost the state $110 million in FY 2016 (State of California Department of Finance 2016). While this credit is targeted at lower income renters, it does not specifically focus on renters who are more rent burdened. It is also nonrefundable, meaning that

[33] In these calculations, household rental cost is capped at the Fair Market Rent value (FMR)

filers must carry a tax liability of greater than $60 or $120 to receive the credit. In contrast, most EITC-eligible income filers do not carry a tax liability and thus cannot access the existing California renter's credit.

Policy designs presented in the report

We model two refundable credits aimed at relieving rent burden that exceeds 50 percent:

- A refundable credit calculated to reduce rent burden to no more than 50% of income (up to a maximum amount), targeted at the lowest-income group.
- A flat, refundable credit for rent-burdened families that phases out at low- to moderate-income levels (adjusted for cost of living).

To model the full impact of credits, we assume that all primary earners, even those not required by their income levels, file taxes. The credits are, further, not awarded with any requirement that filers use SSNs (unlike for the EITC). These conditions ensure that the credits assist the greatest possible number of young children in poverty.

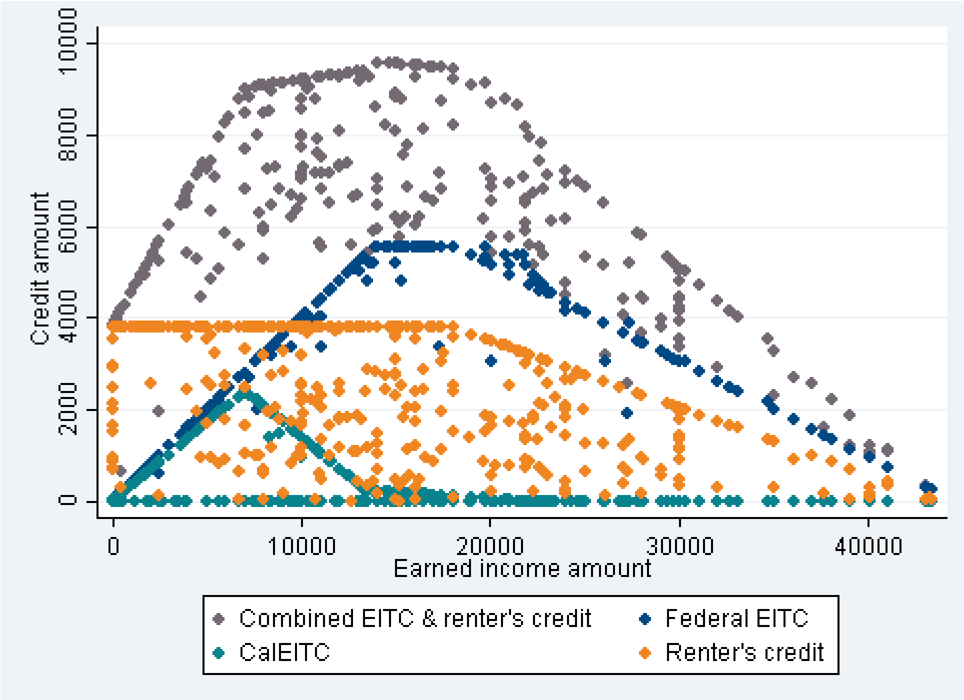
The first scenario provides a credit to rent-burdened filers that makes up the difference between their income and the lesser value of their rent and the Fair Market Rent (FMR) for their residence, up to a cap of $3,900. This cap reflects he median amount needed to relieve severe rent burden (calculated using the 2012–2015 CPM).

This credit phases out on the EITC schedule, sharing earned income and AGI maximums, as well as sharing the maximum income at which recipients become ineligible for the full credit. While this design directly to the amount of rent burden that a family experiences, the cap does limit the responsiveness for highly rent-burdened filers.

Figure F2 illustrates the result in the CPM data for a single filer with two children who is eligible for the credit. As in earlier figures, the existing state and federal credits are shown in green and blue, while the scenario credits are shown in orange, and the sum total of the credits is shown in gray. The flat line created at the maximum credit amounts demonstrates one difficulty of capping a credit that responds directly to rent burden: a number of filers are rent burdened beyond the bounds of even a generous policy.

FIGURE F2

Credit amounts for scenario targeting lowest-income rent burdened, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2012–2015.

NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

The second scenario reframes the current California nonrefundable renter's credit as a flat, refundable credit of $3,900 (in 2016) that phases out at low- to moderate-income levels, adjusted for cost of living.[34] No household imputed to receive a federal rental housing subsidy in the CPM data is allocated a renter's credit in this scenario.

The credit is limited in Region 2 to rent burdened tax filers whose AGIs are below the maximum AGI currently specified by the FTB (ranging from about $39,000 for individuals to about $78,000 for joint filers)[35] and to similar filers in Region 1 with AGIs up to 1.30 times that amount (i.e., the adjustment factor described in Appendix A). This design assists rent-burdened families, accounting for the costs of living for families in higher-cost regions, but does not differentiate between families who may be differently rent-burdened.

Figure F3 illustrates the result in the CPM data for a single filer with two children who is eligible for the credit. As in earlier figures, the existing state and federal credits are shown in green and blue, while the scenario credits are shown in red (region 2) and orange (region 1), and the total credit amounts are shown in gray.

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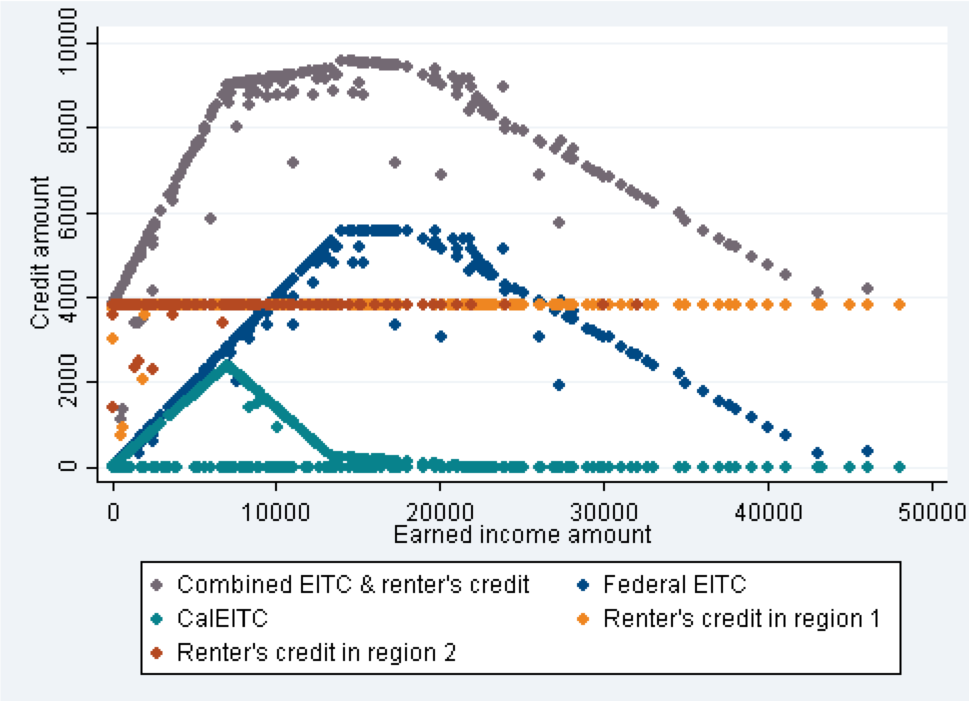
[34] In the augmented ACS data used to create the CPM, median rent burden does not vary widely by family size, so this flat credit is the same across all family sizes.

[35] State of California Franchise Tax Board. 2017. Nonrefundable Renter's Credit.

FIGURE F3

Credit amounts for scenario targeting low- and moderate-income rent burdened, for single filers with two children



SOURCE: Authors' calculations using base California Poverty Measure data for 2012–2015.

NOTE: Each point represents a filer. Points below the credit schedules indicate filers whose credits are calculated based on AGI. Federal EITC given by NBER's TAXSIM. Graph shows values for representative families in 2015 dollars.

See Technical Appendix G for detailed results from both renter's credit scenarios for all populations.

Methodology

The analyses presented rely on the CPM datasets described in Technical Appendix A. For the purposes of this report, we calculate rent burden by dividing total income by the *lower* of self-reported rent or the HUD-determined FMR for the county, which also varies by unit size. Total income, for this credit, refers to financial resources that a family can spend on housing, and includes income from wages and salaries, self-employment, investments, retirement, Social Security, and Supplemental Security Income, as well as credits from the federal EITC and CTC, and CalEITC.

This definition of income is broader than earned income, but more limited than the concept of resources that determines poverty status in the CPM. "Resources" includes both income and safety net programs such as CalFresh, WIC, and free or reduced-price school meals that help families meet basic needs, including housing. For purposes of the policy simulations, we chose to align the income concept used in determining rent burden more closely with what would be reported on a tax return.

Both scenarios deliver credits via tax returns, implying that households may contain multiple tax filing units. When this is the case, we prorate rent paid (or FMR) by the share of gross income attributed to each filing unit. Both scenarios make the credits available to all low-income, rent-burdened people in California, regardless of requirements to file taxes or file using SSNs. In cases where filing units that rent have $0 income (using the definition above), they are assigned rent burden of 100% if they do not share their place of residence with another filing unit. If they do share their residence, then their assigned rent burden is 0%.

Using our expanded definition of income, the statewide median income for filers whose rent burden exceeds 50 percent is $12,607, and the highest income is $80,028. The highest income seen among those who are rent burdened varies substantially across counties by cost of living, ranging from $35,596 in lower-cost counties to $80,028 in higher-cost counties. Median income across low-, middle-, and higher-cost counties is more consistent ($9,312, $10,686, and $13,571, respectively). This distribution means that median-income renters can receive the maximum credit in either scenario in any county. The caps on income and AGI for each credit, however, qualify different ranges of incomes for the credits. One credit specifically includes moderate-income rent-burdened families by raising the income cap in higher-cost counties. The other targets the lowest income rent-burdened families by phasing out on the federal EITC schedule, which has a middling AGI cap, but delivers reduced credits starting at a lower income. These differences are visible in Figures F2 and F3.

In the case of the first scenario, because the credit amount could theoretically be different for all recipients, there is no schedule of rates at which the credit phases out as filers' income approaches the federal EITC eligibility boundaries. Instead, we calculate individual phase-out rates for higher-income filers, by dividing the maximum credit for which a filer might be eligible by the difference between the maximum income at which they could receive the federal EITC and the income at which they would no longer receive the maximum federal EITC (adjusted for higher cost counties).

Additional policy designs

Both renter's credits are designed for a baseline population that includes households with incomes too low to require filing taxes and potentially unauthorized filers, use the lesser value of rent or FMR to award credit amounts, and offer increased credits in higher cost regions. We therefore explore the impacts of each of these criteria on the total cost of the policy, the number of children 0–5 who benefit, and the policy's anti-poverty effects. Table F1 below shows these impacts.

Substituting FMR in cases where self-reported rent is *lower* than FMR extends the credits to the largest number of children 0–5, generates the highest costs, and has the largest impacts on poverty, across both credit designs. At its extreme, for example, the renter's credit that determines severe rent burden and relieves a portion of rent burden based on FMR in the baseline population assists 460,000 children 0–5, and reduces young child poverty and deep poverty by 1.2 and 1.5 percentage points, respectively. This substitution could be thought of as bounding a type of behavioral response—if renters seek units at FMR. Of course other types of behavioral responses would also be expected (e.g., substitution away from home ownership). Substituting self-reported rent in cases where rent is higher than FMR also increases the cost, anti-poverty impacts, and number of children assisted, but by a much smaller margin.

Different populations are affected by these substitutions, and the key policy variant for our purposes is the version where rent alone determines rent burden and the credit. Clearly using the lower of FMR or rent instead of rent alone reduces the total cost of the credit, but not drastically.

TABLE F1
Renter's credit additional designs

Baseline	Number –	Percent –	Deep poverty *4.9%*	Poverty *21.9%*
	Young children assisted		Decrease in young child poverty (percentage point)	
1. Lowest-income rent burdened	**250,000**	**8.3%**	**0.89**	**0.49**
Rent determines credit	260,000	8.8%	0.90	0.56
FMR determines credit	460,000	15.2%	1.20	1.50
Exclude unauthorized	150,000	4.9%	0.39	0.40
Exclude non-filers	190,000	6.3%	0.44	0.50
2. Low- and moderate-income rent burdened	**310,000**	**10.2%**	**1.11**	**1.30**
Rent determines credit	320,000	10.8%	1.11	1.40
FMR determines credit	540,000	17.8%	1.29	2.79
No regional adjustment	310,000	10.1%	1.11	1.29
Exclude unauthorized	190,000	6.4%	0.48	0.98
Exclude non-filers	230,000	7.7%	0.53	1.16
A. Low-cost counties	**30,000**	**9.2%**	**1.27**	**1.27**
Rent determines credit	30,000	9.5%	1.27	1.31
FMR determines credit	60,000	16.2%	1.52	2.51
No regional adjustment	30,000	9.2%	1.27	1.27
Exclude unauthorized	20,000	6.3%	0.54	1.01
Exclude non-filers	20,000	5.9%	0.49	0.88
B. Mid-cost counties	**60,000**	**8.7%**	**0.91**	**1.31**
Rent determines credit	60,000	9.0%	0.91	1.34
FMR determines credit	110,000	16.3%	1.01	2.80
No regional adjustment	60,000	8.7%	0.91	1.31
Exclude unauthorized	40,000	6.5%	0.58	1.05
Exclude non-filers	50,000	6.8%	0.56	1.11
C. High-cost counties	**210,000**	**10.8%**	**1.15**	**1.30**
Rent determines credit	230,000	11.6%	1.15	1.43
FMR determines credit	370,000	18.6%	1.34	2.83
No regional adjustment	210,000	10.8%	1.15	1.30
Exclude unauthorized	130,000	6.4%	0.44	0.95
Exclude non-filers	170,000	8.4%	0.53	1.23

SOURCE: Author's calculations from 2012–2015 CPM.

NOTES: Numbers rounded to the nearest 10,000. County groups defined in Appendix A. See text for details on each alternative scenario.

Limitations

Apart from the imperfect information available in the ACS about tax units, taxes owed, and filing behavior, and the limitations of using self-reported rent values—which are common to all tax scenarios considered—renter's credit calculations also face several other limitations. First is determining the share of rent paid when multiple filing units reside in the same household. Second is the calculation of FMR when a county is heterogeneous.

We make the assumption that the share of rent paid when multiple filers live in one rental unit is proportional to each filer's income. A key implication of this assumption is that filing units with no income are assumed to pay no rent—and thus by definition cannot be rent burdened. A different assumption—e.g., prorating rent by the number of people in each filing unit—would, in contrast, assign rent burden to $0 income filers.

In recent years, HUD piloted and institutionalized using small area fair market rents (SAFMRs), measured at the zip code level, to determine Housing Choice Voucher (HCV) amounts in areas with high concentrations of low-income and HCV recipient populations (8 FR 80567). Replacing FMRs with Small Area FMRs allowed HCV recipients to rent in low-poverty neighborhoods where the SAFMR exceeds the metropolitan-wide FMR, rather than encouraging them to live exclusively in lower-cost, high-poverty neighborhoods. In California, HUD required Public Housing Authorities in the San Diego and Sacramento areas to use Small Area FMRs, while other PHAs had the option to do so (Fischer 2017).

Although the Small Area FMR rule has been temporarily suspended (Fischer 2017), the principle remains relevant to our renter's credit calculation. Our use of FMR as the cap for the credit, when rent exceeds FMR, means that the renter's credit has space to grow as a tool for reducing the concentration of poverty in California. Further, because we impute the credit using current rent in current counties, we do not estimate the cost of the credit and its impacts on poverty if low-income families moved to places with less concentrated poverty. Given that movement would be the major outcome from using Small Area FMRs, a longer-term study would be better able to model the actual costs and benefits of such a renter's credit. We would also expect that the mid- and long-term effects of adopting a renter's credit of any substantial scale would have effects on the types of units rented, the amounts of rents charged, and individuals' work behavior. Such longer-term effects are beyond the scope of the scenarios developed for this report.

Appendix G. Detailed Tables

Table G1 below presents estimated baseline poverty rates for children 0–5 alongside the margins of error for three different confidence intervals. These are presented for the state as a whole, by county cost terciles, and counties (or county groups in cases where counties are not individually identifiable in the public-use ACS). Succeeding columns of the table indicate the rate projected under each scenario; estimates are starred if they are significantly different from the baseline rate at the 90th, 95th, or 99th percentiles. For the housing cost scenarios, a number of counties are unaffected because their housing costs fall under the cut-points simulated. (In every other scenario, at least some individuals in every county are affected.) This includes, for the 90th percentile scenario: the lowest cost tercile of counties, the Alpine/Amador/Calaveras/Inyo/Mariposa/Mono/Tuolumne county group, Butte, the Colusa/Glenn/Tehama/Trinity county group, the Del Norte/Lassen/Modoc/Plumas/Siskiyou county group, Fresno, Humboldt, Imperial, Kern, Kings, the Lake/Mendocino county group, Madera, Merced, the Nevada/Sierra county group, Placer, Riverside, San Bernardino, San Joaquin, Shasta, Stanislaus, the Sutter/Yuba county group, Tulare, and Yolo counties. For the 75th percentile scenario it includes: Fresno, Imperial, Kern, Kings, Madera, Merced, Riverside, San Bernardino, and Tulare counties.

Tables G2 and G3 present additional poverty rate estimates among young children and among other age groups for the state and for low-, mid-, and high-cost counties, respectively. In particular, these tables show estimated deep poverty rates (<50% of the CPM poverty line), poverty rates, and near poverty rates (<150% of the CPM poverty line). The leftmost columns of each table provide the baseline poverty rate. Each succeeding set of three columns presents a comparison: if all existing safety net programs are zeroed out, if CalFresh alone is zeroed out, and the actual rates (before adjusting for inflation and before adjusting for the specific changes discussed in Appendix A).

Tables G4 and G5 present the results of the policy simulations discussed in the report for the population of all Californians. These are again presented statewide and by county cost tier. (County groups are defined in Appendix A.) Finally Table G6 presents the results of the policy simulations statewide for more detailed population subgroups, including children 6–17, adults with children, and adults with no children.

TABLE G1

CPM Poverty Rate Simulations for Young Children, with Margins of Error

County or county group		Confidence interval (+/-)			Housing costs		Minimum wage		EITC		Child credit		Renter's Credit	
	Baseline	90%	95%	99%	1: 90th p'ctile housing cost adj.	2: 75th p'ctile housing cost adj.	$13	$15	2: Low- to moderate -income workers	2: Low- and moderate -income rent burdened	1: 90th pct'le housing cost adj.	2: 75th pct'le housing cost adj.	$13	$15
Statewide	23.0%	0.3	0.4	0.5	21.3%***	20.2%***	21.7%***	20.1%***	22.7%***	21.8%***	21.5%***	18.5%***	22.5%***	21.7%***
Low-cost counties	21.7%	1.0	1.2	1.6	21.7%	21.5%***	20.8%***	20.0%***	21.1%***	21.4%***	18.6%***	16.9%***	21.2%***	20.4%***
Mid-cost counties	19.9%	0.7	0.8	1.0	19.9%***	19.6%***	18.7%***	17.3%***	19.5%***	19.3%***	18.1%***	15.2%***	19.5%***	18.6%***
High-cost counties	24.2%	0.4	0.5	0.6	21.8%***	20.2%***	22.8%***	21.2%***	24.0%***	22.7%***	23.3%***	20.0%***	23.7%***	22.9%***
Alameda County	17.5%	1.2	1.5	1.9	15.6%***	14.8%***	17.4%	16.6%***	17.3%**	16.6%***	16.8%***	15.0%***	17.3%***	16.5%***
Alpine, Amador, Calaveras, Inyo, Mariposa, Mono, and Tuolumne Counties	11.4%	3.4	4.1	5.4	11.4%	10.5%*	11.0%	10.8%*	11.4%	11.4%	11.2%	10.1%**	11.3%	11.1%
Butte County	16.6%	3.4	4.0	5.3	16.6%	15.8%*	16.3%*	14.9%**	15.4%**	16.0%	14.0%***	12.4%***	16.5%	14.1%***
Colusa, Glenn, Tehama, and Trinity Counties	19.3%	4.1	4.9	6.5	19.3%	18.5%*	18.4%*	17.1%**	18.6%	18.9%	17.9%*	17.4%***	19.3%	18.6%
Contra Costa County	19.4%	1.8	2.1	2.8	16.6%***	15.4%***	18.5%***	17.2%***	19.3%	17.9%***	18.2%***	15.6%***	18.9%***	18.5%***
Del Norte, Lassen, Modoc, Plumas, and Siskiyou Counties	21.9%	5.7	6.8	9.0	21.9%	19.2%**	21.0%	19.3%**	21.7%	20.8%	18.3%	16.6%***	21.4%	21.3%
El Dorado County	15.3%	4.8	5.8	7.7	15.0%	14.1%**	13.3%*	13.1%**	14.7%	15.0%	14.7%	11.3%***	15.1%	13.6%
Fresno County	23.2%	1.7	2.0	2.7	23.2%	23.2%	22.2%***	21.4%***	22.3%***	23.1%	19.4%***	17.8%***	22.9%***	21.6%***
Humboldt County	19.1%	5.1	6.1	8.1	19.1%	16.4%**	15.7%**	14.8%***	18.4%*	16.1%**	18.2%**	14.2%***	18.4%	18.4%
Imperial County	14.3%	4.5	5.3	7.1	14.3%	14.3%	14.0%	13.9%	13.5%*	14.3%	11.6%***	11.1%***	13.5%*	13.2%**
Kern County	20.5%	2.3	2.8	3.7	20.5%	20.5%	19.3%***	18.8%***	20.0%**	20.3%**	18.2%***	15.9%***	20.1%***	19.7%***
Kings County	19.5%	4.8	5.8	7.6	19.5%	19.5%	19.0%*	18.2%**	19.5%	18.7%**	16.3%**	16.1%***	18.4%	18.4%
Lake and Mendocino Counties	24.1%	5.8	7.0	9.2	24.1%	22.8%**	22.2%**	19.9%**	23.7%	23.0%	23.3%**	20.8%***	24.1%	24.1%
Los Angeles County	28.0%	0.6	0.8	1.0	25.8%***	24.0%***	26.2%***	24.2%***	27.7%***	26.5%***	26.5%***	22.7%***	27.4%***	26.4%***
Madera County	27.0%	6.5	7.8	10.4	27.0%	27.0%	26.4%	24.9%**	27.0%	26.8%	23.4%***	20.5%***	25.9%	25.5%

County or county group		Confidence interval (+/-)			Housing costs		Minimum wage		EITC		Child credit		Renter’s Credit	
	Baseline	90%	95%	99%	1: 90th p’ctile housing cost adj.	2: 75th p’ctile housing cost adj.	$13	$15	2: Low- to moderate -income workers	2: Low- and moderate -income rent burdened	1: 90th pct’le housing cost adj.	2: 75th pct’le housing cost adj.	$13	$15
Marin County	22.1%	3.8	4.5	6.0	19.5%***	18.9%***	21.3%	21.1%**	22.1%	19.3%**	21.9%	21.1%*	22.0%	22.0%
Merced County	24.8%	3.5	4.2	5.5	24.8%	24.8%	24.3%**	23.8%***	24.7%	24.8%	21.5%***	20.7%***	24.5%*	23.6%**
Monterey and San Benito Counties	29.9%	3.2	3.8	5.1	25.7%***	23.1%***	27.7%***	24.1%***	29.8%	28.5%***	29.4%**	22.5%***	29.0%***	28.9%***
Napa County	22.1%	4.2	5.0	6.7	15.6%***	13.7%***	19.0%***	14.9%***	22.1%	20.9%**	22.1%	17.1%***	21.2%*	20.6%**
Nevada and Sierra Counties	18.6%	6.3	7.5	9.9	18.6%	18.0%	18.0%	14.4%	18.6%	18.6%	17.3%	18.0%	18.6%	18.6%
Orange County	24.8%	1.3	1.5	2.0	23.1%***	21.5%***	23.4%***	21.8%***	24.6%***	23.1%***	24.3%***	21.1%***	24.3%***	23.7%***
Placer County	17.0%	3.2	3.9	5.2	17.0%	16.7%*	16.4%*	15.8%***	17.0%	16.0%***	17.0%	14.6%***	16.9%	16.6%**
Riverside County	21.9%	1.3	1.5	2.0	21.9%	21.9%	20.4%***	18.8%***	21.6%***	21.0%***	20.5%***	17.4%***	21.5%***	21.2%***
Sacramento County	18.7%	1.6	1.9	2.6	18.5%***	17.5%***	17.5%***	16.5%***	18.3%***	17.8%***	16.6%***	14.1%***	18.2%***	16.9%***
San Bernardino County	20.1%	1.3	1.5	2.1	20.1%	20.1%	18.9%***	17.5%***	19.8%***	19.5%***	18.1%***	14.8%***	19.5%***	18.6%***
San Diego County	22.6%	1.2	1.4	1.8	22.2%***	20.7%***	21.6%***	19.9%***	22.4%***	20.8%***	21.7%***	18.5%***	22.0%***	21.1%***
San Francisco County	17.3%	2.5	3.0	4.0	14.5%***	14.0%***	17.3%	16.4%**	17.2%	15.7%***	16.8%**	15.1%***	17.0%	16.9%*
San Joaquin County	18.7%	2.0	2.4	3.2	18.7%	18.6%*	17.1%***	16.3%***	18.3%***	18.3%***	16.2%***	13.5%***	18.2%***	17.4%***
San Luis Obispo County	22.5%	4.5	5.4	7.2	17.8%***	16.1%***	19.9%***	17.4%***	22.3%	21.1%**	21.0%*	17.3%***	21.8%	21.5%*
San Mateo County	19.7%	2.1	2.5	3.4	17.9%***	17.2%***	18.8%***	18.1%***	19.7%	18.3%***	19.5%	18.3%***	19.7%	19.3%**
Santa Barbara County	28.8%	3.5	4.2	5.6	23.3%***	21.2%***	24.7%***	21.6%***	28.6%	27.4%***	28.6%	24.5%***	28.1%*	27.4%***
Santa Clara County	16.4%	1.3	1.5	2.0	11.0%***	10.2%***	15.9%***	15.0%***	16.4%**	15.1%***	16.1%***	14.2%***	16.1%***	15.8%***
Santa Cruz County	32.5%	5.8	7.0	9.2	24.2%***	21.8%***	31.5%*	29.5%***	32.5%	31.9%**	32.0%*	27.2%***	31.1%**	30.9%**
Shasta County	17.1%	3.8	4.6	6.1	17.1%	16.4%	17.1%	15.5%**	15.8%*	16.9%	15.6%*	13.2%***	15.8%*	14.7%**
Solano County	20.6%	2.7	3.2	4.3	16.8%***	14.7%***	19.1%***	17.1%***	19.6%**	19.1%***	18.5%***	14.0%***	20.1%	18.1%***
Sonoma County	23.0%	3.1	3.7	4.9	18.9%***	16.9%***	21.8%***	21.2%***	22.8%	21.0%***	22.3%**	19.3%***	22.5%	21.7%***
Stanislaus County	21.1%	2.5	3.0	4.0	21.1%	19.7%***	19.7%***	17.9%***	20.0%***	20.8%*	17.6%***	15.5%***	20.8%**	19.8%***
Sutter and Yuba Counties	17.2%	3.5	4.2	5.6	17.2%	15.4%***	16.5%**	15.6%**	16.3%**	16.5%	15.1%***	13.9%***	16.6%*	13.7%***
Tulare County	23.4%	2.6	3.1	4.1	23.4%	23.4%	22.7%***	22.0%***	22.9%*	23.2%**	19.7%***	17.9%***	23.1%	22.2%**

County or county group		Confidence interval (+/-)			Housing costs		Minimum wage		EITC		Child credit		Renter's Credit	
	Baseline	90%	95%	99%	1: 90th p'ctile housing cost adj.	2: 75th p'ctile housing cost adj.	$13	$15	2: Low- to moderate -income workers	2: Low- and moderate -income rent burdened	1: 90th pct'le housing cost adj.	2: 75th pct'le housing cost adj.	$13	$15
Ventura County	26.1%	2.9	3.5	4.6	21.4%***	18.6%***	23.2%***	21.1%***	26.1%	24.8%***	25.7%**	22.3%***	25.4%***	24.8%***
Yolo County	16.3%	3.4	4.1	5.4	16.3%	16.1%	15.5%**	14.1%***	16.3%	15.9%	15.7%	12.9%***	14.4%*	14.0%**

SOURCES: Authors' calculations using the 2012–2015 CPM.

NOTES: Baseline estimates include adjustments described in Appendix A. F-tests of equality with baseline poverty computed. Significance indicated at the 10% level (*), 5% level (**), and 1% level (***).

TABLE G2

CPM Poverty Rate Estimates

	Baseline CPM			Without Safety Net Benefits			Without CalFresh Benefits			Original 2012–2015 CPM		
	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty
Age 0–5	23.0%	5.0%	48.5%	38.5%	18.4%	54.4%	27.8%	7.3%	50.8%	24.1%	5.4%	49.1%
Age 6–17	21.7%	4.8%	46.5%	36.0%	17.0%	51.7%	26.0%	6.9%	48.5%	22.7%	5.2%	47.1%
Adults with Children 0–5	19.9%	3.8%	45.4%	34.1%	14.1%	52.1%	24.1%	5.6%	47.7%	21.0%	4.1%	46.1%
Adults with Children 6–17	18.1%	3.7%	40.6%	27.8%	11.2%	44.6%	20.7%	4.9%	41.8%	18.9%	4.0%	41.2%
Adults with no Children (Adults age 18–64)	19.4%	7.8%	33.7%	22.1%	11.3%	35.0%	19.9%	8.3%	33.9%	20.0%	7.9%	34.2%
Adults with no Children (Adults age 65+)	19.1%	5.6%	33.5%	22.6%	10.1%	34.8%	19.3%	5.7%	33.6%	19.2%	5.6%	33.6%
All	19.9%	5.6%	39.7%	28.3%	13.0%	43.1%	22.2%	6.8%	40.8%	20.6%	5.9%	40.2%

SOURCES: Authors' calculations using the 2012–2015 CPM.

NOTES: Baseline estimates include adjustments described in Appendix A (including $10.50 minimum wage, SSI and CalWORKs cost of living increases, California EITC simulations). Both "without" sets of columns are comparable to the "baseline" columns. The final three columns under "original" are the basic 2012–2015 estimates without any adjustments for comparability. The "without safety net benefits" estimates account for the following major means-tested programs: CalFresh, CalWORKs, federal and state EITC, Child tax credit, school meals, WIC, SSI, and federal housing subsidies.

TABLE G3

CPM Poverty Rate Estimates, by County Cost Tercile

	Baseline CPM			Without Safety Net Benefits			Without CalFresh Benefits			Original 2012–2015 CPM		
	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty
Age 0–5												
Low cost counties	21.7%	5.1%	49.9%	47.0%	25.4%	63.8%	29.3%	9.0%	56.1%	23.4%	5.6%	51.1%
Middle cost counties	19.9%	4.3%	48.1%	39.2%	19.6%	56.1%	26.0%	6.8%	51.3%	21.2%	4.6%	48.7%
High cost counties	24.2%	5.3%	48.4%	36.7%	16.8%	52.2%	28.1%	7.2%	49.7%	25.3%	5.7%	48.9%
Age 6–17												
Low cost counties	19.8%	4.2%	46.4%	42.8%	21.7%	58.5%	26.4%	7.7%	51.9%	21.1%	4.6%	47.5%
Middle cost counties	18.6%	4.3%	45.3%	36.0%	17.7%	52.8%	23.7%	6.4%	48.3%	19.5%	4.6%	45.9%
High cost counties	23.2%	5.1%	47.0%	34.8%	15.9%	50.2%	26.8%	6.9%	48.0%	24.1%	5.5%	47.4%
Adults with Children 0–5												
Low cost counties	18.1%	3.8%	45.4%	41.1%	19.5%	59.6%	24.8%	6.8%	51.0%	19.7%	4.2%	46.7%
Middle cost counties	16.9%	3.3%	44.2%	34.6%	15.2%	53.4%	22.4%	5.2%	47.6%	18.0%	3.5%	45.0%
High cost counties	21.1%	4.0%	45.8%	32.8%	12.9%	50.4%	24.6%	5.5%	47.2%	22.2%	4.3%	46.4%
Adults with Children 6–17												
Low cost counties	15.7%	3.7%	39.7%	32.2%	14.0%	48.5%	19.9%	5.5%	43.0%	16.5%	3.9%	40.7%
Middle cost counties	15.4%	3.2%	39.6%	27.4%	11.7%	45.3%	18.7%	4.5%	41.3%	16.1%	3.4%	40.2%
High cost counties	19.4%	3.9%	41.1%	27.3%	10.7%	43.8%	21.5%	5.0%	41.8%	20.2%	4.2%	41.6%
Adults with no Children (Adults age 18–64)												
Low cost counties	19.7%	7.3%	36.0%	24.8%	12.7%	38.4%	21.1%	8.2%	36.5%	20.2%	7.5%	36.6%
Middle cost counties	19.2%	7.6%	33.9%	23.0%	12.3%	35.8%	20.0%	8.4%	34.3%	19.7%	7.8%	34.3%
High cost counties	19.4%	7.8%	33.4%	21.6%	10.8%	34.4%	19.8%	8.2%	33.6%	20.1%	8.0%	33.9%
Adults with no Children (Adults age 65+)												
Low cost counties	17.4%	4.5%	33.1%	21.7%	8.2%	35.4%	18.0%	4.8%	33.3%	17.6%	4.5%	33.3%
Middle cost counties	17.2%	5.2%	31.5%	20.4%	8.7%	33.0%	17.6%	5.3%	31.7%	17.4%	5.2%	31.7%
High cost counties	19.8%	5.9%	34.2%	23.4%	10.7%	35.3%	20.1%	6.0%	34.2%	20.0%	5.9%	34.3%
All												

	Baseline CPM			Without Safety Net Benefits			Without CalFresh Benefits			Original 2012–2015 CPM		
	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty	Poverty	Deep Poverty	Near Poverty
Low cost counties	18.8%	5.1%	41.2%	34.0%	16.5%	49.6%	23.0%	7.2%	44.5%	19.7%	5.3%	42.1%
Middle cost counties	18.0%	5.1%	39.2%	28.7%	13.7%	44.2%	21.0%	6.5%	40.9%	18.7%	5.3%	39.7%
High cost counties	20.6%	5.9%	39.6%	27.4%	12.3%	41.9%	22.4%	6.8%	40.2%	21.4%	6.1%	40.0%

SOURCES: Authors' calculations using the 2012–2015 CPM.

NOTES: Baseline estimates include adjustments described in Appendix A (SSI and CalWORKs cost of living increases, California EITC simulations). Both "without" sets of columns are comparable to the "baseline" columns. The final three columns under "original" are the basic 2012–2015 estimates without any adjustments for comparability. The "without safety net benefits" estimates account for the following major means-tested programs: CalFresh, CalWORKs, federal and state EITC, Child tax credit, school meals, WIC, SSI, and federal housing subsidies.

TABLE G4

Poverty Simulations, All Californians

	EITC		Child credit		Renter's credit		Housing costs		Minimum wage	
	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	$13	$15
Decrease in poverty rate (percentage point)	0.12	0.77	0.58	2.08	0.37	1.24	1.20	1.99	0.94	1.96
Number assisted	1,750,000	7,770,000	2,270,000	10,840,000	2,240,000	3,110,000	27,830,000	30,400,000	9,510,000	12,090,000
Percent assisted, 0–49% of poverty	16.2%	3.6%	32.9%	42.9%	34.5%	35.3%	76.6%	82.9%	10.2%	11.9%
Percent assisted, 50–99% of poverty	9.9%	26.1%	16.3%	64.7%	21.3%	28.1%	75.5%	81.5%	32.2%	38.4%
Median benefit	$220	$1,496	$3,400	$1,798	$3,192	$3,900	$757	$1,208	$2,326	$4,501
Total Statewide Cost or Total Change in resources (or threshold), $ million	$416.9	$4,143.4	$1,812.9	$5,615.6	$2,252.8	$5,239.5	$11,533.0	$18,271.7	$7,499.5	$18,776.6

SOURCES: Authors' calculations using the 2012–2015 CPM.

TABLE G5

Poverty Simulations, All Californians by County Cost Tercile

	EITC		Child Credit		Renter's Credit		Housing Costs		Minimum wage	
	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	1: $13	2: $15
Decrease in poverty rate (percentage point)										
Low cost counties	0.2	0.3	1.5	2.8	0.4	1.3	0.0	0.2	0.7	1.5
Middle cost counties	0.2	0.4	0.8	2.2	0.4	1.2	0.0	0.3	0.9	1.8
High cost counties	0.1	0.9	0.4	1.9	0.4	1.3	1.7	2.8	1.0	2.1
Number assisted										
Low cost counties	250,000	700,000	400,000	1,440,000	170,000	240,000	0	540,000	1,040,000	1,270,000
Middle cost counties	490,000	1,470,000	620,000	2,630,000	400,000	570,000	1,820,000	3,850,000	2,130,000	2,690,000
High cost counties	1,020,000	5,600,000	1,250,000	6,780,000	1,680,000	2,300,000	26,010,000	26,010,000	6,340,000	8,130,000
Percent assisted, 0-49% of poverty										
Low cost counties	18.2%	1.2%	46.6%	52.2%	27.8%	28.6%	0.0%	17.0%	7.7%	8.8%
Middle cost counties	18.9%	2.4%	36.4%	42.4%	29.3%	30.1%	23.5%	48.1%	8.5%	9.6%
High cost counties	15.2%	4.1%	30.4%	41.9%	36.7%	37.5%	100.0%	100.0%	10.9%	12.9%
Percent assisted, 50-99% of poverty										
Low cost counties	17.6%	9.9%	36.9%	68.8%	18.8%	25.0%	0.0%	13.2%	21.6%	24.5%
Middle cost counties	14.1%	17.3%	23.9%	64.2%	17.8%	24.9%	20.3%	44.9%	27.9%	32.1%
High cost counties	7.8%	30.5%	11.7%	64.4%	22.5%	29.3%	100.0%	100.0%	34.6%	41.8%
Median benefit										
Low cost counties	$266	$1,338	$3,400	$2,159	$2,775	$3,900	$61	$447	$2,791	$5,222
Middle cost counties	$272	$1,352	$3,400	$1,700	$3,277	$3,900	$792	$281	$2,481	$4,688

	EITC		Child Credit		Renter's Credit		Housing Costs		Minimum wage	
	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	1: $13	2: $15
High cost counties	$204	$1,572	$3,400	$1,774	$3,224	$3,900	$0	$1,296	$2,212	$4,376
Total Statewide Cost or Total Change in resources (or threshold), $ million										
Low cost counties	$65.2	$289.1	$314.0	$774.7	$156.9	$351.0	$0.0	$114.6	$878.0	$2,043.3
Middle cost counties	$128.6	$619.5	$479.4	$1,301.4	$411.6	$924.8	$51.3	$520.4	$1,733.3	$4,138.5
High cost counties	$223.1	$3,234.8	$1,019.4	$3,539.4	$1,684.3	$3,963.7	$11,481.7	$17,636.6	$4,888.2	$12,594.8

TABLE G6

Detailed Outcomes, by Age Group

		EITC		Child credit		Renter's Credit		Housing Costs		Minimum wage	
	Baseline	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	$13	$15
Poverty Rate											
Age 0–5	23.0%	22.7%	21.8%	21.5%	18.5%	22.5%	21.7%	21.3%	20.2%	21.7%	20.1%
Age 6–17	21.7%	21.5%	20.6%	20.4%	17.5%	21.2%	20.5%	20.1%	19.1%	20.6%	19.3%
Adults with Children 0–5	19.9%	19.6%	18.8%	19.0%	16.2%	19.5%	18.8%	18.3%	17.3%	18.6%	17.2%
Adults with Children 6–17	18.1%	18.0%	17.0%	17.5%	15.4%	17.8%	17.2%	16.8%	16.0%	17.1%	15.9%
Working Age Adults with no Children	19.4%	19.4%	19.0%	19.3%	19.1%	19.1%	18.0%	18.5%	18.0%	18.6%	17.7%
Older Adults with no Children	19.1%	19.0%	18.9%	19.0%	19.0%	18.7%	17.5%	18.1%	17.6%	18.9%	18.6%
All	19.9%	19.7%	19.1%	19.3%	17.8%	19.5%	18.6%	18.7%	17.9%	18.9%	17.9%
Number in Poverty											
Age 0–5	690,000	680,000	660,000	650,000	560,000	680,000	650,000	640,000	610,000	650,000	610,000

		EITC		Child credit		Renter's Credit		Housing Costs		Minimum wage	
	Baseline	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	$13	$15
Age 6–17	1,330,000	1,320,000	1,260,000	1,250,000	1,070,000	1,300,000	1,250,000	1,230,000	1,170,000	1,260,000	1,180,000
Adults with Children 0–5	1,000,000	990,000	940,000	950,000	820,000	980,000	950,000	920,000	870,000	930,000	860,000
Adults with Children 6–17	1,130,000	1,120,000	1,060,000	1,090,000	960,000	1,110,000	1,070,000	1,050,000	1,000,000	1,070,000	990,000
Working Age Adults with no Children	2,520,000	2,520,000	2,470,000	2,520,000	2,490,000	2,490,000	2,350,000	2,410,000	2,350,000	2,420,000	2,310,000
Older Adults with no Children	800,000	800,000	800,000	800,000	800,000	790,000	740,000	760,000	740,000	800,000	790,000
All	7,480,000	7,430,000	7,190,000	7,260,000	6,700,000	7,340,000	7,010,000	7,030,000	6,730,000	7,130,000	6,740,000
Deep Poverty Rate											
Age 0–5	5.0%	4.8%	5.0%	3.6%	3.5%	4.2%	3.9%	4.8%	4.6%	4.9%	4.8%
Age 6–17	4.8%	4.6%	4.8%	3.5%	3.4%	4.0%	3.9%	4.6%	4.4%	4.7%	4.6%
Adults with Children 0–5	3.8%	3.6%	3.8%	2.8%	2.6%	3.1%	2.9%	3.6%	3.5%	3.7%	3.6%
Adults with Children 6–17	3.7%	3.6%	3.7%	3.0%	2.8%	3.1%	3.0%	3.6%	3.4%	3.6%	3.5%
Working Age Adults with no Children	7.8%	7.7%	7.7%	7.7%	7.6%	7.1%	6.8%	7.5%	7.4%	7.6%	7.5%
Older Adults with no Children	5.6%	5.6%	5.6%	5.6%	5.6%	5.2%	5.0%	5.4%	5.2%	5.6%	5.5%
All	5.6%	5.5%	5.6%	5.0%	4.9%	5.0%	4.8%	5.4%	5.2%	5.5%	5.4%
Number in Deep Poverty											
Age 0–5	150,000	140,000	150,000	110,000	100,000	120,000	120,000	140,000	140,000	150,000	140,000
Age 6–17	300,000	280,000	300,000	220,000	210,000	250,000	240,000	280,000	270,000	290,000	280,000
Adults with Children 0–5	190,000	180,000	190,000	140,000	130,000	160,000	150,000	180,000	170,000	180,000	180,000
Adults with Children 6–17	230,000	230,000	230,000	190,000	170,000	200,000	190,000	220,000	210,000	230,000	220,000
Working Age Adults with no Children	1,010,000	1,010,000	1,000,000	1,000,000	990,000	920,000	890,000	980,000	960,000	990,000	980,000
Older Adults with no Children	240,000	240,000	240,000	240,000	230,000	220,000	210,000	230,000	220,000	230,000	230,000
All	2,120,000	2,080,000	2,110,000	1,890,000	1,840,000	1,870,000	1,790,000	2,030,000	1,970,000	2,070,000	2,030,000

		EITC		Child credit		Renter's Credit		Housing Costs		Minimum wage	
	Baseline	1: Lowest-income workers	2: Low- to moderate-income workers	1: Lowest-income families	2: Low- and moderate-income families	1: Lowest-income rent burdened	2: Low- and moderate-income rent burdened	1: 90th percentile housing cost adjustment	2: 75th percentile housing cost adjustment	$13	$15
Near Poverty Rate											
Age 0–5	48.5%	48.4%	46.3%	48.4%	46.6%	48.5%	48.3%	46.9%	45.8%	47.4%	45.9%
Age 6–17	46.5%	46.5%	44.3%	46.4%	44.7%	46.5%	46.2%	44.9%	43.8%	45.6%	44.2%
Adults with Children 0–5	45.4%	45.3%	43.5%	45.3%	43.5%	45.4%	45.2%	43.6%	42.4%	44.2%	42.4%
Adults with Children 6–17	40.6%	40.6%	38.7%	40.5%	39.4%	40.6%	40.4%	39.0%	37.8%	39.6%	38.1%
Working Age Adults with no Children	33.7%	33.7%	33.2%	33.7%	33.6%	33.7%	33.3%	32.5%	31.7%	32.7%	30.8%
Older Adults with no Children	33.5%	33.5%	33.2%	33.5%	33.5%	33.5%	33.0%	32.4%	31.8%	33.2%	32.9%
All	39.7%	39.6%	38.4%	39.6%	38.7%	39.6%	39.3%	38.2%	37.2%	38.7%	37.2%
Number in Near Poverty											
Age 0–5	1,460,000	1,460,000	1,390,000	1,460,000	1,400,000	1,460,000	1,450,000	1,410,000	1,380,000	1,430,000	1,380,000
Age 6–17	2,850,000	2,850,000	2,710,000	2,840,000	2,740,000	2,850,000	2,830,000	2,750,000	2,680,000	2,790,000	2,710,000
Adults with Children 0–5	2,280,000	2,280,000	2,190,000	2,280,000	2,190,000	2,280,000	2,270,000	2,190,000	2,130,000	2,220,000	2,130,000
Adults with Children 6–17	2,540,000	2,540,000	2,420,000	2,530,000	2,460,000	2,530,000	2,520,000	2,440,000	2,360,000	2,470,000	2,380,000
Working Age Adults with no Children	4,390,000	4,390,000	4,330,000	4,390,000	4,380,000	4,390,000	4,330,000	4,240,000	4,130,000	4,260,000	4,020,000
Older Adults with no Children	1,410,000	1,410,000	1,400,000	1,410,000	1,410,000	1,410,000	1,390,000	1,370,000	1,340,000	1,400,000	1,390,000
All	14,940,000	14,920,000	14,450,000	14,910,000	14,580,000	14,920,000	14,810,000	14,400,000	14,020,000	14,570,000	14,000,000
Number Assisted											
Age 0–5	–	210,000	820,000	390,000	1,590,000	250,000	310,000	2,120,000	2,320,000	810,000	1,030,000
Age 6–17	–	370,000	1,560,000	720,000	3,020,000	500,000	620,000	4,300,000	4,730,000	1,630,000	2,060,000
Adults with Children 0–5	–	370,000	1,540,000	530,000	2,710,000	350,000	420,000	3,580,000	3,900,000	1,640,000	2,040,000
Adults with Children 6–17	–	320,000	1,650,000	500,000	2,720,000	390,000	480,000	4,560,000	4,970,000	1,940,000	2,420,000
Working Age Adults with no Children	–	440,000	1,950,000	120,000	760,000	610,000	1,000,000	10,120,000	10,970,000	3,120,000	4,070,000

		EITC		Child credit		Renter's Credit		Housing Costs		Minimum wage	
	Baseline	**1: Lowest-income workers**	**2: Low- to moderate-income workers**	**1: Lowest-income families**	**2: Low- and moderate-income families**	**1: Lowest-income rent burdened**	**2: Low- and moderate-income rent burdened**	**1: 90th percentile housing cost adjustment**	**2: 75th percentile housing cost adjustment**	**$13**	**$15**
Older Adults with no Children	–	50,000	250,000	10,000	50,000	140,000	290,000	3,150,000	3,510,000	350,000	470,000
All	–	1,750,000	7,770,000	2,270,000	10,840,000	2,240,000	3,110,000	27,830,000	30,400,000	9,510,000	12,090,000
Median Benefit											
Units With Young Children	–	$394	$2,293	$3,400	$2,762	$3,277	$3,900	$1,191	$2,008	$2,671	$5,366
Units With Children Age 6–17	–	$406	$2,369	$3,400	$1,700	$3,295	$3,900	$1,129	$1,922	$2,326	$4,593
Units With All Person Age 18+	–	$100	$510	$2,725	$1,700	$3,113	$3,900	$645	$993	$2,243	$4,229
All	–	$220	$1,496	$3,400	$1,798	$3,192	$3,900	$757	$1,208	$2,326	$4,501
Cost ($ million)											
Units With Young Children	–	$186.7	$1,481.8	$888.6	$2,783.9	$457.5	$860.0	$2,360.8	$3,723.9	$1,728.3	$4,263.2
Units With Children Age 6–17	–	$165.1	$1,680.0	$818.7	$2,411.3	$519.6	$961.2	$2,844.2	$4,505.7	$1,880.6	$4,637.7
Units With All Person Age 18+	–	$65.0	$981.5	$105.6	$420.4	$1,275.7	$3,418.4	$6,328.1	$10,042.0	$3,890.6	$9,875.7
All	–	$416.9	$4,143.4	$1,812.9	$5,615.6	$2,252.8	$5,239.5	$11,533.0	$18,271.7	$7,499.5	$18,776.6

SOURCES: Authors' calculations using the 2012–2015 CPM.

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Public Policy Institute of California
500 Washington Street, Suite 600
San Francisco, CA 94111
T: 415.291.4400
F: 415.291.4401
PPIC.ORG

PPIC Sacramento Center
Senator Office Building
1121 L Street, Suite 801
Sacramento, CA 95814
T: 916.440.1120
F: 916.440.1121