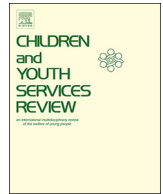




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Reducing poverty among children: Evidence from state policy simulations[☆]

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ABSTRACT

State approaches to reducing child poverty vary considerably. We exploit this state-level variation to estimate what could be achieved in terms of child poverty if all states adopted the most generous or inclusive states' policies. Specifically, we simulate the child poverty reductions that would occur if every state were as generous or inclusive as the most generous or inclusive state in four key policies: Supplemental Nutrition Assistance Program (SNAP), state Earned Income Tax Credits (EITC), Temporary Assistance for Needy Families (TANF), and state Child Tax Credits (CTC). We find that adopting the most generous or inclusive state EITC policy would have the largest impact on child poverty, reducing it by 1.2 percentage points, followed by SNAP, TANF, and lastly state CTC. If all states were as generous or inclusive as the most generous or inclusive state in all four policies, the child poverty rate would decrease by 2.5 percentage points, and five and a half million children would be lifted out of poverty.

1. Introduction

Children face the highest risk of living in poverty compared to working-age and elderly adults as measured by the Supplemental Poverty Measure (Renwick & Fox, 2016). Poor children are less healthy and experience worse health and diminished earnings, productivity, and overall well-being throughout adulthood compared to non-poor children (Almond & Currie, 2011; Chaudry & Wimer, 2016; Currie, 2009). Young children appear particularly vulnerable to the effects of poverty, and numerous studies have linked early life income supplementation programs with adulthood gains in education, earnings, and health (Almond, Currie, & Duque, 2017; Heckman, 2008, 2012). In addition to the social costs of childhood poverty, macroeconomic costs are not ignorable. The authors of a recent National Academy of Sciences report attribute an estimated \$800 billion to \$1.1 trillion in federal expenditures to child poverty annually (Duncan & Le Menestrel, 2019). Yet, for state policymakers looking for the highest-impact expansions to

their portfolio of safety net programs, the gains to adopting more generous or inclusive state policy parameters are not well-established. That is the piece of the child poverty puzzle we aim to address here. We ask: If all states offered the most generous or inclusive support to children and their families seen in other states in the four largest income assistance programs, what would the child poverty rate be? To answer this question, we simulate the child poverty reductions that would occur if all states were as generous or inclusive as the most generous or inclusive state in four key policies: SNAP, state Earned Income Tax Credits (EITC), TANF, and state Child Tax Credits (CTC). In effect, we explore how much child poverty reduction can be wrung out of the most generous or inclusive states' anti-poverty policies.

The Census Bureau and Bureau of Labor Statistics' Supplemental Poverty Measure (SPM) demonstrates that state-level child poverty rates vary from a low of 8.1% in Minnesota to a high of 20.2% in DC (Fox, 2018). While some of this variation is due to differences in demographics, costs of living, and state and local economies, the state

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policies that affect the total resources available to low-income families with children are also an important source of inequality across states. Though the four largest cash- and credit-based income supplementation programs we examine here – TANF, SNAP, EITC and CTC – were enacted at the federal level to bring relief and stability to the lowest-earning families, states have a great deal of autonomy in determining the underlying set of policies that govern their implementation. More restrictive states have enacted policies that reduce benefit size and/or inhibit enrollment by reducing eligibility thresholds or by making the application and recertification process more difficult. Conversely, more generous or inclusive states ensure that the benefits are accessible to a larger portion of the eligible population and that they are relatively easy to access.

We selected this set of policies because they closely align with three principles that have emerged in a burgeoning body of literature as imperative to successful antipoverty program design. First, each provides a cash or near-cash transfer that directly affects the household budgets for families with children. In other words, these programs are intended to impact both short-term income and long-term wealth accumulation. Though these policies inarguably fail to address the root causes of child poverty (i.e. structural barriers, discrimination, access to education, etc.), cash or near-cash transfers have demonstrated effectiveness both domestically and abroad in their causal impact on poverty, income stability, health and well-being (Baird, McIntosh, & Özler, 2011; Banerjee, Hanna, Kreindler, & Olken, 2017; Haushofer & Shapiro, 2016; Muennig, Mohit, Wu, Jia, & Rosen, 2016). Second, three out of four programs are closely aligned with the principle that poor families should have the autonomy to make their own spending decisions, a program feature that is repeatedly linked to cumulative impacts, with the exception of SNAP that is limited to food purchases (Edin & Shaefer, 2015; Hammond & Orr, 2016; Muennig et al., 2016). Third, as a large body of literature has demonstrated that adulthood inequalities manifest in childhood, essential to our policy choices is cash or near-cash availability in childhood (Almond & Currie, 2011; Almond et al., 2017). Though TANF is notably less prevalent than SNAP or the tax credits, we include it because it was the only program conceived as a cash transfer for low-income families with children. We do not include programs such as Section 8 housing subsidies, Medicaid, Unemployment Insurance (UI), Supplemental Security Income (SSI), WIC, and CCDF Child Care stipends because they do not provide cash or near-cash benefits or because they are conditioned on particular circumstances (e.g. a disability, use of child care, unemployment). For further details on each of these and other antipoverty policies, including examinations of their importance to alleviating poverty for different demographic subgroups of the population, see e.g. Bruch, Meyers, and Gornick (2018), Fox, Wimer, Garfinkel, Kaushal, and Waldfogel (2015), and Pac, Nam, Waldfogel, and Wimer (2017). Building on a recent National Academy of Sciences study in which the authors examined a range of antipoverty policies and their collective effects on child poverty (Duncan & Le Menestrel, 2019), our focus is exclusively on those that exclusively supply cash or near-cash benefits to characterize the potential contribution of these policies alone on child poverty.

One approach to estimating the relationship between state policy and child poverty would be to conceptualize generosity in terms of state spending. However, due to distributional differences in the characteristics of the population, this would be subject to selection bias.¹

Our approach is twofold. First we identify, for each program, a state to serve as the benchmark for state-level generosity or inclusiveness, ensuring that what we model is generally feasible to achieve in other states. Second, we simulate the changes in the child poverty rate that would result if all states enacted the most generous or inclusive state's

¹ The authors of a recent National Academy of Sciences publication undertake a rigorous cost-benefit analysis of these and other policies, to which we refer interested readers (Duncan & Le Menestrel, 2019).

policies. This approach accounts for the distributional differences in eligible populations, resulting in practicable child poverty benchmarks.

We measure the efficacy of TANF and SNAP in terms of coverage – the fraction of eligible children and their families enrolled in the program – akin to a definition operationalized by the authors of one study as program ‘inclusiveness’ (Bruch et al., 2018).² While state policy choices drive both benefit levels (generosity) and coverage/enrollment (inclusiveness), the former is also a function of cost of living and demographic distribution of the population (e.g. family size). The latter is more heavily dependent on state policy choices, such as eligibility criteria, and funding allocation preferences, such as that for cash income support. As the efficacy of benefit levels wholly depends upon enrollment, we modeled changes in TANF and SNAP enrollment alone conditional upon benefit levels remaining the same to ensure that our results are driven by factors that states can plausibly leverage, rather than those outside of their realm of control. This choice simplifies interpretation of our results – if we were to simulate changes in both benefit level and enrollment, interpretation of the overall program effect would be less clear, as the resulting effect would mask the competing effects of changing benefit level and enrollment. For the state tax credits – EITC and CTC – we measure generosity as the percent of federal credits represented by state credits.

This exercise grants states two principal insights: First, states can use the net child poverty estimates we generate to set a reasonable target for their combined anti-poverty efforts. Even if a state decides not to adopt the policy parameters we use here, an attainable target might help legislators compare one policy against another using a realistic threshold. Second, states can use these targets to conduct a cost-benefit analysis of their current set of the policies that guide these four anti-poverty programs. Poor-performing states might find that their cost-per-person is high, while their benefit structure results in less-generous or inclusive benefits, shedding light on new opportunities to optimize the poverty-related benefits of their spending.

1.1. Background

States have historically played a large role in anti-poverty programs (Katz, 1996). The federal government took responsibility for the growing need for income support during the Great Depression, establishing the Aid to Dependent Children (ADC) program (later re-named Aid to Families with Dependent Children (AFDC)), colloquially known as “welfare.” The program initially focused on poor widowed mothers and their children. AFDC was extended in the 1962 Public Welfare Amendments to include other poor families, including those where the father was unemployed. There were no time limits associated with benefit receipt, and the work requirements that were in place weren't enforced until 1988.

While there has always been some state-level variation in welfare program implementation and benefit generosity, the major federal programs allowed much less room for state discretion prior to welfare reform, and few states exercised the autonomy in the administration of welfare programs they could have gained through demonstration waivers.³

In the 1992 Presidential election, William J. Clinton campaigned on “ending welfare as we know it” and “making work pay”. He proposed that the AFDC program be reformed by strengthening work requirements, limiting the time that families could receive cash benefits, and

² The term ‘inclusive’ acquires a different interpretation with regard to foreign-born eligibility for SNAP and TANF programs, in particular, as some states allow foreign-born to enroll in these programs, and some do not. Though do not simulate direct benefit receipt among foreign-born from Mexico and Central America, readers should interpret our findings with caution in light of this important policy variation.

³ This section was largely informed by Ziliak (2015).

expanding the EITC to supplement low-wage work. In 1993, as part of President Clinton's first budget agreement with Congress, Congress enacted the largest ever expansion of the EITC, increasing benefits dramatically for families with children.

The 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) replaced AFDC – the primary cash assistance program for low-income families at the time – with Temporary Assistance to Needy Families (TANF). AFDC was jointly financed through federal and state governments, with the federal government providing up to 80% of the costs the states incurred. In contrast, TANF provides states with a fixed block grant allowing savings or extra costs to accrue to the states. Further, PRWORA mandated states to include much stronger work requirements for cash assistance and to restrict benefits to a lifetime maximum of five years. In addition, states were given greater leeway over the administration of their cash public assistance program in terms of benefit amount, time limits, work requirements, and eligibility (Blank, 2002; Garfinkel, Rainwater, & Smeeding, 2010). Some argued that under the new regime, states were encouraged to begin a “race to the bottom” (Figlio, Kolpin, & Reid, 1999; Saavedra, 1999).

As a result of welfare reform granting states latitude in administering welfare benefits (Moffitt, Phelan, and Winkler, 2015), state-level TANF programs diversified considerably more than under previous administrations. States can now discourage participation by increasing the frequency of recertification requirements and/or requiring fingerprinting, or encourage participation through online applications and automatic eligibility for other low-income assistance programs, formally referred to Broad Based Categorical Eligibility (USDA Economic Research Service, 2016). Using California's CalWORKs (the state's version of TANF) eligibility criteria as a common metric, states ranged from covering about 5% of their TANF-eligible population in Georgia to just over 40% in Maine between 2010 and 2012.⁴

Despite the fact that TANF policies are broadly guided by federal policy, the generosity and resulting inclusiveness of these individual policy choices reflects voter preference. For instance, one study examined the variation in TANF policies and benefits among five US states, finding that states who were committed to bolstering the safety net for children, such as California, reflected this mission in their eligibility rules, absence of a time limit, and relatively large cash benefit amounts. Conversely, Texas aimed to make TANF a ‘last resort,’ pushing for employment support over cash assistance with relatively small payments (Hahn, Golden, & Stanczyk, 2012). Further, states can spend TANF funds on a range of cash and in-kind benefits to address budget shortfalls in other areas of state responsibility. For instance, if a state failed to win a Child Care and Development Block Grant (CCDBG) demonstration waiver in a given year, they may decide to allocate a larger portion of TANF funding to fill a gap in child care services as opposed to increasing the availability or generosity of cash benefits. Though these funds would largely affect the same population, that they're earmarked differently may have different policy implications. As up to 30 percent of TANF funds can be allocated to CCDBG and the Social Services Block Grant (SSBG) combined, this may account for a large portion of variation in TANF welfare benefit generosity and access (Ziliak, 2015). To put this in perspective, 35 states spent less than quarter of their TANF funds on cash assistance in 2014 – the remainder was spent on child care, work support, child welfare, and other social services such as pre-kindergarten programs, family formation support, etc. (Bitler & Hoynes, 2016b). Yet, for a state in an economic downturn with relatively scarce employment opportunities, childcare and workforce development spending may be less beneficial than cash assistance and ultimately, fail to affect poverty at the same rate as the cash benefit structure under

AFDC. Along with the fact that TANF is non-responsive to business cycle fluctuations,⁵ it is not surprising that its anti-poverty effectiveness has been outpaced by EITC and SNAP.

Welfare reform encompassed more than just the transition from AFDC to TANF. In an effort to “make work pay”, states played an increasingly important role in the design of tax credit programs. State versions of the EITC currently exist in just over half of the US states with state income taxes, with tremendous variation in their structure and generosity.⁶ Wisconsin was the first to enact a state supplement to the federal EITC in 1983. Today, 29 states have a state supplement to the EITC, 23 of which are fully refundable. States continue to expand and reform their credits by increasing the size of the benefit relative to the federal EITC, changing the refundable status, and changing the income eligibility definition. Not all of these reforms are to the benefit of the worker. For example, in 2017 Connecticut reduced its credit from 27.5 percent of the federal EITC to 23 percent, and Oklahoma and Michigan recently reduced their credits by 70 percent (Williams & Waxman, 2018). As state and local taxes tend to disproportionately burden low-income workers, state EITCs can be crucial for achieving a more equitable tax system (Williams & Waxman, 2018). The percent of the federal EITC provided by states ranges from 3.5% in Louisiana to 40% in Washington DC in 2012 (Appendix 1).

Like the EITC, Child Tax Credits (CTC) are intended to reduce the tax burden of families with children. Unlike the EITC, the CTC extends benefits to middle- and upper-middle-income families as well (Marr, Huang, Sherman, & DeBot, 2015). The refundable part of the CTC – which until recently was named the Additional Child Tax Credit (ACTC) – benefits low-wage workers earning more than \$2500 per year, resulting in a refund of 15 percent of their earnings up to \$1400 per child (Center on Budget and Policy Priorities (CBPP), 2018). Though the federal CTC is available to all filers, state CTCs exist in only a handful of states – New York, North Carolina, Oklahoma, Colorado, and California, only two of which are refundable (Tax Credits for Workers and Their Families, 2016). Also unlike the federal CTC, the additional benefits available to families through the state CTC are generally much smaller and impose age restrictions on the children for whom the benefit can be claimed.

Historically, cash welfare was the primary form of assistance to poor families - subsequent to welfare reform, this is no longer the case. Today SNAP, formerly known as the food stamp program, provides almost 70 billion dollars in assistance to low-income individuals and families each year. Under PRWORA, states were also given new discretion in SNAP administration, resulting in diversification of these policies as well. Though the program was voluntarily adopted by states upon its rollout in 1962, it was available nationwide by 1974 with very little cross-state variation in policies (Hoynes, Schanzenbach, & Almond, 2016). PRWORA gave states latitude to both establish and run SNAP offices, develop applications and some eligibility requirements, and set recertification intervals, resulting in the much wider range of participation rates we see today (Dean, 2016; Ribar & Swann, 2013).⁷ Further,

⁵ With the exception of the short, two-year period between 2009 and 2010 when the American Recovery and Reinvestment Act (ARRA) provided an Emergency Fund for states to help their neediest residents, TANF funding is not contingent on the economy. The need for TANF understandably shifts on account of business cycle fluctuations.

⁶ Seven U.S. states do not have a state income tax (Alaska, Florida, Nevada, South Dakota, Texas, Washington and Wyoming).

⁷ SNAP policy areas with state latitude include: vehicle asset tests, categorical eligibility, transitional benefits, income/benefit counting when determining eligibility, disqualification and sanctions, sanction non-compliance, behavior-related sanctions, length of certification period, reporting changes, interview location, and verification requirements. Reluctance to interact with government agencies is a plausible barrier to uptake among immigrants, as is confusion surrounding eligibility (Van Hook, 2003). See Dean (2016) for a thorough discussion.

⁴ Authors' calculation, basing eligibility on SPM unit resources-to-needs. Note that these and other numbers in this section are smaller than those appearing later in the paper, which are for families with children only.

more generous or inclusive states make a more concerted effort to enroll eligible residents, resulting in improved coverage under similar eligibility scenarios, whereas other states might take advantage of policy flexibilities in order to cover budget shortfalls or other gaps in funding. Much like TANF, PRWORA gave states the ability to manipulate policies to either the benefit or to the detriment of their low-income population. Among those eligible for SNAP in our sample, participation rates ranged from almost 51% in California to about 81% in Michigan between 2010 and 2012.⁸

The proliferation of variation in state welfare policy since 1996 – and its dramatic shift from cash welfare to tax credits and in-kind benefits, particularly SNAP – provides a natural setting for the investigation of the effect of state policies on child poverty. Much of the research following PRWORA examined the law's overall impacts on a range of outcomes such as caseload numbers (Klerman & Danielson, 2009; Ribar, Edelhoch, & Liu, 2008), labor force participation (Meyer & Rosenbaum, 2001), poverty, income, family formation, and fertility changes (Ben-Shalom, Moffitt, & Scholz, 2011; Ellwood, 2000; Moffitt, Phelan, & Winkler, 2020). The few papers that have evaluated the relationship between welfare policy and poverty have generally done so with a focus on TANF (De Jong, Graefe, Irving, & Pierre, 2006; Ziliak, 2007). That TANF is now such a small component of the safety net is the first major limitation of prior literature that we address here. A second major limitation of research on the poverty impacts of welfare reform is that it almost exclusively uses the official poverty measure (Bitler & Hoynes, 2016b; McKernan & Ratcliffe, 2005).

The official poverty measure (OPM) is limited by its focus on only pre-tax income and its use of poverty thresholds that have been updated only for inflation since the 1960s. The Supplemental Poverty Measure (SPM), in contrast, includes taxes paid, tax credits, and both cash and in-kind benefits received in the calculation of resources, and revises thresholds to better correspond to present-day purchasing patterns. SPM poverty thresholds are even adjusted for the relative living expenses of different geographical areas. Finally, the family unit is updated in the SPM to include cohabiters and foster children, reflecting a more complex and realistic family structure.

The SPM was developed after a National Academy of Sciences panel (Citro & Michael, 1995) concluded that the OPM had many limitations and suggested revisions that ultimately became the foundation for the new Supplemental Poverty Measure (SPM). One of the main methodological advantages of the SPM is that it can be used to investigate the impact of various tax credits and in-kind transfer programs on poverty as these are included in its computation. In this paper, we use this facet of the SPM to simulate SPM child poverty rates if all states were as generous or inclusive as the most generous or inclusive state in four policies: SNAP, EITC, CTC, and TANF. Essentially, we are asking: what would the effect on child poverty be if the states engaged in a “race to the top” in anti-poverty policy? We address two major limitations of the prior literature: the extensive focus on TANF, a program that now appears to have an almost negligible effect on poverty reduction (Ben-Shalom et al., 2011; Fox et al., 2015), and the use of an out-of-date measure of poverty.

We estimate reductions in poverty among children in particular because they are a vulnerable group and one that would benefit greatly from improvements in state-level policy generosity. This paper illustrates the impact of divergence in state anti-poverty policies since the mid-1990s, and informs policymakers on the child poverty impact of more generous or inclusive policies in their state.

⁸ Authors' calculations based on SNAP eligibility which we define here as household poverty being equal to or less than 150% FPL. State SNAP programs have more nuanced eligibility criteria that are we are unable to account for using CPS data. Further, as the CPS sample undercounts the highest poverty sample of SNAP recipients (Hokayem, Bollinger, & Ziliak, 2015), official state-level eligibility rates may vary.

2. Data and methods

2.1. Data

We use data from the 2010–2012 Current Population Survey's Annual Social and Economic Supplement (CPS ASEC), augmented with corrections for underreporting of some government benefits from the Urban Institute's Transfer Income Model 3.0 (TRIM3). As described on the TRIM website (The Urban Institute, 2016), TRIM simulates actual program rules in each year to correct for under-reporting of transfer program benefits in the input data, which in this paper is the CPS ASEC. Like most household surveys, the CPS suffers from under-reporting of benefits. For example, the authors of one study (Meyer, Mok, & Sullivan, 2009) conducted a comprehensive analysis of under-reporting problems of ten government transfer programs in five nationally-representative public surveys. They reported that only sixty percent of SNAP dollars are correctly reported in the CPS ASEC; the under-reporting rates of TANF have increased since 2000 and the correct report rates were on average, lower than 70 percent. One recent study compared TRIM to alternative statistical methods for correcting under-reporting and concluded that for descriptive estimations, TRIM is adequate for predicting average poverty rates, as we do here (Mittag, 2019). As TRIM over-assigns benefits to those who report zero gross income in CPS, as well as those below 50% of the poverty level, additional adjustments are required when examining deep SPM poverty. However, we omit deep SPM poverty outcomes from the current study on account of sample size limitations. The authors of a related study (Stevens, Fox, & Heggeness, 2018) find that SPM poverty rates meaningfully fall when using TRIM adjustments to SNAP benefit levels, however the differences are much smaller when examining average enrollment rates as we do here. For these reasons, we use augmented CPS ASEC data with TRIM-adjusted revisions and corrections to the benefit amounts received from SNAP, Supplemental Security Income, and TANF. The CPS ASEC is the source for official poverty and labor market statistics, and provides a large and nationally representative sample of children. We use the 2010–2012 CPS ASEC (survey years 2009–2011) as these are the most recent years for which TRIM data were available at the time of this writing. While a number of states have adopted more generous policies since then (California, for example, created a state EITC in 2015), the benefits of more accurate adjustments for under-reporting outweigh any advantages of using a more recent time period in which the American Recovery and Reinvestment Act (ARRA) and other social policy expansions took place.

We use the SPM (rather than the official poverty measure) because it is a more comprehensive measure of individuals' and families' economic wellbeing. While the official measure compares pre-tax and transfer income to a poverty threshold that has been updated only for inflation since the 1960s, the SPM takes into account taxes paid, in-kind benefits and tax credits received, and re-defines the household unit to be more in line with modern family structure. SPM poverty thresholds are also re-defined to increase gradually over time as families' consumption at the top of the bottom third of the income distribution changes. The SPM also takes relative living expenses into account by increasing poverty thresholds in relatively more expensive locations, and reducing them in relatively less expensive locations. More details on the computation of the SPM can be found in Census Bureau reports (e.g., Short, 2015), which publish SPM rates each year.

We focus on SPM family units with children. While the official measure defines the family unit as individuals bound by blood, marriage, or adoption, the SPM unit also includes cohabiters and their children as well as foster children living in the household and a small number of unrelated minors. SPM unit members have the same resources; if one SPM unit member reports receiving SNAP, all members are considered to “have” the benefit. In addition to the resources that SPM units have at their disposal and the SPM poverty thresholds that apply to their geographic location, we use a variety of demographic

variables in the subgroup analyses. As undocumented immigrants are ineligible for benefits and legal immigrants face a waiting period, we exclude foreign-born non-citizens from either Mexico or Central America from benefit receipt in our simulations, as this definition captures the demographic characteristics of the majority of undocumented immigrants in the United States (Gelatt & Zong, 2018). Although this implicitly assumes that recipients cannot trade or barter benefits or acquire them in some other way, without information on undocumented immigration in the survey, this is the most conservative estimate given the limitations in CPS ASEC data. That being said, we are likely misclassifying a number of individuals as undocumented who are in fact documented, thus not allocating simulated benefits to those who are eligible. As a proxy for not having legal status, this exclusion is undoubtedly overly broad, but its broadness has the virtue of yielding more conservative estimates of the potential poverty reduction that could occur due to state policy.

Further, we use information on the number of children and adults in the SPM unit, as well as pretax cash income-to-needs to identify and prioritize eligible individuals not currently receiving benefits for which they are eligible (income-to-needs is the ratio of an SPM unit's resources to the SPM poverty line).

As we use 2011–2013 CPS ASEC data for calendar years 2010–2012, our policy data characterize state policies from 2010 to 2012. These data come from the University of Kentucky Center for Poverty Research (University of Kentucky Center for Poverty Research, 2016) as well as state government sources in California and New York (New York State Department of Taxation and Finance, (2016), 2016). While we include Washington D.C. in our analyses, we do not benchmark our simulations to D.C.'s policies due in particular to the District's small sample size, its unique demographic composition, and because its policies consistently exceed the level of generosity in other states.

2.2. Methods

We simulate the child poverty impact of four scenarios:

- (1) All states provide TANF to the same proportion of TANF-eligible individuals as receive the benefit in the most inclusive state in this regard;
- (2) All states provide SNAP to the same proportion of SNAP-eligible individuals as the most inclusive state in this regard;
- (3) All states have a fully refundable state EITC that is as large a proportion of the Federal EITC as the most generous state in this regard;
- (4) All states implement a state CTC as generous or inclusive as the most generous state in this regard.

The first two scenarios simulate effects of administrative and policy choices while the last two simulate isolated effects of changes in legal policy. In each case, we simulate the reduction in child poverty—in each state and the nation as a whole—in these four scenarios in which all states are brought up to the policy generosity level of the most generous or inclusive state. Though generosity can be conceived and operationalized in multiple ways, we chose to measure generosity here as both benefit amount (generosity) and the enrollment rate among eligible individuals (inclusiveness), as we describe in depth below. For TANF and SNAP, we do not simulate the reduction in child poverty if all states had the same benefit amount, rather, we model changes in the proportion of eligible individuals receiving benefits, or program inclusiveness, for two reasons. First, many states with a higher cost of living—Hawaii, California, and Alaska—have higher benefit amounts. While it is reasonable to expect that states might provide benefits to the same share of their eligible populations, it may not be reasonable to expect them to offer the same benefit amount given the differences in their cost of living. Second, in the case of TANF, the federal government endows states the autonomy to allocate funding according to their preferences,

ranging from cash income support to workforce development and childcare for higher-earning families. Accordingly, in the effort to simulate plausible state choices rather than immovable factors, we focus on program inclusiveness alone for TANF and SNAP simulations. For the state EITC and state CTC, generosity refers to the size of the state credit relative to federal credits.

TANF is the cash welfare program, SNAP is an in-kind nutrition program, the state EITC is a credit for working families, and the state CTC is a credit for families with eligible children. We simulate generosity and inclusivity in these programs to accommodate the nuanced differences in their scope and coverage. Data on benefits received in the form of cash income are only available annually. An alternative measure of generosity for both TANF and SNAP might be the size of the benefit payment. However, in contrast to daily or monthly measure of benefit receipt, an annual measure of benefits fails to capture income volatility, which is especially prevalent among the lower-income respondents. Having only yearly benefit information also precludes us from using variation in benefit levels and generosity across states. As a result, we focus on cross-state variation in income eligibility and coverage.

For the first two simulations, TANF and SNAP, we operationalize inclusiveness as an expansion in access—measured as the enrollment rate of the eligible population—as the result of more inclusive eligibility criteria. California's cash welfare program, CalWORKs, is among the most inclusive. While Maine currently has a higher proportion of eligible individuals in families with children receiving TANF than does California, California is consistently the highest by this metric during the time period we analyze. The proportion of eligible individuals receiving TANF in California is thus the inclusiveness “target” for the other states in the TANF simulation.⁹ Though SNAP is a federal program, like TANF, there is substantial state-level variation in the fraction of eligible individuals receiving benefits. We use Maine's coverage as the target for the other states because we find that Maine has the highest proportion of SNAP-eligible individuals in families with children receiving the benefit (almost 95%).¹⁰

For the third and fourth simulations—EITC and CTC—we model the state tax credit as a percent of the federal credit as the generosity parameter. The most generous state in the EITC simulation is Wisconsin, which in 2010 gave families with three dependents a state EITC rate of 43% of the families' Federal EITC (see Appendix Table 1 for actual state EITC rates in 2010–2012), meaning that in addition to receiving the Federal EITC, Wisconsin families received an additional 43 percent in their tax return. This was the highest state EITC rate across all three of the years for which we have data.¹¹ Finally, we use New York's Empire State Child Tax Credit as the generosity target for the CTC simulation. While other states like Oklahoma and North Carolina also have state child tax credits during the years for which we have data, New York's is the most generous or inclusive in terms of refundable status, income eligibility, and the size of the credit. As noted earlier, state CTCs are a relatively new policy and as of yet tend to be relatively small. Reflecting this, New York's credit, while the most generous, adds only 33 percent to the federal credit.

As the four simulations are slightly different from one another, we discuss the method for each in turn.

⁹ California also has one of the highest levels of average TANF benefits per person. For this reason, we do not exploit variation in average benefit.

¹⁰ Authors' calculation; for families with children.

¹¹ This is only slightly higher than DC's rate (40%) and somewhat higher than the next most generous or inclusive states—Minnesota had a state EITC rate of 33% and Vermont had a state EITC rate of 32% during 2010–2012. After 2010, Wisconsin's state EITC rate for families with three dependents dropped to 34%. The Wisconsin EITC rate is applied to all families in our simulation.

2.3. TANF simulation

TANF eligibility is determined based on CalWORKs' Minimum Basic Standards of Adequate Care (MBSAC) in the relevant years (California Health and Human Services Agency, 2015). The income eligibility cutoffs are updated on July 1 of each year (i.e. at the beginning of the fiscal year). To obtain the cutoff for each calendar year, we average across fiscal years. For example, the monthly income cutoff for a family of four from July 1, 2009 to June 30, 2010 was \$1239; from July 1, 2010 to June 30, 2011 it was \$1258. For our purposes, we compute the monthly income cutoff for a family of four in 2010 as the average across all years in our sample: \$1248.50 per month or \$14,982 per year.

Appendix Table 2 contains the proportion of people in families with children who are eligible for TANF by California's standards and are receiving it in each state (both before the simulation and after). We use the TANF definition of household eligibility applied to the SPM unit, rather than eligibility at the SPM unit level, in concordance with the true TANF coverage rates. We "bring up" all the states to California's level of TANF coverage by allocating benefits to eligible individuals in families with children who have been prioritized based on predicted benefit receipt from the following model:

$$TANF_{dumm_{si}} = \alpha + \beta_1 childnum_{si} + \beta_2 resourcestneeds_{si} + \epsilon_{si}$$

where $TANF_{dumm}$ is an indicator for whether the individual received TANF, $childnum$ is the number of children in the household who are not foreign-born non-citizens from Mexico or Central America, and $resourcestneeds$ is the ratio of total cash income to the official poverty threshold. The model is estimated for each state (s) separately and yields a prediction for each individual (i). SPM units with more children have a higher predicted probability of receiving TANF, while those with a higher resources-to-needs ratio have a lower predicted probability of receiving TANF.

We rank individuals who are income eligible (i.e. below the MBSAC threshold) but not receiving TANF by their predicted probability of TANF receipt from the above model. Starting from the individuals with the highest probability, we assign individuals and their SPM unit members TANF benefits in the average amount received by people with equivalent predicted probability of TANF receipt. These average benefits are computed from the US population by categories of SPM units' resources-to-needs ratio (low, medium, and high, as defined by tertiles), number of adults in the SPM unit (0–1, 2, 3 or more), number of children in the SPM unit (1, 2, 3 or more), and state inclusiveness tertile (low, medium, and high, as defined by tertiles of average benefits received in each state). This approach approximates actual take up rates under the implicit assumption that the neediest recipients receive the benefits largest among the eligible population. We assign benefit amounts using state inclusiveness tertile rather than actual state benefit amounts because small sample sizes in some states preclude obtaining average benefits in every state by all three of the other characteristics (resources-to-needs, number of adults, and number of children). The average annual benefits received by individuals in each simulation are summarized in Appendix Table 3. We assign benefits to eligible individuals in the simulation until the same proportion of qualifying individuals in each state are receiving TANF as in California.

In order to be deemed eligible for TANF cash assistance in the CPS under California's MBSAC, only income eligibility (in terms of resources-to-needs ratio) and the presence of children in the household are counted. Though these two standards alone are imperfect proxies for actual program eligibility (e.g. incorporating asset tests, home equity limits, vehicle valuation limits, etc.), we do not attempt to simulate benefit amounts based on program rules but rather on the actual benefits received by similar CPS respondents who did receive TANF cash assistance. Importantly, this choice does not omit benefit levels from our simulation, but rather conditions upon benefit levels, simplifying the interpretation of our results such that the poverty effects we

observe are attributable to policy and administrative choices alone. We argue that any remaining shortcomings are largely offset by the advantages of using nationally representative data, representing upper-bound estimates for TANF inclusiveness.

Because undocumented immigrants are ineligible for benefits, the simulation does not directly allocate benefits to any foreign-born non-citizen from either Mexico or Central America. These individuals are able to receive benefits indirectly if someone in their SPM unit is not a foreign-born non-citizen from Mexico or Central America and is allocated benefits in the simulation. We then re-estimate the poverty rate and compute the reduction in poverty due to the simulated expansion of TANF.

In the TANF simulation, those who receive benefits tend to live in SPM units with two adults (45.4%) and three or more children (84.9%). Just 5.4% of individuals who receive TANF benefits in the simulation (indirectly) are foreign-born non-citizens from Mexico or Central America. Among those who are eligible to receive TANF in the simulation, 99.6% have resources-to-needs that are in the bottom third of the resources-to-needs distribution below the poverty line. Finally, the simulation accounts for the reduction in SNAP benefits that occurs when an individual begins receiving TANF. For each additional \$100 in TANF received, \$30 is deducted from SNAP benefits (Institute of Medicine and National Research Council, 2013).

2.4. SNAP simulation

We simulate what the poverty reduction would be if all states were to give the same proportion of eligible individuals SNAP as does the most inclusive state in this regard. While the cutoff for SNAP eligibility is 130% of the Federal Poverty Line (FPL), we use 150% of the FPL to identify potentially eligible families. Families' yearly income may be somewhat higher than the cutoff despite their monthly cash income varying quite dramatically (and the CPS ASEC only contains yearly cash income), making them eligible for SNAP part of the year. This approach implicitly assumes that some of those with newly-assigned SNAP benefits will begin receiving payments in January (for an entire year of benefits) and some will begin receiving payments in the months that follow (for a partial year), replicating actual patterns of SNAP enrollment. We use cash income and official poverty thresholds since this encompasses the definition that would be used to identify eligibility for possible benefits. As in the TANF simulation, foreign-born non-citizens from Mexico or Central America are not eligible to be allocated benefits directly in the simulation. People with these characteristics may, however, receive benefits in the simulation indirectly if someone in their SPM unit is not a foreign-born non-citizen from either Mexico or Central America and receives the benefit, as the maximum benefit received in the SPM unit is given to all members.

We rank individuals who are eligible but not receiving SNAP by their predicted probability from the above model (with the outcome changed to SNAP receipt), and assign individuals and their SPM unit members SNAP benefits in the average annual amount received by people with equivalent propensity scores, starting from the highest ranked (i.e. with the highest probability). The average benefit computation is similar to that of TANF, based on the U.S. population depending on individuals' resources-to-needs (low, medium, and high), number of adults in the SPM unit (0–1, 2, 3 or more), number of children in the SPM unit (1, 2, 3 or more), and state inclusiveness tertile as described above. The average benefits received by individuals in each simulation are summarized in Appendix Table 3. Again, foreign-born non-US citizens from Mexico or Central America are not eligible to receive benefits directly in the simulation; they are, however, eligible to receive benefits indirectly through family members.

Maine is the state with the highest proportion of SNAP-eligible individuals in families with children receiving the benefit (almost 95%), while California and Utah have the lowest proportion of SNAP eligible individuals in families with children receiving the benefit (68%) (see

Appendix Table 2 for the proportion of SNAP-eligible individuals who receive the benefit in each state and the nation as a whole before the simulation and after the simulation). The simulation assigns only as many people and their SPM unit members benefits as is required to obtain the equivalent proportion of eligible individuals receiving benefits as in Maine. We then re-estimate the poverty rate and compute the reduction in poverty due to the simulated expansion of SNAP.

In the SNAP simulation, the majority of individuals who are allocated benefits are in SPM units with two adults (65.3%) and three or more children (57.1%). Fifteen percent of the individuals who receive SNAP benefits in the simulation (indirectly) are foreign-born non-citizen from Mexico or Central America. Among those who are eligible to receive SNAP (i.e. their SPM unit has resources below 150% of the SPM poverty line), 19% have very low resources-to-needs (i.e. in the bottom third of the distribution), 29.1% have medium resources-to-needs (middle third of the distribution), and 52.0% have high resources-to-needs (top third of the distribution). Many families at the lowest end of the income distribution already receive SNAP.

2.5. EITC simulation

We simulate the reduction in the child poverty rate that would be realized if all states adopted the most generous state's EITC benefit rate, which was Wisconsin in 2010 for families with three dependents. Twenty-eight of the fifty states had no state EITC in 2010 at all. Only individuals and families receiving the federal EITC in 2010–2012 were eligible to receive a state EITC in the simulation. However, the CPS ASEC has no information on taxes paid or owed, so tax information is estimated using the U.S. Census Bureau's tax calculator (see [Wheaton & Stevens, 2016](#) for a thorough discussion of the costs and benefits of using tax calculators to estimate tax credits and taxes owed). This tax calculator simulates the amount of Federal EITC individuals are estimated to have received based on their earned income, the rules governing eligibility, etc. While the calculator provides total state taxes paid and received after all credits, it provides no direct information on the amount that individuals receive in state EITC, though this would only produce erroneous estimates among those who file federal tax returns but not state tax returns, an expectedly small fraction of the tax-filing population. Therefore, we compute this quantity by multiplying the amount an individual received in federal EITC by the state EITC rate in their state of residence in each year (Connecticut, Illinois, Indiana, Michigan, and Minnesota changed their rates between 2010 and 2012).

Of the twenty-three states with state EITCs, only twenty were refundable during our period of inquiry. For the three states in which the EITC was not refundable (Delaware, Maine, and Virginia), the computation is slightly more difficult because taxpayers may receive a state EITC amount only up to the amount of taxes they owe; the credit is not distributed as part of a refund. In order to estimate individuals' state EITC in these three states, we first multiply their federal EITC amount by their state EITC rate as before but cap the amount they receive in state EITC at their estimated taxes owed after other credits have been taken into account. This ensures that we do not overestimate the state EITC amounts that respondents receive in states with non-refundable EITC.

Once we have estimated the state EITC that individuals received, we then estimate what they would have received if their state had the most generous (43%) rate by multiplying their federal EITC amount by 0.43. Though the Wisconsin state EITC is based upon three-dependent-children families, we apply this generosity parameter to all EITC recipient-families in our simulations. The final step is to remove from resources the actual state EITC that individuals were estimated to have received (as described above) and replace it with 43% of their federal EITC. We then re-estimate the poverty rate and compute the reduction in poverty due to the simulated expansion of the EITC.

In the EITC simulation, 23.3% of people receiving a state EITC are below the SPM poverty line. Nearly half of people receiving the

simulated state EITC have two adults in the home; 19.0% have one adult and 29.4% have two or more adults. About 32% of simulated state EITC recipients have one child in the SPM unit; 34.8% have 2 children and another 33.6% have 3 or more children.

2.6. CTC simulation

New York State has a refundable state child tax credit (the Empire State Child Tax Credit, henceforth referred to as the "ESCTC") that residents receive in addition to the Federal Child Tax Credit. As described by New York State's Department of Taxation and Finance, New York residents (or an individual married to a New York resident) with a qualifying child (ages 4–17) may receive the credit if they meet one of the following criteria:

- (a) They have either a federal child tax credit or a federal additional child tax credit, or
- (b) Their federal adjusted gross income was \$110,000 or less for individuals married filing jointly; \$75,000 or less for single, head of household, or qualifying widow(er); \$55,000 for married filing separately

For those who claimed the Federal Child Tax Credit, the amount of the credit is either a) 33% of the portion of the Federal Child Tax Credit and Federal Additional Child Tax Credit attributable to the qualifying child, or b) \$100 multiplied by the number of children, whichever is greater. For those who meet the eligibility requirements above but did not claim the federal child tax credit, the ESCTC is \$100 multiplied by the number of qualifying children.

There are two other states with a CTC during 2010–2012: Oklahoma and North Carolina. Oklahoma allows residents to claim either 5% of their Federal Child Tax Credit or 20% of their Federal Child and Dependent Care Credit, whichever is greater. We estimate Oklahoma's CTC as 5% of the combined Child Tax Credit and Additional Child Tax Credit (the refundable portion of the credit); there is no information in the CPS ASEC on the Federal Child and Dependent Care Credit. In North Carolina, there are income eligibility cutoffs for tax filers with dependent children under 17. Individuals with incomes below the threshold receive \$100 per child in credits. Individuals with particularly low incomes (\$40,000 for married filing jointly, \$32,000 for head of household, and \$20,000 for single or married filing jointly) receive \$125 per child. We estimate the CTC in North Carolina using these rules, and subtract the amount from individuals' resources before adding the ESCTC.

After subtracting the estimated state CTC in Oklahoma and North Carolina and removing them from the resources of residents in those states, we estimate the ESCTC in each state using the rules outlined above and compute the Empire State Credit that all individuals in all states would have received if their state had New York's CTC, regardless of child age. We then re-estimate the poverty rate and compute the reduction in poverty due to the simulated expansion of the ESCTC.

In the CTC simulation, only 10.8% of people receiving the CTC are in poverty. The majority of recipients have 2 adults in the home (62.5%), while 13.9% have one adult in the home and 23.6% have 3 or more adults in the home. Twenty-five percent of CTC simulation credit recipients have one child in the SPM unit, 40.0% have two children, and 35.2% have 3 or more children.

Note that the benefits received in these simulations approximate what individuals might have received had they gone through the administrative procedures required to determine benefits receipt. Further, not all individuals who are "assigned" benefits in the simulations would actually take them up because of stigma or lack of knowledge, or because they need the benefits for such a short period of time that it is not worth the hassle of applying. There are also demographic and socioeconomic characteristics that affect benefit take-up rate – not having English as a first language, being elderly, and having less education, etc.

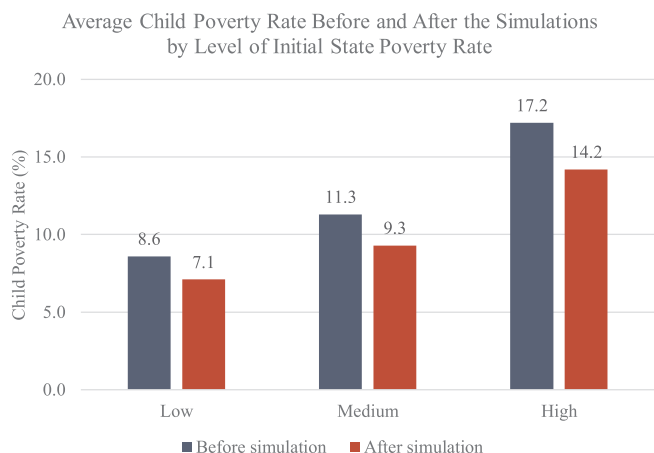


Fig. 1. Simulated average reduction in child SPM poverty under all four policy simulations described in the methods section. Data are from TRIM3-adjusted 2010–2012 Current Population Survey’s Annual Social and Economic Supplement (CPS ASEC). Note: Low child poverty tertile = 5.2–9.7%, medium child poverty tertile = 9.8–12.1%, and high child poverty tertile = 12.2–25.0%.

– and with distributional differences by state. We do not account for these characteristics in our simulation model (i.e. that the elderly are less likely to avail themselves of benefits they are eligible for) to avoid building these inequalities – which should not be assumed to be fixed – into our model.

3. Results

3.1. Simulations’ effects on poverty

Fig. 1 shows the reduction in child poverty brought about by the four simulations in initially low, medium, and high poverty states. State-level results are available in the Appendix. The poverty reductions are relatively large, suggesting that there is a substantial poverty reduction that could be realized by an improvement in state welfare policy. The largest reduction in child poverty is in the high-poverty states where poverty is reduced by 3.0 percentage points, from 17.2% to 14.2%. In states with medium-levels of child poverty, the simulations reduce the poverty rate by 2.0 percentage points, and in the low-poverty states, child poverty is reduced by 1.5 percentage points. In absolute terms, the larger simulation effect in the high poverty states indicates that there is more room for improvement in high-poverty areas where there are a relatively larger number of people available to be brought over the SPM poverty line.

Fig. 2 illustrates the reduction in child poverty in terms of percentage points, broken down by program simulation and grouped into low-, medium-, and high- poverty states (as classified prior to the simulation). The simulation with the largest impact on the child poverty rate – in low-, medium-, and high- poverty states – is the state EITC. The state EITC simulation reduces child poverty by an average of 0.6 percentage points in low-poverty states, 0.9 percentage points in medium-poverty states, and 1.5 percentage points in high-poverty states. In contrast, the poverty reduction realized in the other three simulations does not exceed 1.0 percentage point, even in the high-poverty states.

There are a number of states in which the child poverty rate does not change as a result of a simulation (see Appendix Table 4 for poverty reduction from the simulations at the state level). The TANF inclusiveness simulation is an informative case study of the scenario under which this might occur. While the average TANF benefit amount received in the TANF simulation is relatively large (see Appendix Table 3 for average benefit amounts received in each simulation in each state), very few people have sufficiently low resources to qualify.

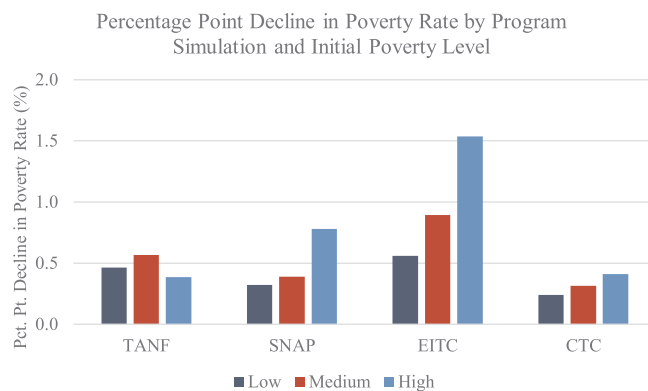


Fig. 2. Simulated reduction in child SPM poverty disaggregated by each social policy described in the methods section. Data are from TRIM3-adjusted 2010–2012 Current Population Survey’s Annual Social and Economic Supplement (CPS ASEC). Note: Low child poverty tertile = 5.2–9.7%, medium child poverty tertile = 9.8–12.1%, and high child poverty tertile = 12.2–25.0%.

3.2. Simulations’ effects on resources-to-needs ratio

As resources from social policies may benefit families even if they are not moved above the poverty threshold, a focus on the SPM poverty rate alone may underestimate the impact of more generous or inclusive state policy on children’s economic wellbeing. A more continuous measure of economic wellbeing is children’s resources-to-needs ratio – the ratio of their SPM unit’s resources to the SPM poverty line. The resources-to-needs ratio allows us to unpack the way in which the simulations function in more detail, unveiling who receives benefits, the amount they receive, and how these features affect our overall results. Fig. 3 summarizes the percentage point increase in the resources-to-needs ratio produced by each of the program simulations. Since the program simulations are expected to primarily impact the poor (and to a lesser extent, the near-poor), we categorize children in the graphs of the resources-to-needs ratio by whether their SPM unit resources are below 100% of the poverty line (i.e. the poor), 100–200% of the poverty line, and above 200% of the poverty line. While we attempted to investigate the impact of an increase in benefit generosity/inclusiveness on children in deep poverty (< 50% of the poverty threshold), we found that sample sizes within states were too small to reliably estimate the simulation models for this subsample. Further, as TRIM adjustments for underreporting are remarkably less reliable among very low-income families, the inclusion of deep SPM poverty would require additional underreporting adjustments, as detailed in Mittag (2019).

Overall, the largest impact of the state anti-poverty policy simulations is on the resources-to-needs ratio of the poor. For children below 100% of the poverty line, the SNAP inclusiveness simulation results in the largest increase in children’s resources-to-needs. In the sample between 100 and 200% of the poverty line, the state EITC generosity simulation results in the largest increase in the resources-to-needs ratio, and in the sample above 200% of the poverty line, the state CTC results in the largest increase in children’s resources to needs. We now discuss each program simulation in turn to further describe which children receive benefits in each simulation, how much they receive, and how this affects the results.

As previously described, the TANF simulation allocates a large benefit to eligible individuals, but the absolute number of these individuals is relatively small due to the relatively low eligibility cutoff. Further, TANF-eligible individuals are almost exclusively below the SPM poverty line and many have near-zero resources prior to the simulation. The low base to which the TANF benefit is added in the simulation increases the magnitude of the “percent increase” in resources-to-needs ratio reported in Fig. 3. The percent increase in resources-to-needs ratio due to the TANF benefit is thus very large for

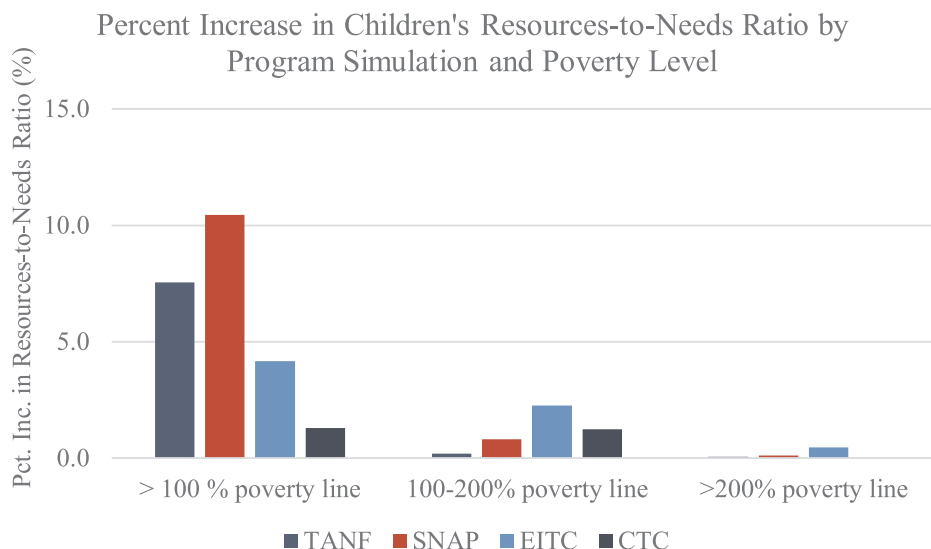


Fig. 3. Percentage point increase in the resources-to-needs ratio on account of each policy simulation described in the methods section. Data are from TRIM3-adjusted 2010–2012 Current Population Survey’s Annual Social and Economic Supplement (CPS ASEC).

poor children (7.5%), whereas the increase is almost negligible in the other poverty categories.

In the SNAP simulation, the average benefit amount is relatively large, however a large number of poor children already receive it, reducing the net impact of the simulation. Children below the poverty line experience an average 10.4% increase in their resources-to-needs ratio while those at 100–200% of the poverty line experience a 0.8% increase in their resources-to-needs ratio. Virtually no children with resources more than twice the poverty line receive SNAP in the simulation so there is no increase in their resources-to-needs ratio. These patterns can be seen in more detail in the state-level results. For example, there is no change in children’s resources-to-needs ratio as a result of the SNAP simulation among the poor (i.e. with < 100% resources-to-needs) in three states: Mississippi, Montana and West Virginia (Appendix Table 7). This is due to the high coverage of the eligible population in these states – 92%, 85% and 89%, respectively – as well as their size. The few people who receive the benefit in the simulation are all at 100–200% of the poverty line – all of the individuals who are in poverty already received SNAP at least one month in the previous year.

The pattern of results in the state EITC simulation is quite different than those in the TANF and SNAP simulations. The amount of state EITC that individuals receive in the simulation is less, on average, than what is received in the TANF simulation (see Appendix Table 3), however relatively more people receive the state EITC in the simulation, and those that do are spread more widely across the income distribution (Appendix Table 8). The EITC is only for working families, so those who have no cash income or are unemployed do not benefit from the EITC. The largest increase in children’s resources-to-needs ratio in the EITC simulation is among children in poverty (Appendix Table 8) due to their very low starting point. Children who are in poverty experience on average a 4.1% increase in their resources-to-needs ratio in the EITC simulation. Children at 100–200% of the poverty line experience on average a 2.2% increase in their resources-to-needs, and children over 200% of the poverty line experience an average of 0.1% increase. While the amount of the average state EITC benefit received in the simulation is much less than that in the SNAP simulation, the number of children who would benefit from a more generous or inclusive state EITC is relatively large.

The state CTC simulation results in a relatively small increase in resources-to-needs in all three poverty categories. The increase is 1.3% on average among children below the poverty line, 1.2% among children 100–200% of the poverty line, and 0.5% among children over

200% of the poverty line. The increase in children’s resources-to-needs ratio is modest due to the size of the CTC, which is substantially less than the average benefit received in the other simulations – about \$519 as compared to \$3269 for TANF, \$1294 for state EITC, and \$4929 for SNAP. While more people receive the CTC than any other benefit in the simulations, its modest size reduces its impact on the child poverty rate and on its improvement of children’s resources-to-needs.

4. Discussion

In this paper, we simulate what the change to child poverty rates would be if all states adopted policies as generous or inclusive as the most generous or inclusive state for each of four anti-poverty programs – TANF, SNAP, state EITC and state CTC. Though not all states stand to benefit from all policy changes (see e.g. Appendix Table 4), the potential improvement to the child poverty rate is substantial; if all states adopted Wisconsin’s EITC policy alone, nearly 2.7 million children would be moved out of poverty. If all states adopted the most generous or inclusive state policy in all four policy areas, a total of 5.5 million children would be pulled out of poverty – a reduction of 2.5 percentage points, on average. Though these effects are sizeable, there is some evidence that our estimates may underestimate the true effect (Hoynes & Patel, 2015). Accordingly, as we discuss below, we expect that the actual effects of the potential policy changes would in fact be much more pronounced.

Whether states are capable of increasing their benefit generosity or inclusiveness in such a manner is another question, as states are constrained from investing in child poverty by voter preferences, revenue, and other expenses and priorities. If states with more abundant resources are also the most generous or inclusive – and those that have fewer resources are the least generous or inclusive – then it could be that less-generous or inclusive states have higher child poverty rates simply because of their lack of capacity to invest in anti-poverty policies given competing priorities and scarce resources. If this is the case, allocating funds to these anti-poverty programs may be infeasible without offsetting other lines in the budget. Alternatively, if there is no relationship between poverty rates and generosity or inclusiveness, states may be allocating funds away from child poverty investments as a matter of choice, rather than necessity, implying that states have some flexibility in prioritizing child well-being. It is of course worth mentioning that state revenue and capacity is subject to states’ choices not just about resource allocation but about how much state tax revenue they bring in in the first place. For example, a number of states choose

to have no or very little state income tax or make other choices that limit the amount of revenue generated that could be used to reduce poverty.

The barriers to generosity in terms of EITC and CTC differ from those pertaining to SNAP and TANF inclusiveness. In order to increase the generosity of EITC and CTC benefits, states can enact a refundable state credit with lower eligibility standards. SNAP coverage relies on the business cycle and on the removal of policy-based eligibility standards and enrollment procedures (see e.g. Bruch et al., 2018; Danielson & Klerman, 2006; Ganong & Liebman, 2013). A recent proposal to expand TANF cash welfare finds that the removal or minimization of work requirements and shifting state spending away from in-kind programming may increase the program's reach (Bitler & Hoynes, 2016a). Other recommendations from the same publication included responsiveness to the business cycle (increase cash welfare funding during economic recessions) and boosting state accountability, findings that corroborate those in prior literature (Klerman & Haider, 2004; Schoeni & Blank, 2000).

There are a number of states in which the child poverty rate does not change as a result of a simulation (see Appendix Table 4 for poverty reduction from the simulations at the state level). The TANF inclusiveness simulation is an informative case study of the scenario under which this might occur. While the average TANF benefit amount received in the TANF simulation is relatively large (see Appendix Table 3 for average benefit amounts received in each simulation in each state), very few people have sufficiently low resources to qualify. The TANF simulation thus allocates benefits to a small number of people in absolute terms, diminishing the anti-poverty effect of the simulated increase in inclusiveness. Since the individuals who are eligible to receive the TANF benefit in the simulation have quite low – if any – resources, the subsequent benefit receipt often does not push them over the poverty line (a point that we consider more fully below). Finally, some of the states already have coverage close to the target, so they have very little room for improvement in the simulation. All of these factors operate to produce relatively small declines in poverty in some states in the TANF simulation and many operate in the other program simulations as well.

In the SNAP simulation, for example, many of the states already had a high proportion of eligible individuals receiving benefits, so simulating more inclusive coverage did not result in large anti-poverty reductions. In contrast, the benefit amounts in the EITC simulation are moderate, but the number of children and families in states without a state EITC before the simulation is large, resulting in a large anti-poverty effect. Finally, the average CTC simulation benefit amount is quite low, and while eligibility is widespread, the simulation results in a relatively small anti-poverty effect. Another factor in the CTC results is that the CTC provides relatively large benefits to higher-earning families.

There are several limitations to the analyses presented in this paper. First, we do not model any behavioral, employment, or labor market changes that might result from the receipt of additional benefits. Though potential behavioral effects such as labor market participation and effort should not be ignored, there is some evidence that these combined behavioral effects are relatively small (Ben-Shalom et al., 2011) and in the case of the EITC (and by extension, likely the CTC) behavioral effects would lead to greater labor force participation, implying that the anti-poverty effects we estimate may be understated (Hoynes & Patel, 2015). TANF and SNAP are thought to have a negative work incentive, however under work requirements and time limits the net effect for TANF should be close to zero. For a detailed discussion of the labor market responses and other behavioral effects of these programs, see e.g. Ben-Shalom et al. (2011) and Duncan & Le Menestrel (2019). Future empirical studies should attempt to model the aggregate impact and magnitude of such aggregate behavioral impacts across programs. The second limitation to our analysis is that we do not model the effect of imposing new state taxes that would be required to finance

increases in benefits. Different financing methods could somewhat alter the distributional impacts of proposed reforms, though unless such financing were significantly regressive in nature, they are unlikely to affect the overall effects on poverty found here. On a related note, we harness data from 2009 to 2011 (survey years 2010–2012) as these more accurately reflect actual tax obligations and underreporting adjustments under TRIM3. What we gain in precision, however, may be lost in generalizability as this period may reflect atypical state policy variation on account of the American Recovery and Reinvestment Act (ARRA) and post-recession recovery. That said, this period may be particularly relevant to the current state of the economy on account of the COVID-19 pandemic. Indeed, evidence drawn from expansions during our period of inquiry may better inform economic recovery than the period immediately before COVID-19 due to similar macroeconomic conditions. Future researchers should consider using more recent data, reflecting a longer post-recession recovery period, conditional upon the accuracy of correcting for underreporting. Though outside the scope of the present paper, more recent innovations in dealing with underreporting should be considered as well. For example, the author of a recent paper compared statistical methods for correcting underreporting for SNAP using linked administrative data (Mittag, 2019), finding that adjustments on the tails of the income distribution are by far the most meaningful. Third, our SNAP and TANF simulations exclude undocumented individuals, for whom poverty among children may have been more significantly affected. Similarly, these individuals are included in the EITC and CTC simulations at the risk of over-ascertaining the effects of these programs (as parental SSNs are required for tax credit eligibility). This important limitation should be addressed in future research, particularly on account of a more recent policy shift allowing child-only SSN eligibility (Duncan & Le Menestrel, 2019). Fourth, as the focus of this study is on cash and near-cash benefits, we do not simulate the effects of scaling up other anti-poverty policies in the present study. As many of these policies convey benefits beyond their monetary value to enrollees, the presumed benefit extends beyond poverty relief into other benefits to health and well-being. Though outside the scope of the present study, a related study presents the results of a similar exercise assigning Medicaid benefits to non-beneficiaries in non-expansion states (Zewde & Wimer, 2019). Future research should consider the merit of a similar approach in consideration of the other policies. At the same time, that the policies we examine here fail to address the root causes of child poverty should not be ignored. Indeed, these policies fail to fully address factors that cause child poverty, such as racial and ethnic discrimination, structural inequalities, and discriminatory access to education. Rather, this set of policies buffers the potentially devastating effects of economic shocks, helping families to better smooth income in times of uncertainty. Accordingly, it is important that future research acknowledges the strengths and limitations of these policies. Finally, future research should consider examining the potential administrative and enrollment costs of the simulated policy expansions we explore here. Precise cost estimates of this nature would enable accurate cost-benefit comparisons across policies to inform future legislative decision making.

Importantly, our results complement those detailed in a recent publication by the National Academies of Science, Engineering and Medicine (Duncan & Le Menestrel, 2019), in which the authors estimated the costs and benefits of reducing child poverty by up to half by leveraging different combinations of state and federal antipoverty policies. Though the authors similarly find that expanding state EITC and CTC may yield the largest effects, they conclude that the costs to do so are by far the lowest, relative to other proposed expansions (see e.g. figure S-3, page 12, also chapter 5).

5. Summary and conclusions

In this study, we focus on the possible consequences for child poverty of an increase in generosity or inclusiveness in state welfare policy

in which states compete to be the most successful in reducing child poverty. We do so with a series of state anti-poverty policy simulations.

Out of the four simulations, the largest reduction in child poverty is realized in the state EITC expansion. If all states had state EITC rates as generous as the most generous state (Wisconsin's policy in 2010 for families with three dependents was 43% of the federal EITC and fully refundable), there would have been 2,699,624 fewer children in poverty (see Appendix Table 2). The equivalent numbers are 816,558 for the CTC simulation, 985,776 for the TANF simulation, and 1,340,499 for the SNAP simulation. In the state CTC simulation, the average benefit amount is quite low and spread through a relatively larger range of the income distribution, reducing its efficiency in poverty reduction. There is somewhat less room for reducing poverty in the TANF inclusiveness simulation than in the state EITC generosity simulation because the current income threshold to receive TANF (even in an inclusive state) is so low that few people qualify for the benefit. In the SNAP inclusiveness simulation, while the average benefit amount is large, many states already cover over 80% of their residents who qualify, again reducing the scope for poverty reduction.

Overall, these results suggest that more generous implementation of state EITC has the greatest potential for reduction of child poverty, compared to TANF, SNAP, and state CTC. However, there is somewhat of a tension between reducing poverty and increasing resources-to-needs, as expanding SNAP would produce the greatest increase in poor children's resources to needs. Finally, it should be noted that the reforms we model are relatively modest – designed not as ideal policies but rather as examples of the effects of expanding policies already in existence. We illustrate that changes to current policies – based on what other states have deemed feasible and appropriate – can have a range of (including somewhat large) effects on child poverty. For example, in the case of TANF, some states saw no change in child poverty (see e.g. Appendix Table 4). Of course, more ambitious reforms, such as a minimum benefit, could have even larger effects – a topic we hope to address in future research. While this paper simulated the effects of four major anti-poverty policies, there are many other policies that affect the economic wellbeing of low-income families. We encourage researchers to apply similar simulation methodology to other policy areas in order to quantify and prioritize areas in which strengthening public policy would produce the greatest increase in public wellbeing.

CRedit authorship contribution statement

Jessica Pac: Data curation, Writing - review & editing, Visualization, Investigation. **Irwin Garfinkel:** Conceptualization, Writing - original draft, Methodology. **Neeraj Kaushal:** Conceptualization, Writing - original draft, Methodology. **Jaehyun Nam:** Data curation, Methodology, Validation. **Laura Nolan:** Conceptualization, Data curation, Writing - original draft, Methodology, Validation, Visualization, Investigation. **Jane Waldfogel:** Conceptualization, Writing - original draft, Writing - review & editing, Methodology. **Christopher Wimer:** Conceptualization, Writing - original draft, Writing - review & editing, Methodology.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.childyouth.2020.105030>.

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