Testing Guaranteed Income Programs for Poverty Reduction: Is Targeted Always Better?

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Information presented here is derived in part from the Transfer Income Model, Version 3 (TRIM3) and associated databases. TRIM3 requires users to input assumptions and/or interpretations about economic behavior and the rules governing federal programs. Therefore, the conclusions presented here are attributable only to the authors of this report.

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Any errors are the author's alone, and all interpretation and analysis is made solely by the author.

2 Abstract

I develop a microsimulation model to test the potential effects on poverty broad expansions to cash payments in the United States social safety net. My primary contribution to the literature on income supports is the implementation of a new model that directly tests the efficiency of different policy designs by defining equivalent program budgets across simulations. I find that broad-based basic incomes could substantially reduce poverty, with a guaranteed income program achieving a 60% reduction. Simulations that include labor supply effects show a modest reduction in efficiency. I also find that modest means-testing does not substantially increase the efficiency of the programs, likely due to incentive effects embedded in my simulations. Importantly, with the US already running high deficits, these same programs would face serious questions about their fiscal costs and sustainability.

3 Introduction

One of the primary goals, if not the primary goal, of social policy is to alleviate poverty. Evidence indicates that, in the US context, the collective weight of the social safety net has

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made major strides toward that goal. For example, research from the US Census Bureau shows that in 2022 the national unemployment insurance program, which acts as social insurance to individuals when they become involuntarily unemployed, pulled more than 400 thousand Americans out of poverty (Strider & Creamer, 2023). In the same year, the Supplemental Nutrition Assistance Program, which provides in-kind benefits for food purchases, reduced poverty by a total of 3.6 million people, including 1.4 million children (Strider & Creamer, 2023). And the Social Security program, which provides cash benefits to retirees, pushed 28.9 million people, and 1.35 million children, above the poverty line (Strider & Creamer, 2023). Using a consistent measure of poverty over decades, these programs have been shown to have a substantial effect: with poverty falling 40% between 1967 and 2012 (Wimer, Fox, Garfinkel, Kaushal, & Waldfogel, 2016).

These different safety net programs use a variety of designs and strategies to reduce poverty. Given the array of programs in effect, there is a fundamental debate within social policy regarding the degree to which redistributive programs should be targeted or universal with the goal of alleviating poverty. Historically, the targeted position has generally argued that universal programs are expensive and dilute the impact of resources that could otherwise go to those who need it the most (Greenstein, 2022). On the other hand, among other points, universalist position generally argues that universal programs are more politically durable since they benefit a greater part of the polity (Kasy, 2018). In recent years, there has been a growing debate about the benefits of a universal basic income program, which is a form of guaranteed income that would be available to a substantial fraction of a population at a sufficient level to match the cost of living (Hoynes & Rothstein, 2019). Researchers have evaluated what such a program would cost and its likely effect on poverty and the distribution of income (Hoynes & Rothstein, 2019; Hartley & Garfinkel, 2023). And many pilot projects have been implemented to directly test the feasibility and effectiveness of such a program (Bidadanure, Kline, Moore, Rainwater, & Thomas, n.d.).

In this paper, I implement a microsimulation model to directly test the poverty-reducing effect of alternative programs to expand income supports in the US social safety net. My primary contribution to the literature on income guarantee design is the implementation of what I refer to as a "fixed budget framework" within my microsimulation model. The standard approach to microsimulation of income support programs is to first determine the size and eligibility for a payment and subsequently calculate the sum of those payments across all eligible recipients to determine the total cost of the program.[1] The fixed budget framework reverses this process. I take an exogenously selected budget and eligibility thresholds, and calculate the corresponding payments for eligible families/individuals associated with that budget. The primary advantage of this approach within the microsimulation model is that I can apply a uniform budget across different income support schemes, which allows me to directly compare the poverty-reducing efficiency of alternative policy designs. I use the 2019 CPS ASEC sample as the foundation of my microsimulation, and develop both static and dynamic versions of this model, the latter of which scales the payments to incorporate both predicted labor supply effects and corresponding revenue effects on the federal budget.

The paper is organized as follows: 1) I describe the data and methodology underlying the model; 2) I set the stage for the analysis by outlining 'the challenge" that policymakers face in choosing the best route to reduce poverty; 3) I describe the results of the microsimulation analysis, including poverty reduction achieved in a "generalized" credit available to families and a targeted child credit available to parents with children; 4) I provide a discussion of these results; and 5) I close with a conclusion of my findings.

[1] For recent examples of microsimulation studies of basic income programs that follow this approach see Hoynes & Rothstein (2019); Hartley & Garfinkel (2023); Duncan et al. (2019); Wiederspan, Rhodes, & Shaefer (2019).

4 Data & Methodology

In this section, I discuss the primary features of my microsimulation model of cash payments programs via expanded income supports.[2] The main source of input data for my microsimulation is the 2019 Annual and Social Economic (ASEC) supplement to the Current Population Survey (CPS), corresponding with 2018 incomes (Flood et al., 2023). I supplement these data with benefit and tax data from the Urban Institute's TRIM3 module (TRIM3, n.d.).

I delineate my microsimulation into four broad categories of income support programs, each characterized by variations in program design and the structure of the corresponding benefit payments: a Universal Guaranteed Income (UGI), a Guaranteed Income (GI), a Phased Guaranteed Income (PGI), and an Earned Income Credit (EIC). The UGI provides an equal payment to all eligible members of the population, with amounts varying exclusively based on the composition and size of the family. The GI targets payments on a sliding scale based on income, where families with no income receive the largest payments, and families above a defined eligibility threshold receive no payment. The PGI mirrors the structure of the GI; however, it provides payments of equal size to families with incomes below a defined intermediate eligibility threshold (referred to as the "kink point"), with any families above this point receiving a payment on a sliding scale proportionate to their income, like the GI. The EIC is similar in structure to the federal EITC. It is defined by a payment subsidy, which provides proportionately larger payments to incomes up to a certain kink point and phases out payments thereafter. Unlike the federal EITC, the EIC in my microsimulation model does not incorporate a flat "earnings disregard" region.

The primary outcome of my microsimulation is a revised version of the Supplemental Poverty Measure (SPM), which makes several changes to the conventional SPM. Although I retain the poverty thresholds and family unit definitions of the conventional SPM, I make a variety of modifications to the resource measure. First, I implement my own tax calculations using the NBER TAXSIM module (version 35) (Feenberg & Coutts, 1993). These calculations generally adapt publicly available code from Ziliak (2019) and Scott-Clayton (2007) to fill in the 35 inputs for the TAXSIM calculator. This includes using the capital gains measure from TRIM3, which is not otherwise available in the ASEC year I use in my model.[3] Second, I delineate tax units for the TAXSIM module based on the tax units defined in TRIM3. I also include SNAP, SSI, and TANF benefit amounts from TRIM3 to correct for underreporting of ASEC benefits by adapting code from Parolin (2019).[4] I do not make any further adjustments to earnings in the ASEC survey, which previous research has found to over-report the concentration of families at zero dollars of earnings (Landry, 2023). This likely biases my results to disfavor an EIC program, since such a program does not provide benefits to families without income by design.

The primary unit of analysis in my microsimulation is the tax unit, as defined in the TRIM3 module. I assume that all simulated benefit payments are distributed via the tax system to these tax units. I assume that all unauthorized residents are ineligible and I impute unauthorized immigrant status in the CPS by adapting code provided by the Public Policy Institute of California for use in its state-based poverty measure developed using the ACS (Bohn, Danielson, Levin, Mattingly, & Christopher, 2013). My microsimulation scales payments to tax units based on an "equivalence scale," which factors in the size and composition of the tax unit (i.e., the number of adults and the number of children) so that larger payments are

[2] A more detailed description of my methodology can be found in the Appendix.

[3] The incorporation of the TRIM3 capital gains measure may cause me to double-count (i.e., over-count) capital gains income in my sample since capital gains should be measured in "other" income. However, excluding the TRIM3 capital gains measure from family resources yields a number of implausibly negative total resource values. This is due to the fact that I use the TRIM3 capital gains measure in my tax calculations, since no direct capital gains measure is available in the CPS.

[4] I describe the effect of my revised SPM measure on poverty levels in Section 5.

simulated for proportionately larger tax units. The equivalence scale for my main results includes a weight of 1.0 for adults and a weight of 0.5 for children, while my results for child credits incorporate a weight of 0 for adults and a weight of 1.0 for children.[5] I assume that all tax units take up payments at a 100% participation rate.[6] I weight my tax units using the ASEC sampling weights for the primary tax filer in the tax unit. I assign the primary tax filer in each tax unit by using the TRIM3 assignment of tax filers. For joint filers, I determine the primary tax filer by determining the filer with the largest individual income.

I implement what I refer to as a "fixed budget framework," which allows me to directly test the poverty-reducing effects of each income support program at set budget levels. Unlike other microsimulation models of anti-poverty programs, a fixed budget approach treats the budget as a key input in the calculation of income support payments. This allows me to define a common budget across all programs and calculate corresponding payment levels associated with that budget. In other words, this framework allows me to directly compare how an additional $1 spent on a given program will reduce poverty relative to an additional $1 spent on another program. All dollar amounts reported are in 2018 dollars unless otherwise noted.

My microsimulation includes both static calculations, which assume no labor supply effects associated with benefit receipt, and dynamic calculations, which factor in predicted labor supply effects based on estimates from the economics literature.[7] For my dynamic calculations, I separately estimate labor supply effects along the intensive and extensive margins, with income and substitution effects modeled for each margin. An added challenge with dynamic calculations in a fixed budget framework is that the movement in labor supply caused by expanded income supports will lead to three potential corresponding changes in the fiscal cost of the program by 1) changing the payment amount that tax units qualify for from the program, 2) increasing (or decreasing) federal revenue from tax units who work more (or less), and 3) changing the costs of other means-tested programs by changing recipients' eligibility for those programs. For simplicity, I ignore the fiscal effects of #3, which would require a more robust simulation of existing social safety net programs. I incorporate the fiscal effects of #1 and #2 into my dynamic calculations via an algoirthm, which iterates over budget amounts until the simulated budget amount for any program, inclusive of these fiscal costs, aligns with the target budget amount to within a margin of error of .01%.[8,9] The budget amounts targeted in my model do not include potential costs associated with the administration of each program.

5 The Challenge

Consider a benevolent policymaker who has the means (monetary capital) and will (political capital) to ameliorate poverty in the United States. What policies should they pursue? This paper tackles this question from a redistributive lens by addressing the following challenge: What is an optimal policy path to reduce poverty via cash payment programs?[10]

[5] The use of an equivalence scale to, in part, determine payment eligibility differs somewhat between each income support program. Additional details regarding its implementation can be found in the Appendix.

[6] The assumption of 100% participation rates is a limitation of my model since it is an overestimate of what participation rates would be if any of the modeled programs were enacted. Ko & Moffitt review the literature and find that means-tested programs have a participation rate between 21% and 82%, depending on the program (2022). A study of participation rates of the first round of COVID-19 relief payments, which more closely mirror the structure of many of the programs that I test in my model, shows that eligible recipients took up those payments at a rate of 92% (Clark et al., 2023).

[7] I detail the labor supply elasticities incorporated into to my model in Table A1 in the Appendix.

[8] Specifically, I incorporate the fiscal effects of #1 and #2 into my dynamic calculations for a GI, PGI, and EIC. For UGI, I incorporate the fiscal effects of #1 and ignore the effects of #2 since it is not applicable to UGI, which does not contingent benefits on income.

[9] For a detailed discussion of my dynamic calculations, please refer to the Appendix.

[10] While I narrowly consider redistributive policies, predistributive policies hold an important place in the anti-poverty landscape. For example, simulations of proposals to expand the minimum wage have been

Quantitative measures of poverty traditionally include three components: 1) a resource measure (income), 2) a resource threshold (poverty line), and 3) the definition of the poverty unit (the family). For every family, f, poverty, V, is traditionally defined as a binary indicator such that $V_f \in \{0, 1\}$, where a family's poverty status equals one if their resources, E, fall below the poverty line, L, and equal to zero if their income is equivalent to or exceeds the poverty line.[11] Formally, this can be written as

$$V_f = \begin{cases} 0 & \text{if } E_f < L_f \\ 1 & \text{if } E_f \geq L_f \end{cases} \tag{1}$$

Based solely on this framework, the mathematical problem of eliminating poverty seems relatively straightforward. That is, a benevolent policymaker needs only to "top-up" the resources of any family in poverty such that their total resources meet or exceed the poverty line. For any family in poverty, which I redefine as f_1 for simplicity, this "resource gap", A, is defined as the difference between the poverty line and a family's resources. Taking the sum of all family-level resource gaps yields the population-level resource gap, or the amount of resources required for all families to escape poverty.

$$\sum_{f_1=1}^{n} A_{f_1} = \sum_{f_1=1}^{n} L_{f_1} - \sum_{f_1=1}^{n} E_{f_1}. \tag{2}$$

Unfortunately, the benevolent policymaker faces a more difficult problem than indicated by a program that exclusively targets the resource gap, for three primary reasons. First, a pure "top-up" policy would likely produce incentive effects at crosscurrents with the policymaker's anti-poverty goals. Each family below the poverty line would face a dollar-for-dollar reduction from the top-up program for each additional dollar they earned. Thus, family members would face no monetary incentive for higher pay or additional work up to the poverty threshold. Second, the administrative mechanisms available for distributing subsidies/benefits does not correspond one-to-one with the broader definitions of the family used by the Census Bureau to construct poverty measures. Benefits are generally distributed individually or to a tax unit. These benefits can be *correlated* with the definition of the family used in poverty measures, but do not overlap perfectly. Practically, this means that even if we ignore the first incentive concern outlined above, some payments would inevitably be distributed to families in excess of what is strictly needed to raise a family above the poverty line.[12] Third, if we again assume away incentive concerns, administrative costs associated with implementing and administering a cash payment program would require some amount of additional funding over and above the specific quantity of the total resource gap. Relatedly, imperfect program participation can also be considered an administrative cost, in that additional state capacity (i.e., investment) may be required to ensure 100% take-up among all eligible recipients.

I craft my microsimulation to address the first two issues, namely incentive effects associated with predicted labor supply changes stemming from income support programs, as well as measurement of poverty using the standards of the SPM. In regard to the third issue,

found to reduce poverty (Acs, Giannarelli, Werner, & Ofronama, 2022).

[11] For the purposes of this analysis, I consider an absolute measure of poverty, meaning the resource threshold or poverty line contains some objective standard for determining the sufficiency of a family's resources. Conversely, a relative measure defines poverty compared to some distributional population standard, such as the 50th percentile of household incomes.

[12] Using a simple example, if there are two equally-sized tax units in a multi-generational family (all occupying the same residence), any income support program will hypothetically make payments available in equal amounts to each tax unit. However, the equivalence scale in the SPM does not count all members of the family equally, because equivalence scales assume there are economies of scale of costs in larger families. The SPM equivalence scale would make it difficult to scale payments to perfectly target the poverty lines for all variations of family composition.

practically speaking, the costs of program administration are low and, therefore, a lesser problem. However, depending on the program in question, they are not zero.[13] On the other hand, the lack of participation among eligible individuals/families is an important shortfall in anti-poverty programs. I follow the standards of most microsimulation to assume 100% takeup. However, incorporating this dimension of anti-poverty programs, as well as program administration, into my microsimulation is an important avenue for future research.

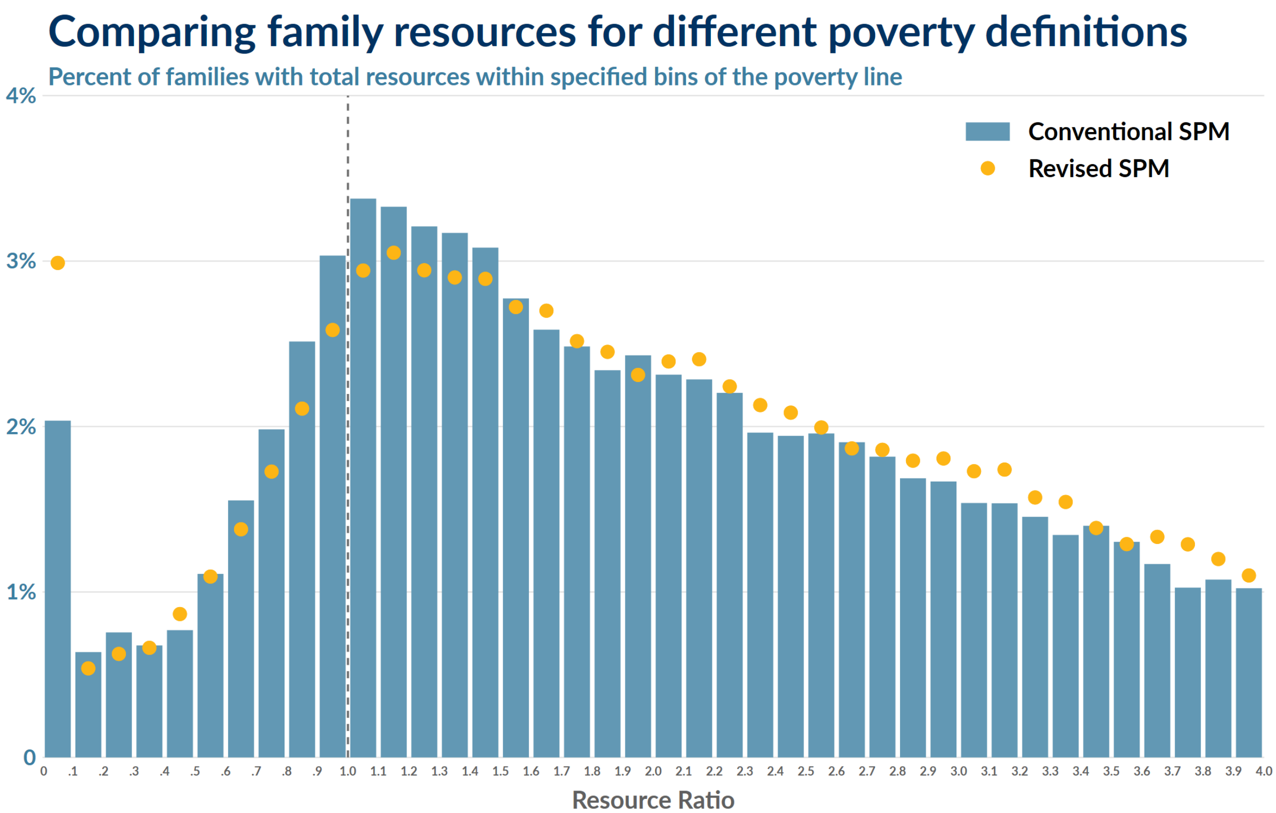
Even if the resource gap is incomplete for policy implementation, it is a useful measure to examine in gaining a better understanding of the scope of poverty. Using the 2019 ASEC supplement to the Current Population Survey, I directly measure the gap among US families. Based on the Census Bureau's conventional Supplemental Poverty Measure, the total resource gap is equal to $173.3B. Using my revised SPM, the figure is $151.3B. For child poverty, the total resource gap is $50.9B and $41.3B using the conventional and revised SPM, respectively.

In Figures 1 and 2, I disaggregate these total resource gaps to illustrate the distribution of family resources relative to the poverty line, which I refer to as the resource ratio. Specifically, I use histograms to show the percent of families with total resources within specified bins of the resource ratio, with each bin corresponding to a tenth of a unit of the resource ratio. For example, the bin that falls between.1 and .2 illustrates the percentage of families with resources that fall between.1 and.2 of the value of their poverty line.

In Figure 1, I show the distribution of resource ratios for all families. A notable element of this distribution is the concentration of poverty among families with zero or near-zero resources. In my revised SPM measure, the concentration in this part of the distribution is even more acute. Conversely, in Figure 2 the concentration at zero or near-zero is less pronounced among families with children. Among this sub-group, there is a greater concentration of families at or near the poverty line. It is also important to note that, relative to the conventional SPM, my revised SPM tends to underreport poverty closer to the poverty line.

[13] For example, Social Security incurs administrative costs of .5% of total program costs (on Budget and Policy Priorities, 2023), estimates of the administration of the Earned Income Tax Credit shows costs of lower than 1% (Greenstein, Wancheck, & Marr, 2019), and the Supplemental Nutrition Asssitance Program sustains administrative costs of 5% to state governments and less than 1% to the federal government(on Budget and Policy Priorities, 2022).

Figure 1

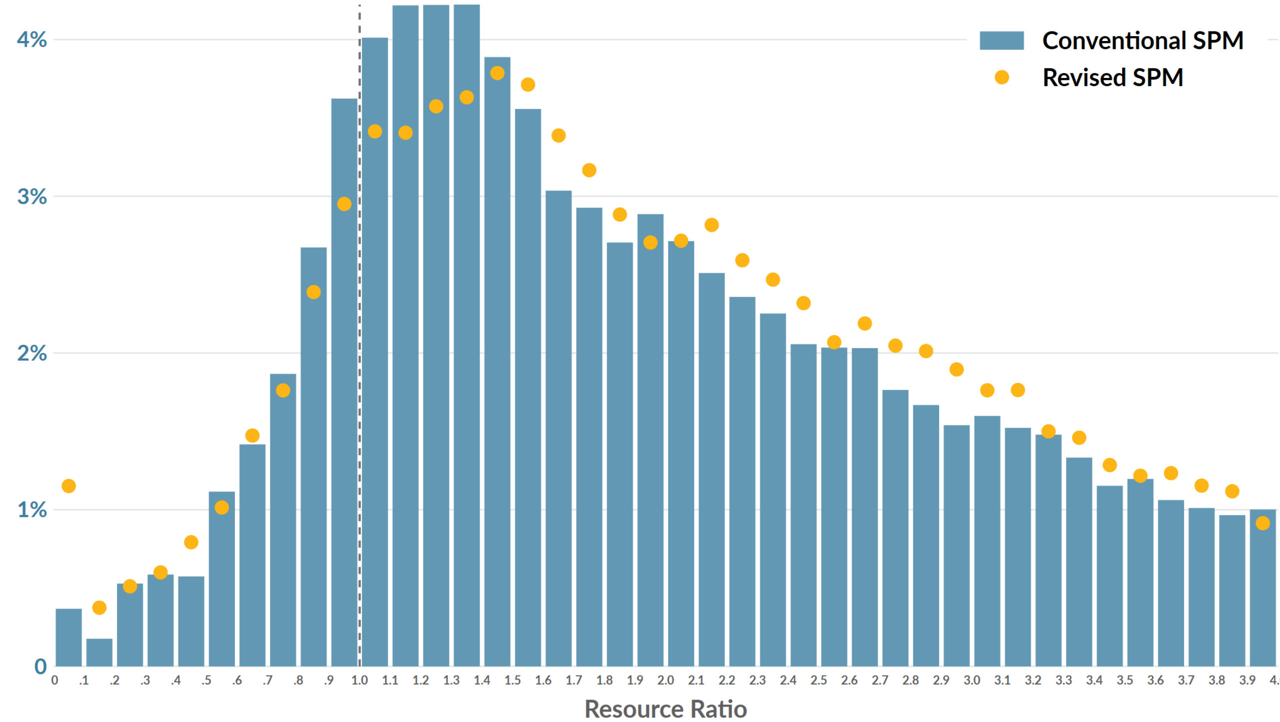


Source: Authors' analysis of IPUMS-CPS and TRIM3.
Sample: All families.
Notes: Percent of families with total resources falling within a given ratio of the poverty line (e.g., the first bar shows the percent of families with resources below 10% of the poverty line).

Figure 2

Comparing family resources for different child poverty definitions

Percent of families with children with total resources within specified bins of the poverty line



Source: Authors' analysis of IPUMS-CPS and TRIM3.
Sample: Families with children.
Notes: Percent of families with total resources falling within a given ratio of the poverty line (e.g., the first bar shows the percent of families with resources below 10% of the poverty line).

6 Results

In Figure 3, I show how the prevalence of simulated poverty in the population changes given different budget amounts for all four income support programs for every $100 billion budget increment up to a $1.5 trillion budget.[14] For each program, I report static estimates, which show no labor supply effects, and dynamic estimates, which show predicted labor supply effects based on elasticities from the economics literature.

A few notable trends are apparent from Figure 3. First, for a given program, the size of the program budget and poverty rates are negatively correlated, meaning that a higher program budget yields a lower poverty rate. This holds true regardless of whether the simulation estimates originate in the static or dynamic model. Second, the strength of the relationship between budget and poverty depends both on the program in question and on whether the effects of labor supply are included. It is clear that in this simulation, GI comes out ahead with the largest reductions in rates of poverty for a given budget. Third, across all programs, the dynamic estimates show higher poverty rates than the static estimates for a given budget, illustrating a weaker relationship between poverty reduction and budget levels. Lastly, each program exhibits a declining return to scale, meaning that there is a smaller simulated reduction in poverty for every additional dollar invested in a given program.

[14]In Figure 3, I assume an eligibility threshold of $100k for single person tax units across the GI, PGI, and EIC programs. This threshold scales based on the equivalence scale of the tax unit. For the GI and EIC programs, the kink point is set at $50k. This eligibility threshold is largely similar to the COVID relief payments JH. I also assume that citizenship or simulated authorized residency is required for program eligibility.

To better compare the precise differences between the simulated results of each program, I reformulate Figure 3 into new visualizations showing the *percent* reduction in poverty for selected budget amounts at $50 billion, $100 billion, $500 billion and $1 trillion. In Figure 4 I show these estimates for my static calculations, which exclude predicted labor supply effects. Based on my policy parameters, I find that a $50 billion investment in income support programs would yield a reduction of between 2.3% and 5%, depending on the program design. At $100 billion, the reduction is proportionately similar, with a range of 4.56% to 10.27%, depending on the program design. The returns to scale of additional spending on poverty reduction does decline at $500 billion and $1 trillion. At a $500 billion budget poverty declines by a range of 15.58% to 39.61% across all four programs. With the exception of the EIC, my simulation of a $1 trillion budget shows that poverty would be reduced by more than half, with a 60.63% reduction in poverty among all families based on the Guaranteed Income program.

In Figure 5, I juxtopose the preceding static estimates with estimates from my dynamic calculations, which incorporate predicted labor supply effects. Across the board, these dynamic estimates are lower than the corresponding static estimates. This reflects the fact that, with the exception of the EIC, income and substitution effects are predicted to be negative, with corresponding negative effects on labor supply choices. For the GI program, the dynamic estimates for poverty reduction are about 89% of the corresponding static estimates. For the PGI program, the hit to poverty reduction is smaller: with dynamic estimates making up about 91%-92% of the corresponding static payments. In the case of the UGI, the gap between dynamic and static calculations is smallest, with dynamic calculations only about 5% and 7% smaller than static calculations for the $50 billion and $1 trillion budgets, respectively. Since the UGI is universal, it only incorporates income effects, which ultimately causes more muted labor supply effects than other programs. However, as the program budget increases, the labor supply effects that arise from income effects also increase. This ultimately leads to a larger difference between static and dynamic calculations for a $1 trillion than a $50 billion program. For the EIC program, dynamic calculations account for 92.6% and 87.6% of the reduction from static calculations for a $50 billion and a $1 trillion budget, respectively. I report extended results for these same figures, with static and dynamic estimates, for different demographic groups in the Appendix.

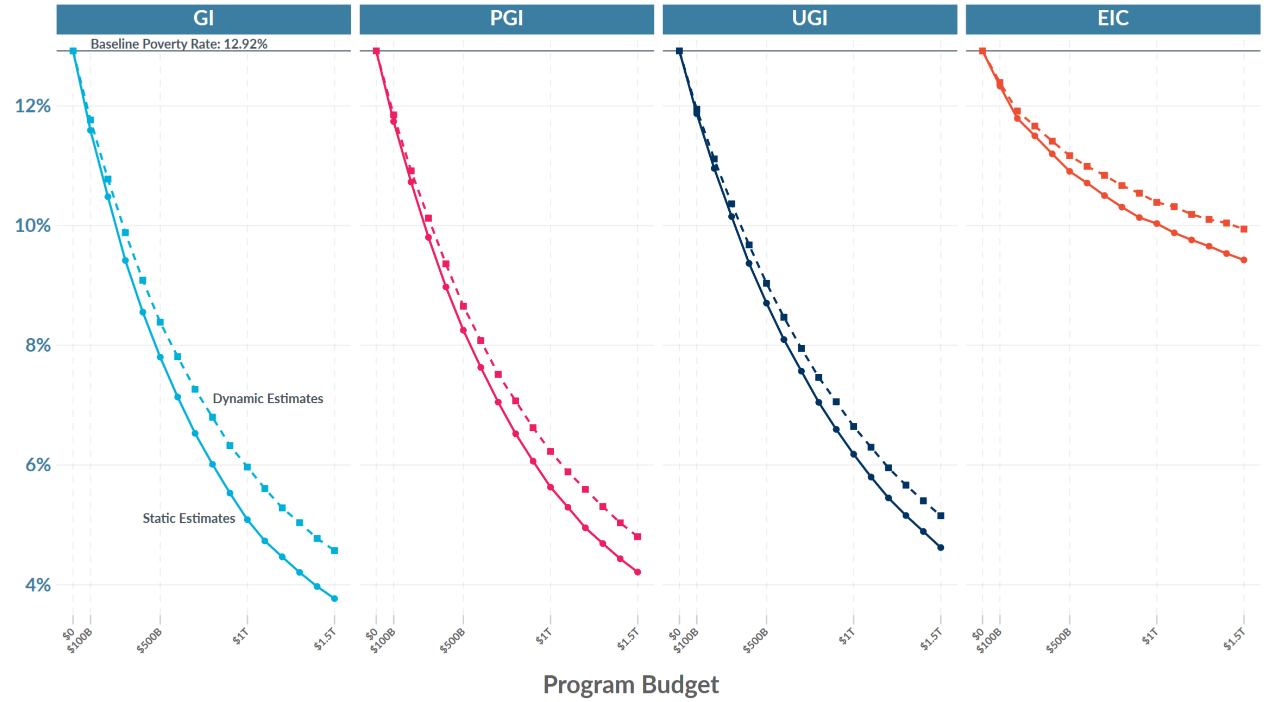
In Figure 6, I show how child poverty responds to income support programs that are exclusively available to tax units with children, with varying budget amounts for each program in increments of $50 billion up to $700 billion. Many of the takeaways from this analysis are the same as shown by the preceding analysis of programs available to tax units without children: child poverty rates and budget are negatively correlated, there is a decreasing return to reductions in child poverty with additional investment in income support programs, and dynamic estimates show higher child poverty rates than corresponding static estimates. It is also clear that if a policymaker cares exclusively about child poverty, or substantially prioritizes reductions in child poverty relative to adult poverty, targeting income support programs to families with children is a more efficient route to achieve reductions in that metric — child poverty rates hit 4% with a $700 billion GI program as opposed to $1.4 trillion spent to achieve a 4% rate among child and adult poverty.

In Figure 7, I transform the estimates from Figure 6 to show static estimates for the percent reduction in child poverty rates for income support programs targeted at children. Across the programs, the EIC generally shows the smallest percent reductions in child poverty, while GI shows the largest. Based on the program parameters I use, a $50 billion program would yield a reduction in child poverty of between 8.77% to 17.7% depending on the program. A $350 billion program would yield a 25.4% to 60.65% reduction.

Figure 3

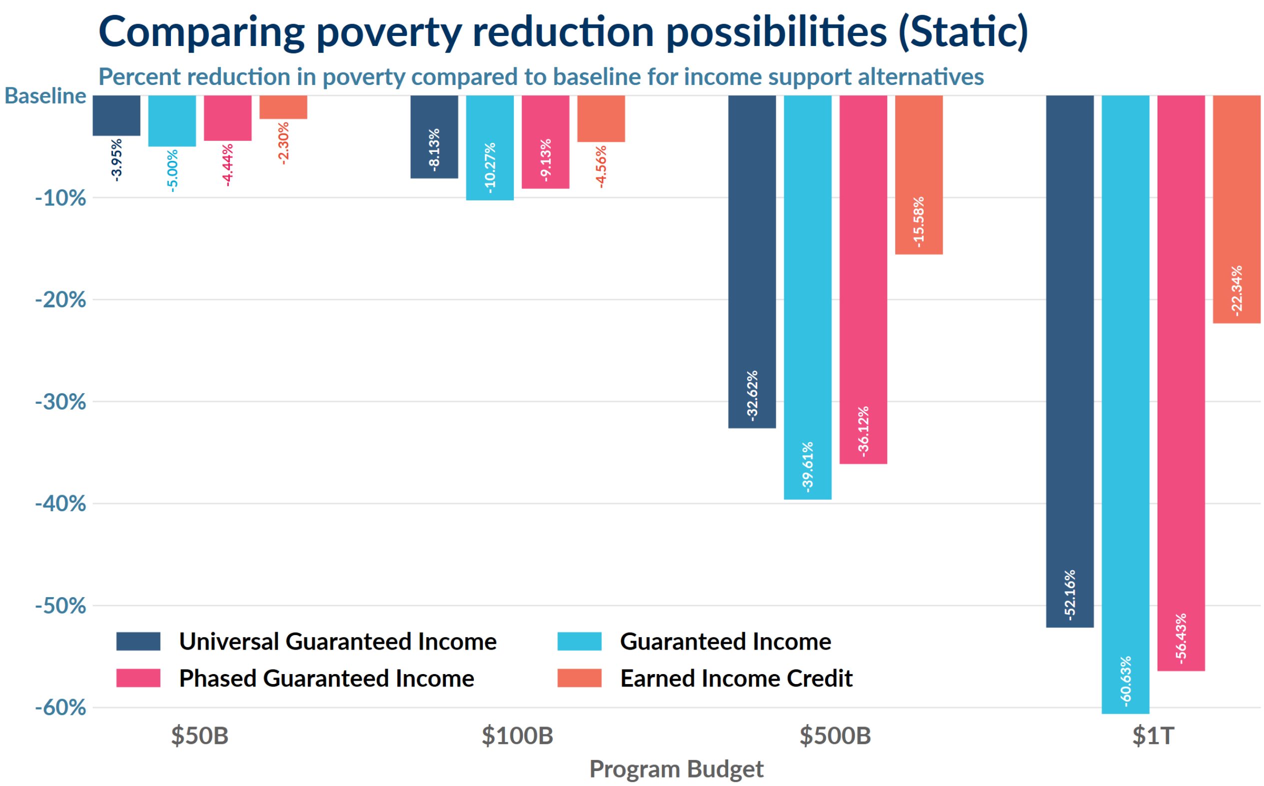
Poverty reduction achieved by different programs

Percent of individuals with resources below the poverty line



Source: Authors' analysis of IPUMS-CPS and TRIM3. **Sample:** All families.
Notes: This chart illustrates the reduction in poverty rates achieved by alternative income support programs. Program budgets are shown in either billions (B) or trillions (T) of dollars. Static estimates refer to simulations that omit predicted labor supply effects. Dynamic estimates refer to simulations that incorporate predicted labor supply effects. For the GI, PGI, and EIC programs eligibility thresholds are set at a $100k baseline for single adult tax units (and are scaled up based on tax units' equivalence scale). Kink points are set at 50% of the corresponding eligibility threshold. Citizenship or simulated authorized residency is required for program eligibility.

Figure 4



Source: Authors' analysis of IPUMS-CPS and TRIM3. **Sample:** All families.
Notes: This chart illustrates the reduction in poverty rates achieved by alternative income support programs at different budget levels. Program budgets are shown in either billions (B) or trillions (T) of dollars. All estimates are based on static calculations, meaning predicted labor supply effects are omitted. For the GI, PGI, and EIC programs eligibility thresholds are set at a $100k baseline for single adult tax units (and are scaled up based on tax units' equivalence scale). Kink points are set at 50% of the corresponding eligibility threshold. Citizenship or simulated authorized residency is required for program eligibility.

Figure 5

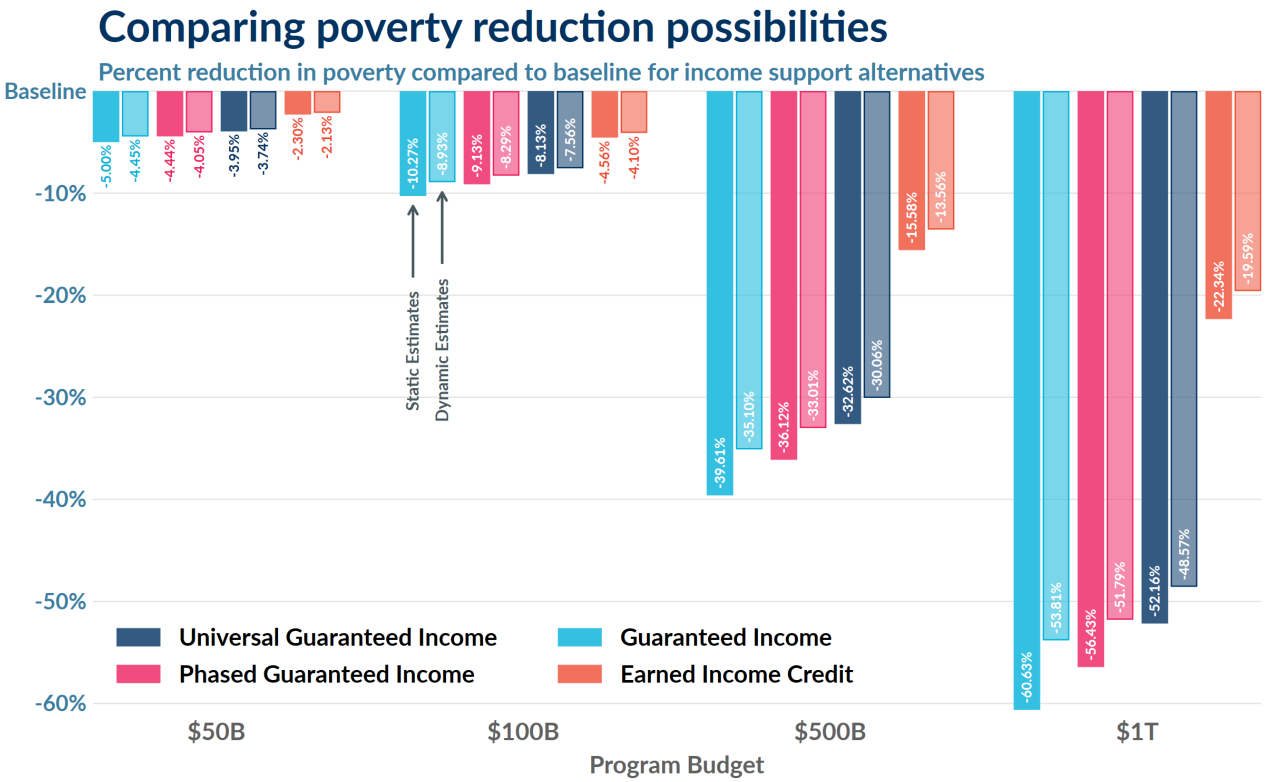


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Figure 6

Child poverty reduction achieved by different programs

Percent of children with resources below the poverty line

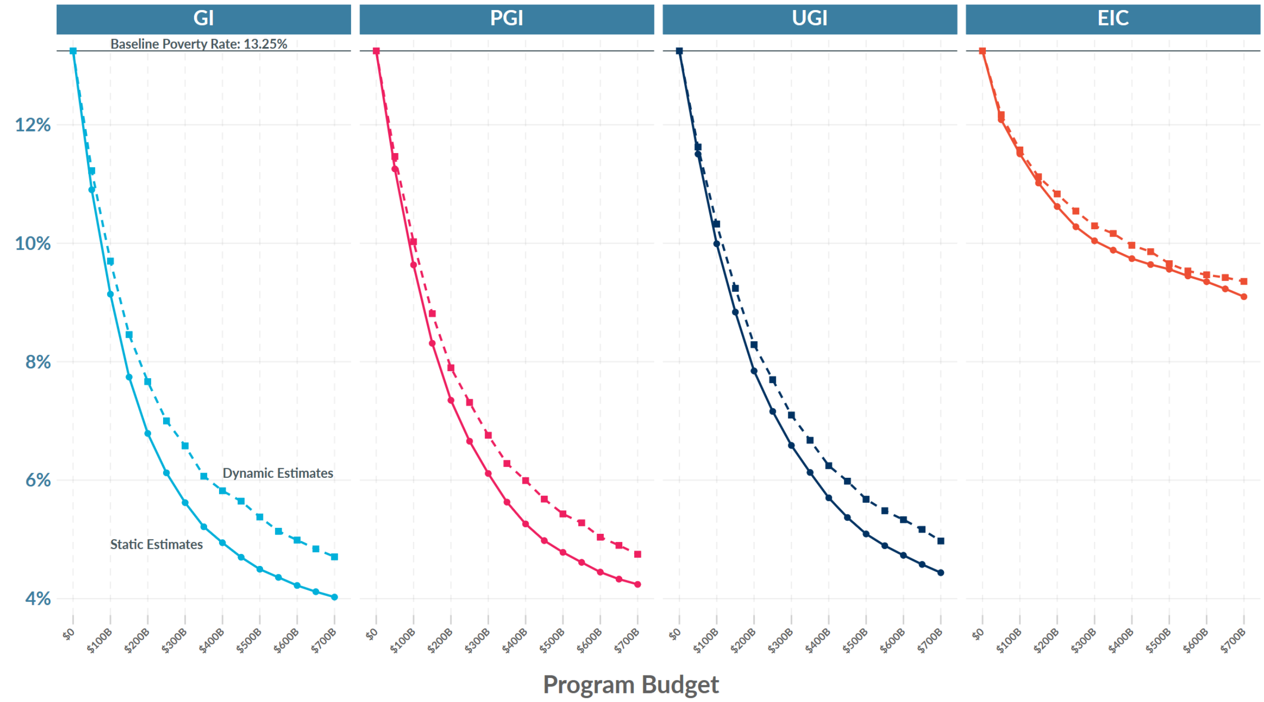

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Figure 7

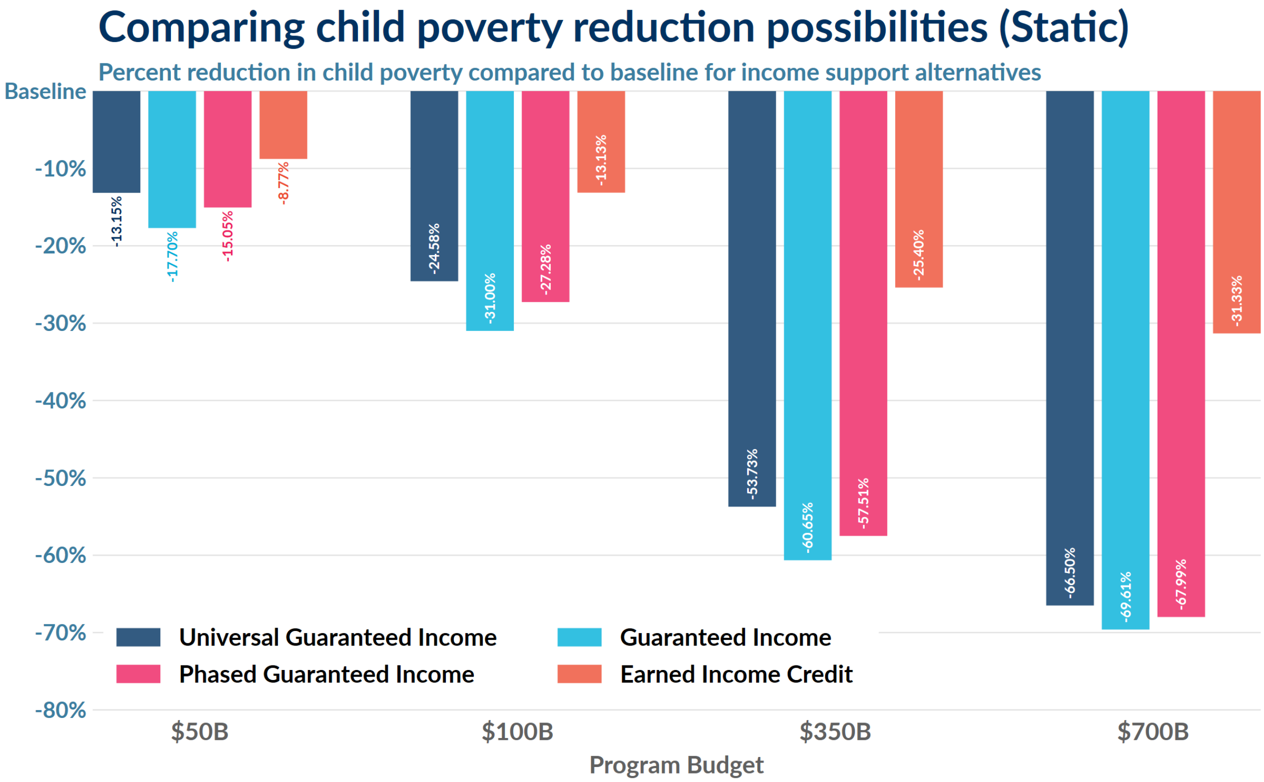

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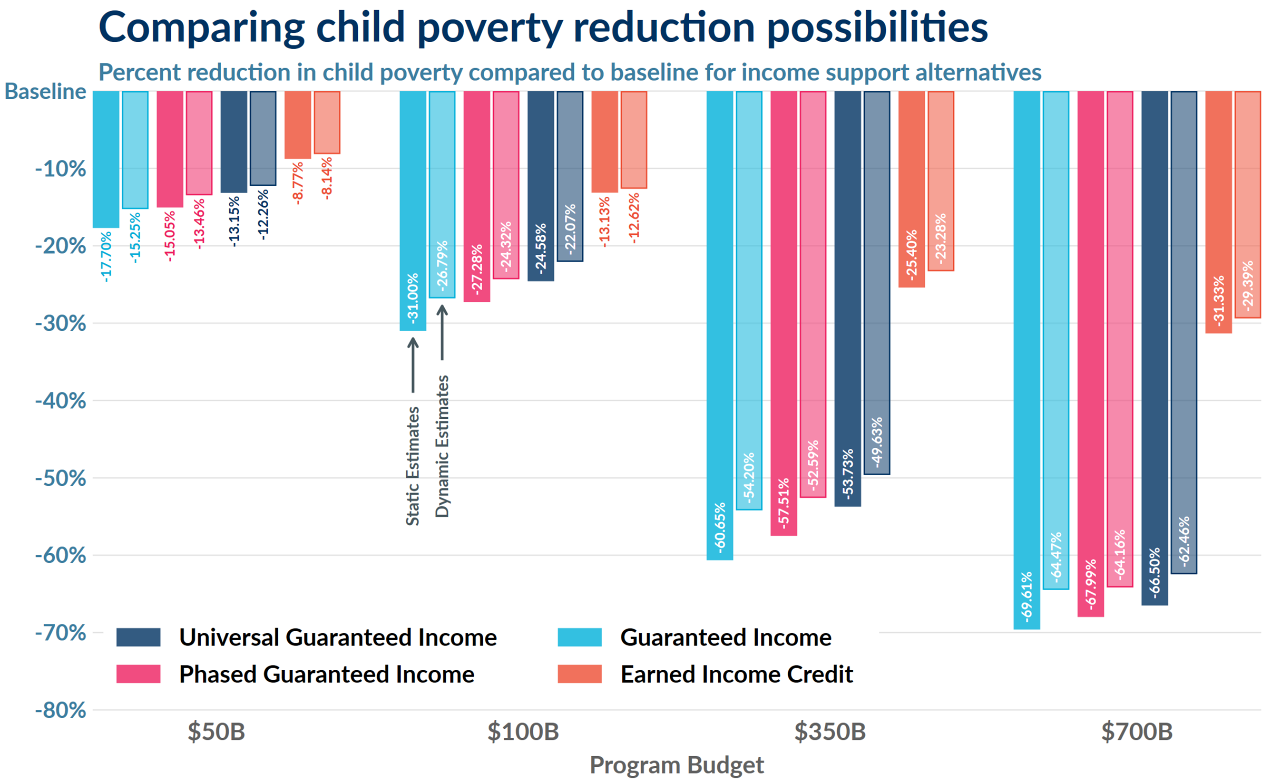
Figure 8



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Notes: This chart illustrates the reduction in poverty rates achieved by alternative income support programs at different budget levels. Program budgets are shown in either billions (B) or trillions (T) of dollars. Static estimates refer to simulations that omit predicted labor supply effects. Dynamic estimates refer to simulations that incorporate predicted labor supply effects. For the GI, PGI, and EIC programs eligibility thresholds are set at a $100k baseline for single adult tax units (and are scaled up based on tax units' equivalence scale). Kink points are set at 50% of the corresponding eligibility threshold for the PGI and EIC programs. Citizenship or simulated authorized residency is required for program eligibility.

7 Discussion

The results of my microsimulation model indicate that, based on either static or dynamic estimates, a GI model outperforms the other three income support programs in the degree of poverty reduction for a given budget. This holds true for either a child credit targeted at families with children or a credit available to the general population. Therefore, even when taking into account predicted labor supply effects, the GI program provides the most targeted investment to families and individuals below the poverty line. This indicates that it comes closest to mirroring the "top-up" program described earlier in the paper, without the accompanying substantial incentive effects on work that such a top-up program would induce. This is due to the fact that, unlike the dollar-for-dollar phaseout rate of the top-up program, the GI program reduces benefits at a more gradual rate.

Interestingly, an EIC performs worse relative to the other income support programs tested. This is likely due to the fact that it does not provide direct resources to families/individuals who have zero resources (i.e., are out of the labor force). Figure 1 illustrates that there are a substantial number of families/individuals with zero resources. This group is outside the target range of an EIC, which only provides a credit to tax units with an AGI greater than zero dollars and less than the eligibility threshold. The efficiency of an EIC relative to other programs does not improve when assessing dynamic estimates. This is in spite of the fact that these dynamic estimates incorporate a model of mothers entering the labor force due to the introduction of an EIC. It is likely that the EIC would perform better if my model incorporated corrections for underreporting of earnings reported in the literature, particularly the overconcentration of families at zero dollars of earnings in the ASEC (Landry, 2023). The dynamic effects do substantially reduce labor supply distortions in the case of a child credit. In other words, the differences between the static and dynamic estimates are smallest for an EIC targeted at children compared to any other program. This is due to the fact that the eligible population for the child credit, parents, more closely aligns with the group of potential dynamic entrants, aka mothers.

It is important to note that, while more efficient overall, the poverty-reducing efficiency of a GI is less apparent in the dynamic estimates than the static estimates. For example, my dynamic estimates indicate that a \$100 billion GI will reduce poverty at a 1.18 times greater rate than a UGI of the same size. Compare this to the 1.26 times greater rate of poverty reduction predicted by my static estimates. Interestingly, the differential between the GI and UGI shrink as the budget grows, showing the increasing pull of higher phaseout rates associated with higher budgets, and the concomitant rising substitution effects on individual labor supply decisions. A GI with a \$500 billion investment would yield poverty reductions at a 1.16 times greater rate than UGI. Assuming a \$1 trillion investment, GI's advantage would fall to 1.11 times. For dynamic estimates, the difference between a GI and a PGI are even smaller.[15]

These results are an illustration of the "iron triangle" of income support policy, which states that policy design cannot optimize a program to simultaneously minimize costs, minimize labor supply effects, and maximize reductions in poverty (Blundell, 2003). My results suggest that *some* additional efficiencies in poverty reduction per dollar, particularly at low budget levels, can be achieved via a more targeted program. As the target budget grows, however, so does the total magnitude of predicted labor supply effects, which ultimately minimizes program-by-program differences in poverty reduction. Under different assumptions regarding labor supply effects, particularly greater substitution effects, its possible that the differences in poverty levels between targeted and universal programs would be non-existant.

My model also indicates that substantial reductions in poverty can be achieved, on the order of 50+%, given sufficient budget levels for anti-poverty efforts. It is less clear whether these *sufficient* budget levels are also *feasible* budget levels.

First, it is important to note that from an international fiscal perspective, the budget levels I test are not extreme, in the sense that anti-poverty investments at scale would not push the US government beyond spending levels of other industrialized peers. For example, a program that cost \$1 trillion in 2018 would cost about \$1.079 trillion in 2021 based on the CPI-U inflation index. A program of this scale is equivalent to approximately 4.6 percent of GDP in 2021. The size of total government spending in the US was about 44.9 percent of GDP in 2021.[16] Thus, I estimate that in 2021, the size of the US government would expand to approximately 49.5% of GDP with the implementation of the income support program in question. Out of 32 OECD countries, such a program would move the US from the 19th highest rate of government spending as a fraction of the economy to the 10th spot, in line with the ranking of Iceland and Denmark. A more targeted investment in child poverty would cost less and would yield a correspondingly smaller change in the US ranking relative to peer countries.

Second, from a pure fiscal policy perspective, it is less clear whether the US could afford some of the larger policies that I model. Of course, questions of whether one can "afford" a program are tied to politics — and can more simply be expressed as a question of what policies a country *prioritizes*. Still, politics aside, funding the US government at its current

[15] It is possible that the differences in dynamic estimates between a more targeted or more universal program could be further reduced with the incorporation of administrative costs into the model, particularly if those administrative costs differ between a universal versus targeted program. This seems plausible since means-testing and income verification must represent some added cost to an administrator.

[16] Based on "General Government Spending" as reported by OECD (2024).

levels *plus* a robust anti-poverty program would pose significant fiscal challenges, for no other reason than the *existing* levels of government pose significant fiscal challenges.

There is no objective level of debt that could be considered unsustainable — particularly for the US, which occupies a special place in the global financial system as one of the few global reserve currencies — however, the longterm sustainability of US debt levels continues to garner attention.[17] In 2022, the US government debt reached $25.7 trillion dollars, or nearly 120% of GDP. Recent research in economics indicates that, a priori, these levels are not necessarily alarming, as long as the growth rate in the national economy outpaces the prevailing interest rates that the national government must pay to finance its debt (Blanchard, 2019). However, such a strategy could put the US at-risk of a financial crisis if there is ever a serious question of whether growth will continue to outpace interest rates (Mankiw, 2022). While prevailing rates in recent decades were low, the experience of recent years, with a historically rapid pace in the tightening of monetary conditions, reinforces the fact that low rates are not an economic law. Other research indicates that there could be substantial economic costs in waiting to stabilize debt levels (CBO, 2022a).

If the US fiscal situation is, in fact, not sustainable, revenue and spending will have to be brought in line relative to the status quo. This will likely occur through a mixture of increases in levels of taxation and decreases to expenditure levels. The CBO regularly releases a report outlining policy options for reducing the deficit, which include potential changes to both revenue and expenditures (CBO, 2022b). These incorporate many policies that could hypothetically be used to fund an expansion of income support programs such as those outlined in this paper. However, many of these policies may ultimately be required to stabilize the debt, leaving more limited options for funding such an expansion of income support programs. And aside from issues of fiscal sustainability, any package of policies that is used as a set of "pay fors" related to any expansion of income support programs will have their own poverty impact. For instance, Rosenberg et al. (2018) show how a carbon tax would affect tax burdens, including its affect on low-income households. This means that any goal to reduce poverty to a certain level will have to account for any poverty impact on the revenue side of the equation.

Of course, my model is flexible, with programs that can be scaled up or down depending on the desired budget input. This means that a policymaker could target an income support program to their preferences and at such a level as the fiscal situation allows. Furthermore, I have outlined a set of estimates based on a targeted child credit, which would further reduce the costs of any potential program by limiting the universe of eligible recipients to families with children.

8 Conclusion

In this paper, I test the possibilities to reduce poverty via expansions to income supports in the United States, with special attention to the possibilities of basic income programs. I find that poverty could be substantially reduced via new income support programs implemented as tax credits, as either generalized payments or payments targeted specifically to parents.

An important conclusion from this work is that targeting programs via means-testing does not seem to substantially improve the efficiency of poverty outcomes relative to universal programs. The dynamic estimates, which incorporate labor supply effects, show some

[17] The US' position has historically provided it with cheap financing of US government debt via with significant demand for bonds used to pay for any liabilities that require funding over and above existing revenues. Furthermore, as a sovereign authority over its money supply, the US cannot technically go bankrupt since it can always print more money to cover public obligations. Of course, these assets are not above reproach. Monetizing the debt via money printing will, at some point, devalue the currency base via inflation. And the privileged position of the US in global financial markets is at least in part permitted by the perception that the US will reliably pay its debtors.

improvement in the anti-poverty efficiency for targeted relative to universal programs; however, the substitution effects embedded in the dynamic model ameliorate these gains. A Guaranteed Income program showed the widest gap between static and dynamic estimates due to these substitution effects. This is particularly true for larger budget amounts where substitution effects would be highest.

There are important avenues to develop further this research. First, future research should investigate developing a microsimulation model of a set of revenue policies to fund a revenue package for potential expansions to income supports, including the cumulative poverty impacts of such a package. Second, it should consider the effects of income support programs on prices in the economy, including potential inflationary effects of these policies and the incidence of these labor subsidies on the cost of labor (i.e., modeling whether these subsidies are internalized by labor or internalized by capital in the form of lower wages). Third, future work should consider how the results of the model could change based on simulation of program administration costs and program participation. Lastly, implementing alternative policy simulations that vary the other eligibility/generosity parameters in the model is an important avenue for future research. For example, a simulation that includes undocumented immigrants in the eligible population for income supports may actually improve the poverty-reducing efficiency of the tested programs. A future model could also incorporate long-term earnings effects, like those in Goldin, Maag, & Michelmore (2022).

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