

ENHANCING THE SAFETY NET FOR ELDERLY AND DISABLED ADULTS

TECHNICAL APPENDIX

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Technical appendix

Introduction and summary

We develop a novel microsimulation of older adult resources and poverty that adjusts survey results for underreporting of retirement, Social Security (Old-Age and Survivors Insurance), and means-tested support including the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and housing subsidies. The corrected data give a more accurate picture of older adults' financial lives than existing public microdata, allowing us to better estimate poverty rates under current and proposed law and to project the cost of the proposed reforms.

The model proceeds in four steps:

Correct survey microdata for underreported income

We take public survey data on the demographics, income, and expenses of individuals in 2021 (the 2022 Current Population Survey Annual Social and Economic Supplement or CPS ASEC) and correct them for commonly underreported income sources: retirement and Old-Age and Survivors Insurance (OASI) income (using Bee and Mitchell, 2017) and means-tested support such as SNAP, TANF, and housing subsidies (using the Urban Institute's Transfer Income Model 3, or TRIM3).

Estimate asset eligibility of aged adults with low income

Because the CPS ASEC lacks detailed asset data, we use the 2022 Health and Retirement Study (HRS) to estimate the probability that an older adult whose income is low enough to qualify for Supplemental Security Income (SSI) also passes the asset test, under both current and proposed asset rules. We fit a logistic regression on demographic characteristics so that predicted asset eligibility varies systematically across groups rather than being assigned at a uniform rate.

Model SSI under current law

After correcting individuals' income for underreporting, we model the SSI eligibility calculation under current law, randomly assign asset eligibility using the HRS estimates, and enroll eligible units until the simulated program matches aggregate administrative statistics.

Model proposed law

Finally, we build on the current-law model to simulate the effects of our proposed policies. This allows us to estimate both the projected cost of each policy and its impact on the supplemental poverty rate among older adults.

Throughout the model, we measure poverty using the Census Bureau's Supplemental Poverty Measure (SPM), which compares each SPM unit's total resources—cash income plus in-kind benefits, less taxes, work expenses, and medical out-of-pocket costs—to a

threshold that varies with family composition, housing tenure, and local housing costs. We retain the official thresholds and resource definition, modifying only the components our model adjusts or simulates: reported SNAP, TANF, and housing subsidies are replaced with their TRIM3-simulated values; retirement and Social Security income are corrected with our imputation based on the National Experimental Well-being Statistics (NEWS); reported SSI is replaced with our simulated benefits; and each proposed policy's benefits (or expense reductions, in the case of the Medicare reforms) are added to unit resources.

Table A1 shows how the supplemental poverty rate and gap change through various stages of the model. The stages apply the same SPM thresholds to progressively adjusted resources.

TABLE A1

Supplemental Poverty Measure poverty rate and gaps by modeling stage

Poverty gap is the aggregate difference between all impoverished units' total resources and poverty threshold, in billions U.S. dollars

Demographic group	CPS ASEC		TRIM & NEWS		Baseline model		Policy model	
	Poverty rate	Poverty gap	Poverty rate	Poverty gap	Poverty rate	Poverty gap	Poverty rate	Poverty gap
Aged 65+	10.1	54.0	5.9	31.9	5.6	30.4	2.2	14.6
Aged 80+	13.1	13.2	7.2	6.4	6.9	5.9	2.6	2.0
Male Aged 65+	8.9	23.2	5.2	13.6	4.9	13.0	2.2	6.7
Female Aged 65+	11.2	30.7	6.5	18.3	6.2	17.4	2.3	7.9
Noncitizen Aged 65+	24.7	6.1	21.1	5.0	20.6	4.9	13.4	3.5

Source: Authors' calculations.

Note: CPS ASEC: Current Population Survey Annual Social and Economic Supplement; NEWS: National Experimental Well-being Statistics; TRIM: Transfer Income Model



The following sections describe each stage of the model in detail.

Correcting the Current Population Survey for income underreporting

Our microsimulation uses the 2022 CPS ASEC as its primary source of detailed microdata on individual and family income sources, essential expenses, and demographics. While rich, the survey has well-known accuracy issues in key variables, particularly income. This problem is especially pronounced for older adults, who may have several sources of income such as savings (annuities and other retirement savings accounts), private pensions, Social Security, and safety net income that can easily be confused or forgotten. While there have been efforts to modify the CPS to reduce these errors, administrative data show that significant gaps remain between reported and actual income.

We incorporate two sources that address these discrepancies. The first, TRIM3, developed by the Urban Institute and the Office of the Assistant Secretary for Planning and Evaluation (ASPE), is a microsimulation of major government transfer programs, such as SNAP, TANF, and housing subsidies. The other is the NEWS from the Census Bureau, which uses administrative data to correct survey respondents' Social Security and retirement benefits. While TRIM3 is designed to be incorporated directly into the CPS, NEWS's microdata are strictly confidential, so we developed a novel method to use its aggregated results, which we present in greater detail later.

Correcting for safety net programs with TRIM3

The Urban Institute's TRIM3 combines public CPS ASEC microdata on family and individual income with detailed program rules to estimate eligibility for various safety net programs. It then randomly enrolls households until aggregate simulation statistics (e.g., number of beneficiaries, total benefits) match administrative reports for those programs.

Because TRIM3's inputs—CPS microdata, program rules, and administrative benchmarks—are all public, its simulated microdata can be published in full. In our model, we replace reported CPS ASEC income with TRIM3's simulated values for underreported housing subsidies, SNAP, and TANF.

While TRIM3 has an SSI microsimulation, we do not use it directly, for three reasons. First, the SSI eligibility calculation TRIM3 conducts assumes the accuracy of the reported CPS ASEC income sources, such as retirement income and Social Security. We know this is not the case and take steps detailed in the next section to correct for these errors. Second, while we can observe the microsimulation inputs (CPS ASEC) and results, we cannot observe the intermediate processes and parameters used to produce them. By simulating the SSI program ourselves, we can ensure that the only difference between the baseline and policy simulations is our proposed changes to the eligibility calculation, not the accumulated effect of subtle implementation decisions. While the difference is likely trivial for policies that increase benefits among existing beneficiaries, our proposed SSI changes also significantly increase the pool of eligible SSI recipients. Finally, TRIM3 conducts an asset eligibility test on predicted aggregate countable assets, but our policies require that certain asset classes be disregarded rather than included. We therefore cannot modify the TRIM3 asset test to implement our proposed changes.

We do, however, indirectly use the TRIM3 SSI model in two ways. First, rather than manually coding every state's SSI supplement eligibility rules, we take the computed SSI state benefits from currently eligible older adults in TRIM3. We then use a Tobit regression model with a lower bound of zero to predict the state supplement for older adults who are newly eligible for SSI under our policies, using predictors such as state, marital status, living situation, disabilities, and various common interactions (e.g., state and marital status). Second, we do not manually model SSI eligibility for individuals under 18. Instead, we adopt

the TRIM3 calculations; any resulting errors should have little effect on our results, as less than 0.7% of SSI-eligible older adults live with an SSI-eligible child.

Correcting for retirement income underreporting with NEWS

The greatest sources of income underreporting in the CPS ASEC—and thus of overestimated poverty among older adults—are retirement income and Social Security benefits. The Census Bureau’s NEWS project corrects survey responses by linking them to administrative records from other government agencies. As discussed in the main paper, this correction lowers the 2021 poverty rate among older adults from 10.7% to 6.1%. However, because the underlying data are sensitive, the Census Bureau publishes only headline poverty rates by broad demographic category, making the results difficult to incorporate into a microsimulation.

We develop a method using tables from Bee and Mitchell (2017)¹, members of the NEWS project team, which provide the most detailed available figures on underreporting of OASI and retirement income among older adults in the CPS ASEC. The method has four steps: estimate an initial probability of underreporting from each individual’s characteristics; rake and rescale these probabilities to match population-level and subgroup targets; run a lottery on the final probabilities; and assign each underreporter an estimated amount of “forgotten” income based on their reported income.

Estimate probability of underreporting

We use Bee and Mitchell (2017) to estimate the probability that an older adult falsely reported having no Social Security or retirement income², given their demographic characteristics. For various categories, such as marital status, sex, and race, Tables 6A and 6B report the percentage of older adult survey respondents in each category level (e.g., “male” for the category “sex”) who are true negatives, false positives, false negatives, and true positives. Because the method is identical for both OASI and retirement income, we describe the process only for retirement income. Note that all respondents who report receipt of SSI or SNAP are excluded from the following process and assumed to have no underreported income. This is because the average amount of income not reported by false negatives typically exceeds the eligibility threshold for these programs, so SSI or SNAP receipt acts as a signal that income is genuinely low.

¹ Our method is limited due to the age of these estimates, which were published in 2017, but study survey and administrative data from 2012. The CPS ASEC has undergone methodological changes since then to reduce underreporting bias, as evidenced by the shrinking gap between survey poverty rates and NEWS poverty rates. If this is a concern, we suggest uniformly scaling each individual’s false-negative probability (p_i^* , derived through this section) by a modest scalar (0.85-0.95) until the resulting poverty rate matches the appropriate year’s NEWS publication. We do not require a scalar to drop below the NEWS’ published poverty rate for 2021 of 6.1%.

² Retirement income is defined as the sum of pension, distribution, annuity, disability, and survivor income. As Bee and Mitchell (2017) suggest, we also include VA pension, survivor, and disability payments because many respondents misclassify their military pensions as VA benefits.

For each category level h_k in category $H = \{h_0, h_1, \dots\}$, we calculate two statistics: the false-negative rate ϕ_{h_k} and the net false-negative rate $\bar{\phi}_{h_k}$. The first is the proportion of negatives (true negatives + false negatives) that are false negatives. Thus, ϕ_{h_k} is the probability that an individual with category level h_k is a false negative, conditional on not reporting retirement income. On the other hand, $\bar{\phi}_{h_k}$ is adjusted for false-positive reporters, so that $\bar{\phi}_{h_k}$ represents the actual discrepancy between the proportion of individuals with h_k who report retirement income and the proportion of individuals with true retirement income.³ The proportions of false negatives, true negatives, false positives, and resulting ϕ and $\bar{\phi}$ for all older adults are shown in Table A2.

TABLE A2

Income reporting rates from CPS ASEC

Income source	True negative	False negative	False positive	False negative rate (ϕ)	Net false negative rate ($\bar{\phi}$)
Retirement	0.35	0.28	0.04	0.45	0.39
OASI	0.08	0.07	0.06	0.46	0.06

Source: Authors' calculations using Bee & Mitchell (2017) Table 6

Note: CPS ASEC: Current Population Survey Annual Social and Economic Supplement; OASI: Old-Age and Survivors Insurance



We now extend this initial setup to estimate the probability that an individual with multiple category levels $h_k \in H$, from the set of categories $\mathcal{H}$, is a false negative. First, we conduct a log-odds transformation (denoted $\phi' = \ln \frac{\phi}{1-\phi}$) of each ϕ_{h_k} so that we can sum them and still recover probabilities bounded by (0,1).

Next, we apply a raking algorithm that adjusts the weighted probabilities of individuals with category level h_k to equal the predicted rate of false negatives, ϕ_{h_k} . The process begins by assigning every older adult with no reported retirement income a baseline log-odds of being a false negative, for which we use the population-level ϕ' . In each step, we select a

³ We construct $\bar{\phi}_{h_k}$ because if we gave income to ϕ_{h_k} of individuals with a_k using, the final proportion of individuals with retirement income exceeds the true proportion by the proportion of false-positives. This problem might be resolved by taking income away from a proportion of h_k who report non-zero retirement income according to the false-positive proportion, but we find this method of randomly removing people's reported income without a strong signal to be crude.

category $H \in \mathcal{H}$.⁴ Then for each level $h_k \in H$, we adjust the existing weighted log-odds (p_i^0) for all individuals with h_k by the necessary α (computed through bisection) so that the group's weighted average matches the predicted false-negative proportion, ϕ_{h_k} .

$$\phi_{h_k} = \frac{\sum_{i \in h_k} \sigma(p_i^0 + \alpha) * w_i}{\sum_{i \in h_k} w_i}$$

Note that σ is the inverse log-odds function.⁵ Once the optimal set of p_i^* is derived from raking, we transform them from log-odds back to probabilities. Before this transformation, we account for false positives by scaling all individuals' p_i^* by the necessary factor θ such that:

$$\theta * \frac{\sum_i p_i^* * w_i}{\sum_i w_i} = \bar{\phi}$$

This guarantees that the population-level weighted probabilities equal the population-level net false-negative rate. While this pulls the optimal p_i^* away from their subgroup targets, ϕ_{h_k} , we prioritize the population-level target and accept some loss of precision within subgroups.

When conducting this procedure for OASI income, an additional step is required. Note that in Table 6A of Bee and Mitchell (2017), many subgroups have false-positive proportions exceeding their false-negative proportions, resulting in a $\bar{\phi}_{h_k} < 0$. Thus, after completing our first raking step so that the log-odds are optimally set for ϕ'_{h_k} , we conduct a second raking pass in which the computed probabilities from the first stage are adjusted to meet $\max\{\bar{\phi}_{h_k}, 0\}$.⁶ We take the results from this second rake and treat them as p_i^* , setting SSI or SNAP recipients to zero and conducting a scalar adjustment to meet $\bar{\phi}$.

This process is relatively accurate in achieving its objective, setting probabilities that meet the overall and subgroup net false-negative rates. By construction, the population-wide net false-negative rates are met exactly for both retirement and Social Security income. The average subgroup deviation is only 0.05% for retirement income and -2.6% for Social Security income.

Once the optimal probabilities are estimated, we randomly decide whether each nonreporter is a false negative using a simple Bernoulli trial.

⁴ The order of categories influences the outcome, as the final category will meet its targets exactly, while the earlier categories will have their optimal targets adjusted to meet later targets. We iterate over 50 random orderings of the categories and select the iteration that converges.

⁵ We set the objective to be raw proportions rather than log-odds due to Jensen's inequality, which implies that the optimal set of log-odds will differ from the optimal set of proportions.

⁶ The primary consequence of this method is sacrificing the accuracy of subgroups with positive net false-negative rates, such as "male", because these groups' probabilities are driven near zero to accommodate individuals who belong to negative net false-negative rate groups.

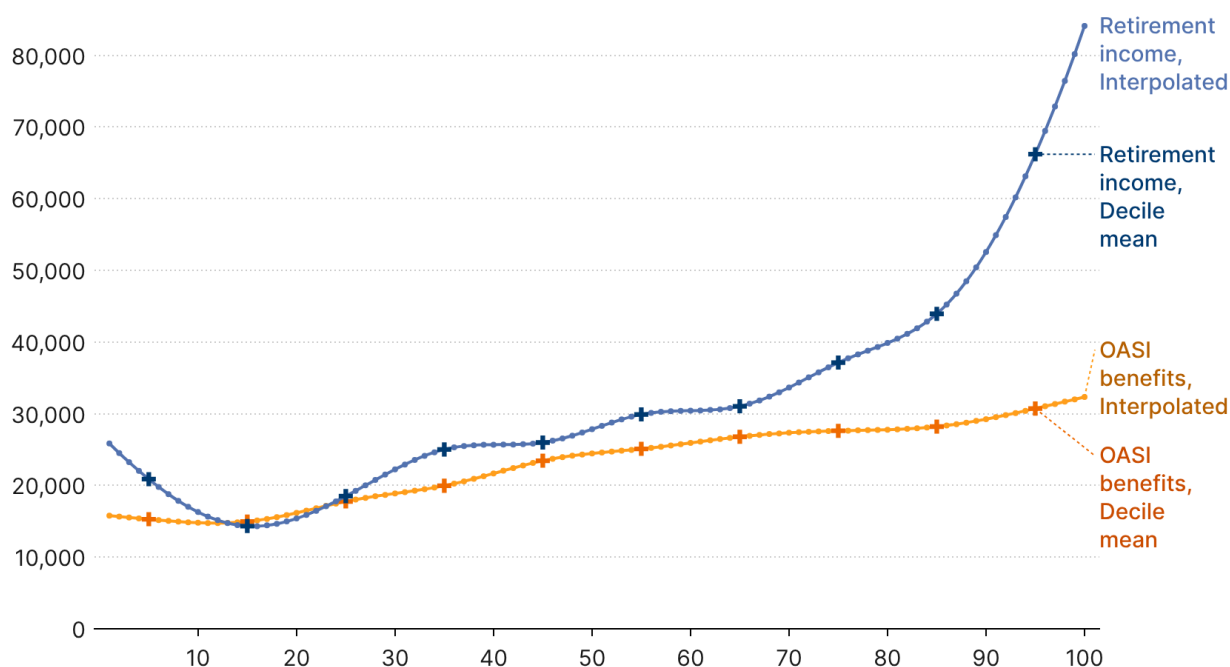
Adjust income for underreporters

Once we have identified which respondents are underreporters, we need to determine what their missing income should be. For this, we use Table 8 from Bee and Mitchell (2017), which gives the average retirement and Social Security income, according to administrative data, for each decile of CPS ASEC income. We can infer, for example, that an underreporting aged unit⁷ in the first income decile of CPS ASEC has an average retirement income of \$20,883 (after inflating to 2021 U.S. dollars). Because our population of interest (older adults in poverty) is in the lowest decile of income, we interpolate the deciles into percentiles to achieve greater granularity and variability across aged units. We use linear interpolation in log-space, then extrapolate our curves beyond the 5th and 95th percentile anchors. Figure A1 below shows the relationship between an aged unit's income percentile and its predicted retirement or Social Security income.

FIGURE A1

Mean administrative income by CPS ASEC aged unit decile, with percentile interpolation

Inflated to 2021 U.S. dollars



Source: Authors' calculations using Bee & Mitchell (2017) Table 5.

Note: "Aged Unit" is defined as an individual over the age of 65, or a married couple where one member is over 65.

CPS ASEC: Current Population Survey Annual Social and Economic Supplement; OASI: Old-Age and Survivors Insurance

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⁷ Defined as an unmarried individual aged 65 and over, or a married couple where at least one spouse is aged 65 and over.

Observe that, for retirement income, the average is greater for the first decile than the second and third, so the interpolated and extrapolated values increase toward the first percentile. This indicates that many older adults who report no retirement income—and thus appear to have near-zero total income—are likely forgetting a substantial source of income. Combined with the high rate of false negatives, this is why NEWS attributes a significant portion of measured poverty among older adults in the CPS ASEC to underreported retirement income.

Estimate asset eligibility

Due to the lack of asset and wealth information on the CPS ASEC, we cannot predict the asset eligibility of respondents using these data alone. Other microsimulations, including TRIM3, have compensated for this by predicting the amount of wealth required to generate the reported wealth income. We opt for a different approach because SSI's baseline asset limits are very low (\$2,000 for an individual, \$3,000 for a couple). Even small quantities of cash held in a checking or savings account would disqualify an individual but are unlikely to produce enough interest for the respondent to report it on the survey.

Instead, we turn to the HRS, which contains detailed and accurate data on income and assets for a sample of older adults (aged 50 and older). By simulating both the income and asset eligibility of HRS respondents, we can use multivariable logistic regressions to predict the probability that a CPS ASEC respondent who is eligible for SSI due to their income and aged or disability status would also be asset eligible.

We first model the SSI income and asset eligibility calculation using the HRS's detailed variables on income, assets, and debt.⁸ We repeat this for both current and proposed law. While the income component is relatively straightforward, there is one notable shortcoming in the asset data that had to be addressed. SSI allows households to exempt the value of one vehicle from their assets, net of what is owed. The HRS, however, reports the total transportation assets owned by a household, and provides no further information on the type, number, or value of those vehicles. Because the HRS contains no information with which to predict vehicle values, we set a \$15,000 maximum exemption. We believe this level is unlikely to underestimate most SSI-eligible households' primary vehicle exemption, although it is likely that some households (e.g., those with two moderately valuable cars) receive too large an exemption. This is an unfortunate limitation of our model.

Once we know the asset and income eligibility status of HRS respondents under current and proposed law, we can estimate the share of income-eligible respondents who are asset eligible. A simple implementation could use this share to randomly assign asset eligibility to anyone in the CPS with income eligibility. We use a method that leverages respondent

⁸ In each instance where we calculate income and asset eligibility for the microsimulation, including the CPS, we assume that respondents who report receiving SSI income meet both standards, even if the data suggests otherwise. Furthermore, we don't unenroll any respondent and only change their benefits if they are an increase from current levels.

characteristics observable in both the HRS and CPS, such as marital status, disability status, age, race, sex, and wealth income. We do so by fitting a Firth logistic regression of asset eligibility on these observable characteristics, but only among individuals who are income eligible for SSI and aged or disabled. We repeat this under both current-law and proposed-law income and asset rules.

Our resulting estimates of asset eligibility rates for various subgroups are shown in Table A3.

TABLE A3

Estimated percentage of the population with SSI asset eligibility, conditional on being income- and status-eligible

	Current law	Proposed law
Couple, both eligible	56%	72%
Couple, one eligible	49%	60%
Single, Aged 65+	66%	76%
Working-age adult (aged 18-65)	61%	81%

Source: Authors' calculations.

Note: SSI: Supplemental Security Income



This demonstrates an important feature of our policy proposal. Many more older adults are made income eligible due to increased benefit rates and disregards. These marginal households, however, might be too wealthy to pass the asset test. Yet the table shows that even after expanding the pool of income-eligible households, the asset policies are generous enough to substantially increase the overall asset eligibility rate.

Current-law model for baseline

To ensure that our policy model has an appropriate counterfactual, we create a microsimulation of the SSI program under current law using the same underreporting-adjusted CPS ASEC (NEWS and TRIM3) and the HRS asset eligibility method.

We conduct the income eligibility calculation for all adults using the current-law rules and 2021 federal benefit rates. Note that because we use annualized income data, we are unable to capture respondents who are eligible for only some months. We can only model an annualized version of the program in which average monthly income is used in the eligibility calculation. While we do carefully model married couples in which only one

spouse is aged or disabled, we do not model benefits for disabled minors and instead use the eligibility amounts provided by TRIM3.

The model has three notable limitations. First, as discussed above, rather than manually researching and assigning SSI state supplements to individuals without SSI state supplement data in TRIM3, we use a Tobit regression (lower bound at zero) on current eligibles to predict the hypothetical state supplements for new eligibles. Once the income eligibility calculation is complete, we apply the current-law Firth logistic regression estimated on the HRS to CPS respondents who are income eligible. Second, we are unable to predict which respondents would have a benefit reduction due to in-kind support and maintenance. Finally, we treat citizenship as a necessary condition for SSI eligibility (unless the respondent reports receiving SSI benefits). While these features may be feasible to model, we decided they were out of scope for this initial model; they may be included in future iterations.

Lastly, we algorithmically enroll eligible units into SSI until our modeled program matches aggregate statistics from the 2021 Social Security Administration (SSA) program report. In particular, we aim to match the total number of participants aged 65 and older (2.2 million), total federal benefits to participants aged 65 and older (\$11.9 billion), total adult participants (7.5 million), and total federal benefits to adult participants (\$54.0 billion).⁹ We automatically enroll any respondent who reports already having SSI benefits. Our algorithm (greedy hill-climbing with random restarts and 2-opt swaps) achieves a solution within 0.001% of each of these targets.

This baseline model provides several important insights into the current SSI program. We estimate that 3.9 million older adults have income and assets sufficiently low to qualify for SSI under current law, implying a 53.5% participation rate to match the administrative statistics of 2.2 million participants. Among those older adults who we predict are eligible for SSI, only 1.5 million report having SSI benefits on the CPS ASEC (implied 39% participation). The SSI program has 11.4 million eligible individuals, 63% of whom must participate to match administrative data.

Our baseline model estimates that the supplemental poverty rate among older adults is 5.7%, which is lower than both NEWS (6.1%) and TRIM3 predict. There are two reasons for this. First, we combine the effects of retirement income and OASI benefit underreporting (NEWS) with transfer income underreporting (TRIM3). Second, by first accounting for the NEWS underreporting, our current-law SSI model can more efficiently distribute benefits to the older adults who remain in poverty, not just those who appear to be in poverty.

⁹ The SSA report provides a snapshot of participants and benefits for the month of December 2021. We target the count of participants for that month, then target the monthly outlays times 12.

Proposed-law model

In the final phase of our microsimulation, we take the results from the baseline and model each of our policy proposals. We briefly discuss how each proposal is handled in turn, then describe how the final cost estimates are computed.

SSI and SNAP reform

We begin our SSI model by repeating the income eligibility calculation from the baseline model, but with the following changes to the policy parameters (deflated from 2027 to 2021 U.S. dollars):

1. Increase the federal benefit rate by \$70 for individuals and \$105 for couples
2. Increase the general and earned income disregards to \$60 and \$200, respectively
3. Exempt 40% of OASI benefits from countable income

We then conduct the revised asset test by applying the Firth logistic regression estimated on the HRS under the proposed asset rules. We treat all recipients of SSI from the baseline model as automatically asset eligible; otherwise, the independent random-number lotteries in the two models could take asset eligibility away from simulated baseline recipients.

The final step of SSI and SNAP reform is to increase participation rates among older adult units and make enrollment automatic for dual-eligible units participating in one program. We accomplish this with the same participation algorithm used in the baseline model, with the following objectives:

1. 90% SSI participation rate in older adult units
2. 90% SNAP participation rate in older adult units
3. Baseline (65.6%) SSI participation rate in working-age adult units
4. Baseline (70.1%) SNAP participation rate in working-age adult units

The algorithm uses the hard constraint that any older adult unit enrolled in SSI or SNAP must automatically be enrolled in both if eligible for both. Note that our policies do not affect the SNAP eligibility pool, so objective four is achieved easily, but we keep it to avoid enrolling SNAP units with many working-age recipients. The algorithm reaches a solution with less than 0.02 percentage-point deviation from each objective.

Our model predicts significant increases in eligibility and participation in SSI and SNAP. Before applying the asset test, the income reforms increase the number of older adults eligible for SSI from 5.6 million to 10.1 million. After applying the asset test, the baseline model has 3.9 million eligible older adults, while the policy model has 7.6 million. Finally, after simulating a significant increase in participation, the number of older SSI and SNAP beneficiaries increases from 2.2 million to 6.8 million and from 5.0 million to 10.1 million, respectively.

Medicare reform

We implement two simple reforms to the Medicare program. Both are relatively straightforward to model thanks to the CPS's detailed health care expenditure data.

The CPS reports the amount that each individual spent out of pocket on medical care (excluding premiums and over-the-counter purchases) in the year. We compute the amount that each older or Medicare-enrolled individual or couple spent beyond the proposed \$5,000 maximum out-of-pocket cap, and add that amount to their household resources.

Similarly, the CPS reports the amount spent on Medicare premiums, including adjustments from CPS for responses that require corrections. We compute each Medicare-enrolled individual's and couple's new premium under our policy—8.5% of income beyond 150% of the federal poverty line, or \$0 for those enrolled in SSI, SNAP, or Medicaid. We then add the difference between the old and new premiums to each household's resources. Note that the new premium may be higher, especially for higher-income Medicare enrollees.

Furthermore, the proposed law would set a maximum premium sufficient to prevent the aggregate premium revenues from decreasing. For simplicity, we set the maximum premium to be twice the Medicare Part B and Part D premiums in 2021. This affects our cost estimates, but not our poverty estimates, since one would have to have income several times the poverty line to reach the artificial premium cutoff.

Social Security reforms

We model two policies that were previously included in a proposal to restore Social Security solvency while improving the program's progressivity, as these policies may have poverty-reducing effects.

The first is an alternative survivor benefit, under which surviving spouses receive 75% of the couple's combined Social Security benefits, up to 150% of the median benefit. Note that this benefit is an alternative, not an add-on: if the traditional benefit amount (the larger of the survivor's own and their late spouse's OASI benefits) is greater, they receive that instead.

Unfortunately, the CPS ASEC does not have data on the survivor and late spouse's OASI benefits, so we must estimate them. We can infer that each survivor's current benefit was the larger of the two spouses' benefits, so we need to predict the lower benefit amount. We accomplish this by estimating a Tobit regression on couples in which both members are living and aged 65 and older. The outcome variable is the lower OASI benefit among the couple, and we use predictors such as the higher OASI benefit, sex, age, citizenship, disability status, and various predictors of economic status (wealth income, employment industry before retirement, education). The Tobit regression has a lower bound at zero and an upper bound equal to the higher spouse's OASI benefit, guaranteeing that the estimated lower OASI benefit is nonnegative and bounded above by the current survivor benefit. Using this regression, we then predict the lower OASI benefit for the surviving spouse,

calculate the alternative benefit, and add the difference to their resources if it is greater than the current benefit.

We find that 817,000 survivors have greater benefits due to the alternative, averaging just over \$2,000 (2021 U.S. dollars) in additional income per year.

The second is a benefit for grandparents providing the majority of financial support for their grandchildren. This program was previously modeled in the American Community Survey and CPS, with the results published [here](#). We remodeled it in this version of the CPS ASEC to investigate the estimated size, impact, and scope of the program after adjusting for underreported income and modeling our other poverty-reducing policies.

As we suspected, the number of households eligible for the grandparent caregiver benefit decreased moderately from our [previous version of the model](#) that used the 2024 CPS ASEC without NEWS adjustments. We predict about 33,000 fewer grandparent caregivers are eligible to receive benefits in our new model, though the average benefit amount increased somewhat. These differences could largely be due to population differences between the 2024 and 2021 CPS. The effect on the program's overall cost is modest, with outlays \$16 million lower in the model years, adjusted for inflation.

Housing voucher expansion

The final policy we model is an expansion of housing vouchers for older adults in poverty. We use current [Section 8 and 202 program statistics](#) to estimate that a 20% expansion would add 264,000 Section 8 vouchers and 24,000 Section 202 vouchers. They provide approximately \$14,600 and \$7,300 in annual benefits, respectively.

We construct the eligibility pool by identifying households that meet all of the following conditions:

1. Has an older adult
2. Does not currently receive housing subsidies
3. Does not own their residence and pays cash rent
4. Is below the poverty line

We then enroll households via a greedy hill-climbing lottery that maximizes the number of vouchers used without exceeding the supply. We get extremely close to this objective, fully distributing the Section 202 vouchers and all but one Section 8 voucher.

Proposed-law model without interactions

In addition to the combined reform, we estimate the effect of each policy—and each provision of the SSI reform (the benefit-rate increase, income disregards, asset expansion, and increased participation)—in isolation. For each scenario, we begin from the baseline model, apply only the provision in question while holding all other rules at current law, and recompute eligibility, participation, resources, and poverty using the same methods described above. Costs are then projected over the budget window using the same inflation

and demographic adjustments as the combined estimate. Note that these isolated effects do not sum to the effect of the full reform, because the provisions interact: for example, the higher federal benefit rate raises benefits for households that only the expanded disregards make eligible, and increased SSI participation raises SNAP enrollment among dual-eligible units. Such interactions are captured only in the combined simulation, so the isolated estimates should be read as indicators of each provision's relative importance rather than as additive components of the total cost.

Cost estimates

Having simulated the effects of each policy on the CPS ASEC respondents, we finally need to estimate the total cost of each policy, adjusted for both inflation and demographic growth.

We first find the total cost of each program in the model year by aggregating the differences between baseline and proposed benefits. We can then find the nominal cost of each program in future years using the [Consumer Price Index \(CPI\)](#) through 2025, then the [CPI projections](#) from the Congressional Budget Office (CBO) thereafter.

Finally, we must account for demographic trends during the budget window. We use [CBO's demographic projections](#) as the basis, tracking trends separately for minors, working-age adults, and older adults. For most programs, this is relatively straightforward because our expenditures strictly target a single demographic (e.g., survivor benefits grow only with respect to the number of older recipients, while it is more appropriate to project grandparent caregiver benefits with the number of minors). However, for other policies, such as SSI, multiple demographic groups are affected. To account for this in “mixed programs,” we compute the proportion of expenditures that go to each of these groups and use those proportions as weights in creating a “pooled” demographic trend.

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