April 29, 2024

Updating the Benefit-Cost Model

In the Benefits and Costs of a Child Allowance (Garfinkel et al., 2022), published in the *Journal of Benefit-Cost Analysis (JBCA)*, the authors developed a model to calculate the benefits and costs of cash transfers to families with children. A key element of the model is the standardization of a wide variety of estimates across and within studies of impacts for an annual $1,000 increase in transfer income. Since then, we, the benefit-cost research group at Columbia's Center on Poverty and Social Policy, have built on this research focused on cash transfers for children and their families to estimate the benefits and costs of other policy reforms (e.g., see Hartley et al., 2022, on child care assistance) and we believe, and hope, that others may also build on this work in diverse ways. As new studies broaden and deepen our understanding of the impacts of cash and near-cash transfers or methods for estimating the benefits of cash and near-cash benefits, we will update the model periodically. This document records the refinements we have made to our model to date. Each update forms its own section, numbered as 1 for the first update, 2 for the second update, 3 for the third update…. For each update, we briefly summarize what has been updated, saving details for the appendix. All updates share the same appendices. Each appendix contains multiple subsections for multiple updates (ex: Appendix B includes detailed summaries of new studies included in all updates. Section B.1 of Appendix B includes detailed summaries of new studies included in the first update).

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1. Update as of April 26th, 2024

Since the publication of Garfinkel et al. (2022), we have updated our benefit-cost model by incorporating new literature on causal impact estimates and refining methodological improvements. We identified several studies that provided new evidence on the impacts of cash and near-cash transfers on children's future earnings, children's health and child welfare. We refined the method we have used to calculate avoided expenditures and victim costs of crime by using estimates on cost per crime from Cohen (2005) instead of from Heckman et al. (2010), and by using self-reported age-crime relationship from Schulman et al. (2013) instead of that reported by the Criminal Justice Information Services Division (2019). We have also updated the model by choosing a social discount rate of 2% rather than 3%, in accordance with the latest revision of government guidance on regulatory analysis (The White House 2024). In consequence of these updates, a $1,000 increase in household income from cash and near-cash transfer generates $8,342 social benefits, and the child allowance policy analyzed in Garfinkel et al., (2022), with $97 billion of fiscal cost per year, generates social benefits of $1,541 billion per year.

1.1. New literature

Through a meta-analytic approach, we identified several new studies on the effects of cash and near-cash benefits in childhood (Barr & Smith, 2023; Barr et al., 2023; Schmidt et al, 2023; Deshpande & Mueller-Smith, 2022; Jones et al., 2022; Rittenhouse, 2022; Batra & Hamad, 2021; Spencer et al., 2021; Braga et al., 2020; East, 2020; Song, 2019; Jo, 2018; Kovski 2022). Half of these studies do not meet one or more of our selection criteria and are excluded from our analysis. See Appendix D for a discussion of our selection process. Six of these studies meet our selection criteria (Barr & Smith (2023); Barr et al. (2023); Schmidt et al. (2023); Rittenhouse (2022); Braga et al. (2020); Song (2019)), two of which emphasizing the importance of providing cash to children in the first year of life and are discussed in the next subsection 1.1.1: Barr et al. (2023) and Rittenhouse (2022). Barr & Smith (2023) is used to develop new estimate effects on crime. Braga et al. (2020) and Song (2019) are used to create new estimates of effects on children's health and health expenditures, which are incorporated into our main analysis. Schmidt et al. (2023) is used to create a new estimate on parents' mental health, but because we treat mental health as a supplementary outcome, this new estimate is not counted as part of our main estimate of benefit and cost. Section A.1. of Appendix A presents detailed summaries and standardizations of the two studies on receiving cash in the first year of life. Section B.1. of Appendix B presents detailed summaries and standardizations of the accepted studies with main outcomes. Section C.1. of Appendix C presents accepted studies with supplementary outcomes.

1.1.1. Cash in the first year of life

Barr et al. (2023) and Rittenhouse (2022) use the natural experiment arising from the Earned Income Tax Credit (EITC) timing, by which federal income taxes and tax credits in the current year are based on income and family structure in the prior year. Children born in December are eligible for EITC benefits during the first year of their life, yet children born only a few days later in January are not eligible until the following year. Barr et al. and Rittenhouse study the effect of getting EITC benefits in the first year of life on, respectively, future earnings in adulthood and involvement in the child protective service system. Both find very large impacts.

Our standardization of the Barr et al. study finds that the impact on adult earnings of getting a cash benefit early in the first year of life is about 60% as large as the total estimated impact of getting a cash transfer throughout childhood, on average. We do not incorporate this estimate of effects of receipt early in the first year into the set of estimates that are averaged to produce our main estimate of total childhood effects because it is not comparable to our other estimates; it is a partial estimate and thus is smaller, both theoretically and empirically, than the benefit of getting cash transfers both in the first year of life and in the rest of the years of childhood. Thus, including this estimate in the mean would bias the average toward zero. In addition, the estimates that are averaged to produce our main estimate in the JBCA paper include, to various degrees, the effects of getting a transfer in the first year of life. Most of the studies we use are based on Food Stamps and the EITC. Two of the Food Stamp studies (Hoynes et al. (2016); Bailey et al. (2020)) focus on the effects of being eligible in utero through age 5. Consistent with the Barr et al. finding that disproportionate benefits accrue early, these papers found that benefits are largest for those eligible in utero or the first year (for those not eligible for Food

Stamps until age 6 or older, long-term effects are zero). Thus, simply adding the new estimate to the old estimate would involve double counting of early-life benefits and overstate the true impact. Furthermore, the EITC studies also capture in-utero benefits for roughly half of children. Virtually all second-born and higher-order children (who constitute about 45% of children according to our own estimate through 2019 Current Population Survey) receive both in utero and during their first months of life. For these reasons, we do not incorporate the estimates of Barr et al. into our main analysis. However, that paper lends further confidence that the average long-term benefit of a transfer in the first year of life, and for that matter in utero (see Almond et al., 2011), is larger than the average benefit of transfers later in childhood. These results underscore the policy relevance of investments for children in utero and during the first year of life, and they also support an interpretation of our main estimates of net social benefit as potentially understated based on the inclusion of evidence from studies across childhood that may not fully account for the special impacts of assistance early in the first year of life.

The Rittenhouse (2022) estimate of the effects on Child Protective Services involvement of getting a cash transfer in the first year of life (present discounted value of $53 in reduced child welfare expenditures), is larger than our previously estimated impact of getting a cash transfer throughout childhood on the same outcome ($21). Since the Rittenhouse estimate again focuses on the impact of the first year, it represents a lower-bound relative to the total childhood impacts of cash transfers. Our previous evidence was lower in magnitude and based on only one study, therefore we incorporate this new estimate of savings in child protective service spending by averaging the two together for our main analysis. We expect that this update is an improvement, and it still may understate the social benefit related to child protective service outcomes.

The literature updates bolster our finding that cash transfers during childhood produce substantial net social benefits. Further, strong evidence for high returns to investments in the first year of life are noteworthy both for policy design as well as the interpretation of long-run benefits.

1.2. Methodological updates

The most important update to our model is in the calculation of avoided expenditures and victim costs of crime, and this update involves both incorporation of new literature and improved methods. The estimate in Garfinkel et al. (2022) relies on one quasi-experimental study, Bailey et al. (2020). We update this estimate by adding a new quasi-experimental paper on the impact of cash transfers on crime, Barr & Smith (2023). Using administrative data on crime and exploiting within-county differences in the availability of Food Stamps in the 1960s and 1970s, Barr & Smith found that being exposed to Food Stamps in utero through age 5 reduced violent-crime and property crime in adulthood. In addition to incorporating this new study, we have updated the crime estimate in a few other ways. First, we now convert the impact on incarceration in Bailey et al. (2020) and the impact on arrests in Barr & Smith (2023) into impacts on crime. Garfinkel et al. (2022) assume that impacts on incarceration equal impacts on crime. We have revised this assumption because not all crimes are reported to the police, lead to arrest, or lead to incarceration. We make the conversion from incarceration or arrest to crime by using statistics provided by the Federal Bureau of Investigations (FBI, 2019) and the Department of Justice (2022).

Second, we have updated the measurement of cost per crime, which we use to monetize the impact of transfers on crime; instead of using the figure in Heckman et al. (2010), we now use the figure in Cohen (2005). The figure in Heckman et al. represents the costs of all crimes committed by the Perry Preschool participants. It does not represent cost per crime and it is not generalizable to the U.S population. Thus, it is inappropriate to use the figure in Heckman et al for our calculation. Third, with respect to the lifetime distribution of crime, which we use to calculate the present discounted value of avoided crime, we now use the age-crime relationship estimated by Schulman et al. (2013) instead of the distribution estimated by the Criminal Justice Information Services Division (2019). Schulman et al. use self-reported crime data from NLSY97 survey, the benefit of which is that crime is less likely to be underreported (especially for those at a young age) in self-reports relative to administrative data. Finally, instead of assuming that the reduced-crime benefit starts at age 9 (the average age of beneficiary of a child allowance), we assume that it can start at any age between 0 and 16 years old to better account for the age distribution of criminal activities Taking all changes into account, a $1,000 increase in cash transfer now leads to $1,232 decrease in expenditures on crime and victimization costs of crime (instead of a $1,746 decrease, as seen in Table 3 of the JBCA paper). For more detailed summaries and calculations of the crime estimate please see appendix B below.

The second methodological update concerns children's future earnings. In Garfinkel et al. (2022), the authors discounted the face value of children's future earnings by 25%. The discounting was based on Altonji et al (2022)'s finding that 25% of increased earnings come from increased hours of work and Garfinkel et al., (2022)'s conservative assumption that workers derive no utility from increased hours of work. Rätzel (2012), however, found that utility and hours of worked has an inverse U-shaped relationship, that utility increases with hours of worked up to 7-8 hours for men and 4-5 hours for women and then decreases. For some of the policies analyzed (ex: child allowance, child care subsidy), our analysis sample is composed mainly of low-income families, who are more likely to be underemployed than overemployed. Thus, our analysis sample is less likely to suffer from utility loss of overemployment and we should not discount their earnings by 25%, but should count 100% of their earnings.

The third methodological update concerns the social discount rate. The Office of Information and Regulatory Affairs (OIRA) has recently updated its guidance on regulatory analysis (The White House, 2024). It argues that a social discount rate of 2% should be used in regulatory analysis. The rationale is that the 3% or 7% discount rate used by government agencies so far does not align with the more recent U.S economic data. In fact, the 3% or 7% discount rate is too high, causing underestimation of policies with long-term benefits (such as a child allowance). The 2% discount rate is calculated using the latest U.S economic data, allowing researchers to place the right value on future benefits and costs of policies.Garfinkel et al., (2022) used a social discount rate of 3% in their baseline analysis. We update their baseline results by using a social discount rate of 2%.

1.3. Updated results on standardized estimates and net social benefits

Table 1.1 below replicates Table 3 in Garfinkel et al. (2022), which shows the present discounted value of benefits and costs from a $1,000 increase in cash transfer. Table 1.2 presents the updated benefits and costs per $1,000 following the first update (without the update of the social discount rate from 3% to 2%), incorporating both new literature estimates and the methodological updates on crime and children's future earnings. Updated numbers are bolded. Benefits on children's future earnings have increased from $1,083 to $1,444. Benefits on children's health and longevity have increased from $2,250 to $3,165. Estimates on costs of crime have decreased from $1,746 to $1,232. Savings on child protection costs have increased from $21 to $37. Table 1.3presents the updated benefits and costs per $1,000 following the first update, including the update of the social discount rate from 3% to 2%. All benefits and costs have become larger under a lower social discount rate.

Table 1.4 below presents the total fiscal costs and social benefits from Garfinkel et al. (2022) and the updated social benefits following the first update (including the update of the social discount rate from 3% to 2%). The first row presents fiscal costs, which stay unchanged at $97 billion following the update. The third row presents social benefits from Garfinkel et al. (2022), at $929 billion. In the subsequent four rows, we present net social benefits under each individual change we have made during the first update. Incorporating new literature estimates on children's health and child protection costs has the biggest impact, increasing net social benefits to $1,118 billion. Refining the methodology we have used to calculate crime cause net social benefits to decrease to $819 billion. By counting the full value of children's future earnings, net social benefits increase slightly to $997 billion. Using a lower social discount rate of 2% increases net social benefits to $1,339. Adopting all of these updates mentioned above would lead net social benefits to increase to $1,541 billion, giving us a cost-benefit ratio of 1 to 15.

Table 1.1. Present discounted value of monetary benefits and costs for single child, single parent low-income families per $1,000 increase in household income: Garfinkel et al. (2022)

	Direct +	**Indirect =**	**Total**
	Beneficiaries	**Taxpayers**	**Society**
Child allowance transfer	$ 1,000	$ -1,000	$ 0
Increased future earnings of children [a]	$ 1,083	$ 0	$ 1,083
Increased future tax payments by children	$ -303	$ 303	$ 0
Decreased neonatal mortality	$ 10	$ 0	$ 10
Increased children's health and longevity	$ 2,250	$ 0	$ 2,250
Increased parents' health and longevity	$ 378	$ 0	$ 378
Avoided expenditures on other cash or near-cash transfers	$ -20	$ 20	$ 0
Avoided expenditures on child protection	$ 0	$ 21	$ 21
Avoided expenditures and victim costs of crime	$ 0	$ 1,746	$ 1,746
Increased costs of children's education	$ -302	$ -72	$ -374
Avoided expenditures on children's health care costs [b]	$ 8	$ 67	$ 76
Avoided expenditures on parents' health care costs [b]	$ 0.29	$ 2.35	$ 2.64
Increased payment due to increased children's longevity	$ 229	$ -229	$ 0
Increased payment due to increased parents' longevity	$ 77	$ -77	$ 0
Decreased tax payments from parents	$ 61	$ -61	$ 0
Administrative costs [d]	$ 0	$ -4	$ -4
Excess burden for taxpayers [e]	$ 0	$ -219	$ -219
Total [f]	$ 4,473	$ 497	$ 4,970

Notes: [a] Future earnings are valued at 75% of the face value ($1,444). This is because some increases in earnings come from increased hours, and our upper-bound estimate is 25%. To be conservative, we assume the recipient gets no surplus from increased earnings that come through additional hours.

[b] Reductions in health care expenditures reduce both out-of-pocket costs to beneficiaries and public and private insurance costs to taxpayers. Out-of-pocket medical expenditures are about 11% of national health expenditures in 2019 (Centers for Medicare & Medicaid Services, 2019). We allocate 11% of the reduced health care costs to beneficiaries and 89% of the costs to taxpayers at large in the form of reduced taxes and insurance premiums.

[c] Details on how we estimate decreases in parent taxes are included in Appendix A5.I.c.

[d] Based on administrative costs of Social Security benefits, we set administrative costs to 0.4% of costs of the allowance.

[e] Excess burden is assumed to be equal to 40% of the net increase or decrease in the present discounted value of taxes. Neither decreases in victim costs nor reductions in health insurance premiums, 71% and 33% respectively of total taxpayer benefits, are counted in the calculation of excess burden.

[f] The total may not equal the sum of the columns due to rounding.

Table 1.2. Present discounted value of monetary benefits and costs for single child, single parent low-income families per $1,000 increase in household income: Results following the first update of the BCA model, without the update of the social discount rate from 3% to 2%

	Direct +	Indirect =	Total
	Beneficiaries	**Taxpayers**	**Society**
Child allowance transfer	$ 1,000	$ -1,000	$ 0
Increased future earnings of children [a]	**$ 1,444**	**$ 0**	**$ 1,444**
Increased future tax payments by children	$ -303	$ 303	$ 0
Decreased neonatal mortality	$ 10	$ 0	$ 10
Increased children's health and longevity	**$ 3,165**	**$ 0**	**$ 3,165**
Increased parents' health and longevity	$ 378	$ 0	$ 378
Avoided expenditures on other cash or near-cash transfers	$ -20	$ 20	$ 0
Avoided expenditures on child protection	**$ 0**	**$ 37**	**$ 37**
Avoided expenditures and victim costs of crime	**$ 0**	**$ 1,232**	**$ 1,232**
Increased costs of children's education	$ -302	$ -72	$ -374
Avoided expenditures on children's health care costs [b]	**$ 15**	**$ 118**	**$ 133**
Avoided expenditures on parents' health care costs [b]	$ 0.29	$ 2.35	$ 2.64
Increased payment due to increased children's longevity	$ 229	$ -229	$ 0
Increased payment due to increased parents' longevity	$ 77	$ -77	$ 0
Decreased tax payments from parents [c]	$ 61	$ -61	$ 0
Administrative costs [d]	$ 0	$ -4	$ -4
Excess burden for taxpayers [e]	**$ 0**	**$ -273**	**$ -273**
Total [f]	**$ 5,756**	**$ -6**	**$ 5,750**

Notes: [a] Future earnings are valued at 100% of the face value ($1,444).

[b] Reductions in health care expenditures reduce both out-of-pocket costs to beneficiaries and public and private insurance costs to taxpayers. Out-of-pocket medical expenditures are about 11% of national health expenditures in 2019 (Centers for Medicare & Medicaid Services, 2019). We allocate 11% of the reduced health care costs to beneficiaries and 89% of the costs to taxpayers at large in the form of reduced taxes and insurance premiums.

[c] Details on how we estimate decreases in parent taxes are included in Appendix A5.I.c.

[d] Based on administrative costs of Social Security benefits, we set administrative costs to 0.4% of costs of the allowance.

[e] Excess burden is assumed to be equal to 40% of the net increase or decrease in the present discounted value of taxes. Neither decreases in victim costs nor reductions in health insurance premiums, 71% and 33% respectively of total taxpayer benefits, are counted in the calculation of excess burden.

[f] The total may not equal the sum of the columns due to rounding.

Table 1.3. Present discounted value of monetary benefits and costs for single child, single parent low-income families per $1,000 increase in household income: Results following the first update of the BCA model

	Direct +	**Indirect =**	**Total**
	Beneficiaries	**Taxpayers**	**Society**
Child allowance transfer	$ 1,000	$ -1,000	$ 0
Increased future earnings of children [a]	$ 1,940	$ 0	$ 1,940
Increased future tax payments by children	$ -407	$ 407	$ 0
Decreased neonatal mortality	$ 10	$ 0	$ 10
Increased children's health and longevity	$ 4,892	$ 0	$ 4,892
Increased parents' health and longevity	$ 549	$ 0	$ 549
Avoided expenditures on other cash or near-cash transfers	$ -26	$ 26	$ 0
Avoided expenditures on child protection	$ 0	$ 37	$ 37
Avoided expenditures and victim costs of crime	$ 0	$ 1,432	$ 1,432
Increased costs of children's education	$ -329	$ -79	$ -408
Avoided expenditures on children's health care costs [b]	$ 21	$ 170	$ 191
Avoided expenditures on parents' health care costs [b]	$ 0.36	$ 2.89	$ 3.24
Increased payment due to increased children's longevity	$ 450	$ -450	$ 0
Increased payment due to increased parents' longevity	$ 114	$ -114	$ 0
Decreased tax payments from parents [c]	$ 61	$ -61	$ 0
Administrative costs [d]	$ 0	$ -4	$ -4
Excess burden for taxpayers [e]	$ 0	$ -300	$ -300
Total [f]	$ 8,275	$ 67	$ 8,342

Notes: [a] Future earnings are valued at 100% of the face value ($1,940).

[b] Reductions in health care expenditures reduce both out-of-pocket costs to beneficiaries and public and private insurance costs to taxpayers. Out-of-pocket medical expenditures are about 11% of national health expenditures in 2019 (Centers for Medicare & Medicaid Services, 2019). We allocate 11% of the reduced health care costs to beneficiaries and 89% of the costs to taxpayers at large in the form of reduced taxes and insurance premiums.

[c] Details on how we estimate decreases in parent taxes are included in Appendix A5.I.c.

[d] Based on administrative costs of Social Security benefits, we set administrative costs to 0.4% of costs of the allowance.

[e] Excess burden is assumed to be equal to 40% of the net increase or decrease in the present discounted value of taxes. Neither decreases in victim costs nor reductions in health insurance premiums, 71% and 33% respectively of total taxpayer benefits, are counted in the calculation of excess burden.

[f] The total may not equal the sum of the columns due to rounding.

Table 1.4. Aggregate annual benefits and costs of a $3,000/$3,600 child allowance: Garfinkel et al. (2022) and results following the first update of the BCA model (in $billions).

	Direct +	**Indirect =**	**Total**
	Beneficiaries	**Taxpayers**	**Society**
Child allowance transfer	$ 97	$ -97	$ 0
Total benefits			
Garfinkel et al. (2022)	$ 686	$ 243	$ 929
New literature (on children's health and child welfare)	$ 858	$ 259	$ 1,118
Methodological update (on crime)	$ 686	$ 133	$ 819
Methodological update (on children's future earnings)	$ 753	$ 243	$ 997
Methodological update (on social discount rate)	$ 1,041	$ 298	$ 1,339
New literature and methodological updates	$ 1,373	$ 169	$ 1,541

1.4. Plan for the next update

So far, we have not used any mental health outcomes to construct estimates on health, especially when general health outcomes (ex: self-reported health) and mental health outcomes are both examined in a study. In the future, we may use mental health outcomes to construct estimates if such outcomes are the only health outcomes analyzed by the study.

We are also interested in a sensitivity analysis where we test the sensitivity of our results to the standard error of the coefficients reported in the impact studies.

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Appendix A. Impact Studies on the Additional Effect of Cash Transfer during the First Years of Life

A.1.

A.1.a. Barr et al. (2023)

Authors found that exposure to larger child-related tax benefits, primarily EITC, during infancy led to a $295.2 (s.e. 150.1) increase in average future earnings (including spouse's earnings if present) around ages 23-25 and a $433.4 (s.e. 198.4) increase in average earnings around ages 26-28. The same exposure led to a 0.023 (s.e. 0.011) or 2.3 percentage-point increase in the probability of graduating from high school. Authors used administrative tax data and North Carolina education data. The sample included children born one month before and after January 1st in 1981-1982, 1985-1986, and 1991-1992. Eligibility for EITC benefits was approximated with parents' tax information or whether the children were eligible for free and reduced-price lunch. The research design relied on the difference in EITC benefits and dependent exemption caused by a birthday cutoff, where children born on December 31st (treatment group) are eligible to receive these benefits in the following year when they are aged 0-1 but children born on January 1st (comparison group) are not. However, the treated children would also lose tax benefits one year earlier than the control children. This difference in benefits around a cutoff date motivated authors to adopt a regression-discontinuity design. Other controls in the model included birth year fixed effect, parents' age, child's gender, and predicted adjusted gross income of parents.

Authors estimated that the birthday cutoff led to a $1,291 ($2015) difference in child-related tax benefits during the child's first year of life, the equivalent of $1,385.7 in 2019 dollars. However, the treated children would lose tax benefits one year earlier than the control children. Receiving $1,385.7 at age 0 is more valuable than receiving it 18 years later at age 17. The difference between $1,385.7 and the present discounted value of $1,385.7 that arrives at age 18 years later is $547. We assume that the earnings increase discovered by the authors are the results of this $547 difference. We assume that the $295.2 increase in earnings around ages 23-25 and the $433.4 increase in earnings around ages 26-28 were also denoted in 2015 dollars and converted them into $316.85 and $465.19 in 2019 dollars. If a $547 increase in child-related tax benefits led to a $316.85, and $465.19 increases in earnings, then a $1,000 increase in benefits would lead to a $579 (316.85*1000/547) increase around ages 23-25 and a $850 (465.19*(1000/547)) increase around ages 26-28. Even though the authors examined the impact of being exposed to child-related tax benefits during the first year of life, to be consistent with other calculations we have made to not overstate yearly effects, we assume that children are exposed to EITC throughout the entire childhood but only derive benefits in increased earnings from the first year of payment. Dividing increases in earnings by 18 years of exposure, we obtain a $32 increase in earnings around ages 23-25, and a $47 increase in earnings around ages 26-28. The analysis sample includes children exposed to EITC, not children that actually received EITC. To obtain a treatment-on-the-treated effect, we divide the $32 and $47 increases by the estimated take-up rate of EITC during the study period (1981-1992). EITC take-up was estimated to be 70% during the mid-1980s and 81%-86% by 1990 (Scholz 1990; Scholz 1994). We took the average of this range of take-up rates, 78%, and used it for the calculation. Dividing $32 and $47 by 0.78, we conclude that a $1,000 increase in household income from cash transfers would increase earnings around ages 23-25 by $41 and increase earnings around 26-28 by $61. We use the average of the increases in the two age periods as the increase in earnings per year, $51. Assuming that child beneficiaries are on average 9 years old, and increased future earnings start at age 22 and last until age 64, we calculate the present discounted value. To be consistent with Garfinkel et al. (2022), we take future earnings at 75% of their face values assuming some disutility of work and that higher earnings come from more work hours (as opposed to higher wages). We conclude that a $1,000 increase in household income from cash transfers would increase the present discounted value of children's future earnings by $642.

As explained in the main text for update no.1, we did not incorporate our estimate of this study into our mean estimate.

A.1.b. Rittenhouse (2022)

Authors found that being eligible for larger child-related tax benefits during infancy led to a 0.001 (s.e. 0.00149) or 0.1 percentage-point decrease in having any referrals to Child Protective Services (CPS), a 0.000897 (s.e. 0.00140) or 0.0897 percentage-point decrease in having any CPS investigations through age 2, a 0.000775 (s.e. 0.000569) or 0.0775 percentage point decrease in foster care placement through age 2, a 0.00729 (s.e. 0.00344) decrease in the number of referrals to CPS through age 2, a 0.00658 (s.e. 0.00263) decrease in the number of CPS investigations through age 2, and a 0.612 (s.e. 0.290) decrease in days spent in foster care through age 2. Effects are larger for low-income households. Eligibility of larger benefits led to a 0.00579 (s.e. 0.00301) or 0.579 percentage-point decrease in having any referrals to CPS, a 0.00547 (s.e. 0.00286) or 0.547 percentage-point decrease in having any CPS investigations through age 2, a 0.00255 (s.e. 0.00124) or 0.255 percentage-point decrease in foster care placement, a 0.0190 (s.e. 0.00731) decrease in the number of CPS referrals, a 0.0171 (s.e. 0.00561) decrease in the number of CPS investigations, and a 1.880 (s.e. 0.646) decrease in the number of days spent in foster care. Authors used data from the Children's Data Network, which housed data on birth records, death records, and CPS records in California. The sample included children born within 60 days of January 1st to first-time mothers between November 1999-March 2017 (n=1,181,675). Low-income households were defined as those whose predicted incomes were below 200% of the federal poverty line. To estimate the causal impact of cash transfer, authors used a regression-discontinuity design, where children born in December (treatment group) are eligible for tax benefits in the following year when they are age 0-1 but children born in January (comparison group) are not. However, the treated children would also lose tax benefits one year earlier than the comparison children. Other controls in the model included re-centered birth year fixed effect.

We use the results for low-income children because they are more likely to be eligible for EITC. We use the results on the probability of having CPS investigations as it is also examined by the other child welfare literature we use--Berger et al., 2017. Using ACS data, authors estimated that among low-income household, children born in December received $2,881 ($2017) more child-related tax benefits during the first year of life than children born the next month in January, the equivalent of $3,012.59 in 2019 dollars. However, the treated children would also lose tax benefits one year earlier than the control children. Receiving $3,012.59 at age 0 is more valuable than receiving $3,012.59 18 years later at age 17, which only has a present discounted value of $1,823 using a 3% social discount rate. We contribute the effects discovered by the paper to the difference between $3,012.59 and $1,823, around $1,190. If $1,190 led to a 0.547 percentage-point decrease in the likelihood of having CPS investigations, then a $1,000 benefit would lead to a 0.46 (0.547*1000/1190) percentage-point decrease in the likelihood of having CPS investigations. The effect discovered by the paper was an intent-to-treat effect. We further divide the 0.46 percentage-point decrease by 0.7945, which was the estimated EITC participation rate in 2008 (the middle of the study period) according to Jones (2014). This adjustment yields a 0.58 percentage-point decrease in CPS investigation. According to Fang et al. (2012), the average per-year cost per investigated child is $7,728 (2010 dollars), the equivalent of $9,082 (2019 dollars). A 0.58 percentage-point decrease in CPS investigation is thus worth $53. We conclude that a $1,000 increase in household income from cash transfers would bring $53 worth of benefits in reduced expenditures on child welfare per year.

Appendix B. Summaries and Standardizations of New Impact Studies

B.1.

B.1.a. Children's Health from One Month of Age Onward

Braga et al. (2020)

Authors found that exposure to EITC during childhood increased health between ages 22-27: increased the probability of having excellent or very good health by 0.017 (s.e. 0.004) or 1.7 percentage points, decreased the probability of being obese by 0.008 (s.e. 0.004) or 0.8 percentage points, decreased the probability of having functional limitation by 0.004 (s.e. 0.002) or 0.4 percentage points, and decreased the probability of having high blood pressure by 0.001 (s.e. 0.002) or 0.1 percentage points. Authors then examined whether the health impact between ages 22-27 would differ by the age of exposure. When health was measured by the probability of reporting excellent or very good health, exposure between birth and age 5 increased the probability by 0.010 (s.e. 0.004) or 1 percentage point, exposure between age 6-12 increased the probability by 0.004 (s.e. 0.003) or 0.4 percentage point, and exposure between 13-18 increased the probability by 0.005 (s.e. 0.002) or 0.5 percentage point. Authors also examined whether the beneficial health impact was persistent and found that the impact could last until age 51. Authors used 1968-2017 Panel Study of Income Dynamics (PSID) data. The analysis sample included 2,393 individuals. Authors took advantage of the variation in maximum EITC credits across states, time, and family size. Treatment was average annual maximum EITC credit during childhood, given the child's state of residency, year, and size of family. Other controls in the model included individual characteristics (year of birth, race, gender, parents' education, parents' marital status, sibling fixed effects), state characteristics (GDP per capita, unemployment rate, income tax rate, minimum wage, maximum welfare benefits, tax revenues), state fixed effects, year fixed effects, state-by year fixed effects, and state-specific time trends.

All the health impacts summarized above come from a $100 increase in the average annual maximum EITC credit exposed (2017 dollars), or $104.57 in 2019 dollars. If being exposed to an increase of $104.57 in annual maximum EITC credit increased the probability of having excellent or very good health by 1.7 percentage points, then we linearly extrapolate to $1,000 EITC benefits would increase the probability by 16 percentage points (1.7*1000/104.57). To avoid overstating the per-year effect, we assume that children in the analysis sample are exposed to EITC through their entire childhoods (age 0-17), a total of 18 years. Dividing 16 percentage points by 18 gives us a 0.9 (16/18) percentage-point increase per year. To obtain a treatment-on-the-treated effect, we further divide the estimate by an estimated EITC take-up rate. The middle of the study period is 1993 and according to Scholz (1994) the EITC participation rate in 1990 was around 83 percent. Dividing 0.9 percentage points by 0.83 gives us a 1.09 (0.9/0.83) percentage-point increase. We value improvement in health using QALY. We measure quality of life on a scale of 0-5, with 0 corresponding to death and 5 corresponding to excellent health (full scale includes death, poor, fair, good, very good, or excellent, with each corresponding to 0, 1, 2, 3, 4 and 5 respectively, so the maximum increase is 5 points). If death has a QALY value of $0 and excellent health has a full QALY value of $126,628, then an increase in one unit of health corresponds to 1/5th of the value of QALY. Valuing the 1.09 percentage-point increase by 1/5th of QALY results in a $276 increase in health per year. We assume that increased health in adulthood takes place from ages 22-78. We conclude that a $1,000 increase in household income from cash transfer per year would increase the present discounted value of children's adulthood health by $5,248.

Song (2019)

The author found that exposure to an increase of $1,000 in the maximum EITC in utero through age 18 increased the probability of being in good health by 0.036 (s.e. 0.011) or 3.6 percentage points. The same increase lead to a 0.075 (s.e. 0.021) or 7.5 percentage-point decrease in obesity, a 0.058 (s.e. 0.021) or 5.8 percentage-point decrease in smoking, and a 0.032 (s.e. 0.015) or 3.2 percentage-point increase in drinking. When differentiating exposure by age, the author found that an increase of $1,000 in the maximum EITC in utero, ages 0-5, and ages 13-18 would increase the probability of being in good health by 0.035 (s.e. 0.015), 0.076 (s.e. 0.016), and 0.054 (s.e. 0.016), respectively. The same exposure at ages 6-12 would instead decrease the probability of being in good health by 0.031 (s.e. 0.023). The author used 1968-2017 PSID data and took advantage of the variation in maximum EITC credits across states, time, and family size. Treatment was average annual maximum EITC credit during childhood given the child's state of residency, year, and size of family. Other controls in the model included birth cohort fixed effects, state and year fixed effects, state-specific time trends, number of siblings, gender and race.

The 3.6 percentage-point increase in the probability of being in good health was a result of a $1,000 increase (2017 dollars) in maximum EITC exposure, the equivalent of $1,045.67 in 2019 dollars. A $1,000 increase in EITC exposure in 2019 would thus lead to a 3.4 (3.6*1000/1045.67) percentage-point increase in probability of being in good health. We divide 3.4 percentage points by 18 assuming the exposure effect is spread across all childhood years, and we obtain a per-year increase of 0.19 (3.4/18) percentage points. To obtain a treatment-on-the-treated effect, we further divide 0.19 by an estimated EITC take-up rate during the middle of the study period (year 1993), around 0.83. This yields a 0.23 percentage-point increase. Valuing the 0.23 percentage point increase by 1/5th of QALY results in a $58 increase in health. We conclude that a $1,000 increase in household income from cash transfers would increase children's adulthood health by $58 per year. Assuming that increased adulthood health occurs between ages 22-78, we obtain a present discounted value of $1,111 in increased adulthood health, following a $1,000 increase in household income from cash transfer per year

B.1.b. Avoided Health Expenditures for Children

Given the increase in children's health we have calculated based on the results of Song (2019) and Braga et al. (2020), we calculate the resulting decrease in health expenditures. We follow the method of Garfinkel et al. (2022). Given our standardization estimates above, we conclude that a $1,000 increase in household income from cash transfers would lead to a $70 decrease in health expenditures in adulthood following Song (2019), or a $328.14 decrease in health expenditures in adulthood following Braga et al. (2020).

B.1.c. Avoided Expenditures and Victim Costs of Crime

In order to calculate avoided expenditures and victim costs of crime from cash transfers, we need to know: 1) the average monetary cost per crime, 2) lifetime distribution of criminal activities, 3) the impact of cash transfers on crime. In the section below, we discuss the evidence we have collected on these three components and how we use them for the calculation.

Cost per crime

Cost of crime includes both victimization cost and criminal legal system costs (ex: police, incarceration, court). We use Cohen (2005)'s estimate on total cost per crime (minus the cost of lost productivity of criminals to avoid double counting as we are already counting future earnings increases of children).

Because incarceration only applies to people ages 18 and above, for cost per crime committed before age 18, we need to further subtract incarceration cost from the total cost. Since Cohen (2005) did not provide an estimate on incarceration cost per crime, we estimate incarceration cost by calculating what percentage of criminal legal system cost is incarceration cost and what percentage of total cost is criminal legal system cost. We first estimate the percentage of criminal legal system cost that is incarceration cost. According to Table 4.1 of Cohen (2005), in 2015, incarceration cost per capita is $261 and criminal legal system cost per capita is $855. Incarceration cost is thus 30.5% (261/855) of criminal legal system cost. We then estimate the percentage of crime cost that is criminal legal system cost. Table 5 of Miller et al. (2021) presents that per violent crime, criminal legal system cost is $5,529 ($2328+$3201), and total cost minus perpetrator work loss is $90,401. Criminal legal system cost is thus 6.1% of total cost for violent crime. Per non-violent crime, criminal legal system cost is $707 ($274+$433), and total cost minus perpetrator work loss is $2,250. Criminal legal system cost is thus 31.4% of total cost for non-violent crime. According to Table 4 of Miller et al. (2021), there are 24,117,831 violent crimes and 120,999,583 total crimes, suggesting that there are 96,881,752 non-violent crimes. Weighting 6.1% and 31.4% by the percentage of total crimes that are violent and non-violent, we conclude that for all crimes, criminal legal system cost is 26.4% of the total cost of crime. Since total cost of crime includes criminal legal system cost and victimization cost, our calculation based on Miller et al. (2021) suggests that victimization cost is 73.6% of the total cost of all crimes.

[1].

Our calculations suggest cost per murder is $8,158,816 in 2019 dollars ($8,006,490 pre-age-18), cost per robbery is $29,070 ($28,527 pre-age-18), and cost per assault is $41,224 ($40,454 pre-age-18). We use the unweighted average of Cohen's estimate on rape and on other sexual assault for cost per rape- $119,001 ($116,779 pre-age 18). Cohen doesn't have an estimate for property crime. The FBI considers burglary, larceny, motor-vehicle theft, and arson as property crime. Our calculations suggest cost per burglary is $2,887, per larceny is $4,344, per motor vehicle theft is $8,499 and per arson is $35,245.

In order to calculate the cost per property crime, we need to know what percentage of property crimes are burglary, larceny, motor vehicle theft, and arson. According to the FBI (2019), there are 1,245,410 violent crimes (including number of rapes under revised definition) and 6,959,072 property crimes (including arson, which FBI imperfectly estimates to be around 33,395). Among violent crimes, 16,425 (1.32%) are murder and manslaughter, 139,815 are rape (11.23%), 267,988 (21.52%) are robbery, and 821,182 (65.94%) are aggravated assault. Numbers of simple assaults are not reported and thus not included in the calculation. Among property crimes, 1,117,696 (16.06%) are burglary, 5,086,096 (73.09%) are larceny-theft, 721,885 (10.37%) are motor vehicle theft, and 33,395 (0.48%) are arson. FBI likely underestimates the true level of crime because not all crimes are reported to the police. We thus obtain data on the percentage of victimizations that are reported to the police from self-reported victimization data. According to Table 5 of the report of Department of Justice, in 2021, among violent crimes, only 25% (0.3/(0.3+0.9)) of rape victimizations are reported to the police, followed by 58.82% (1/(1+0.7)) of robbery and 62.96% (1.7/(1.7+1)) of aggravated assault. Data on murder is not available. We assume that 100% of murder are reported to the police. 31.20% (27.8/(27.8+61.3)) of property victimizations are reported to the police. Among property crimes, only 41.30% (5.7/(5.7+8.1)) of burglary are reported to the police, 76.74% (3.3/(3.3+1)) of motor vehicle theft are reported to the police. Data on larceny and arson is not available. We assume that larceny has the same report rate of other theft- 26.48% (18.8/(18.8+52.2)). We assume that all arson is reported to the police. We combine two data sources to estimate the true level of crime. We assume that the percentage of victimizations reported to the police stay the same from 2019 to 2021. In 2019,

[1] An alternative calculation based on Cohen (2005) suggests that criminal legal system cost is 10.1% of total cost of crime. Table 6.2 of Cohen (2005) presents that for all crimes committed in the United States in 2017, criminal legal system cost is worth a total of $211,764 million. Total cost minus perpetrator work loss is worth $2,094,702 million. Criminal legal system cost is thus 10.1% of total cost of crime. The Cohen estimate on the percentage of total cost that is criminal legal system cost would suggest much higher social benefits for reducing crime, so we cautiously rely on the more moderate results based on Miller et al. (2021), which would give us smaller estimates on cost per-crime before age 18.

there should be 16,425 (16425/1) murder, 559,260 rape (139815/0.25), 455,580 robbery (267988/0.5882) and 1,304,230 (821182/0.6296) aggravated assault. Thus, within the true level of violent crime, 0.7% are murder, 23.95% are rape, 19.51% are robbery, and 55.84% are aggravated assault. There should be 2,706,000 burglary (1117696/0.413), 19,208,129 larceny-theft (5086096/0.2648), 940,638 motor vehicle theft (721855/0.7674) and 33,395 arson (33395/1). Thus, within the true level of property crime, 11.82% are burglary, 83.92% are larceny, 4.11% are motor vehicle theft and 0.15% are arson. Using numbers we have calculated, we conclude that the cost per property crime is $4,388 ($3,967 pre-age-18).

Age-crime Relationship

We use the age-crime relationship discovered by Schulman et al. (2013). Authors found that the proportion of youth engaging in any type of crime peaks in adolescence (ages 15-16) and decreases as youth enter adulthood. The authors used self-reported crime data from waves 1-7 of the National Longitudinal Survey of Youth, 1997 Cohort (NLSY97) survey. Two measures of criminal behaviors were created: offending and index offending. Offending was constructed based on categories for whether the respondent had committed assault, property damage, other property crime, theft below $50, theft above $50, and the selling of drugs in the past year. Given that queries on these crimes could sometimes confuse serious offenses with minor ones, authors constructed another measure on index offending, replacing responses on theft with responses on the details of theft. Index offending was constructed for categories of whether the respondent had committed assault, shoplifting above $50, the stealing of a purse or wallet, stealing of things from a locked building, stealing of cars and other motor vehicles, stealing of things using a weapon, and the selling of drugs in the past year. The authors first analyzed the age pattern of offending and index offending with descriptive statistics, then through structural equation modeling.

We use figure 1 of Schulman et al. (2013), which presents the proportion of NLSY97 youth committing any type of offenses or index offenses from ages 12-22. We focus on the distribution of index offenses since this measure looks at more serious crimes and is less likely to confuse trivial offenses with serious ones. To estimate the proportion of youth committing index offenses beyond age 22, we assume that the proportion is half of the proportion at age 22 from ages 23-44, a quarter of the proportion at age 22 from ages 45-64, and zero from ages 65 and beyond. We approximate the age-crime relationship of violent crime using the age-crime relationship of assault. Since we calculate that within violent crimes, 0.7% are murder, 23.95% are rape, 19.51% are robbery, and 55.84% are aggravated assault (see the previous section for the calculation), we attribute 0.7%, 23.95%, 19.51% and 55.84% of the age-crime relationship of violent crime to murder, rape, robbery, and assault. For instance, if figure 1 shows that 9% of youth aged 12 commit violent crimes, given that 0.7% of violent crimes are murders, we estimate that 0.6% (9%*0.7%) of youth aged 12 commit murders. We assume that the proportion of youth committing property crime is the sum of the proportion of youth committing all crimes in figure 1 except assault.

The Impact of Cash Transfer on Crime

Bailey et al. (2020)

Bailey et al. (2020) find that exposure to food stamps at age five or younger decreased the probability of being incarcerated by 0.0008 (s.e. 0.0004) or 0.08 percentage points. Based on data from the 2001-2013 American Community Survey matched with the 2000 Census Long Form (n=7,705,000), the authors use a difference-in-difference framework exploiting the county-by-county introduction of food stamps. Models control for county of birth, birth year, and birth state fixed effects as well as 1960 county-level characteristics interacted with a linear birth-cohort trend.

We use Bailey et al. (2020)'s results to measure the impact of a $1,000 increase in household income on the present discounted value of crime. To translate their estimate of the intent to treat to an estimate of the treatment on the treated, we divide 0.08 percentage points by the percentage of children in this age group who received food stamps, 16 percent. Thus, the treatment-on-the-treated outcome is a 0.5 percentage-point increase for a cumulative exposure of 7 years, or a 0.07 percentage-point decrease in the probability of being incarcerated per year. The average annual food stamps value per person in 1972 (near the midpoint of the study period) was $994 per year in 2019 dollars (Department of Agriculture, 2021). Assuming average households have three individuals, the total household food stamps value would be $2,982, on average. The impact of a $1,000 benefit in 2019 dollars is thus 0.07 percentage points times the ratio of $1000/2982, or 0.024 percentage points. Since the paper studies the impact of exposure from conception to age 5, to avoid overstating long-run benefits we assume that child recipients were exposed to food stamps through the entirety of childhood (in utero through age 17) but only derived benefits for future earnings during the first 7 years of payments. We multiply results by the 7/19 of years in which they derive benefits, decreasing the impact to a 0.009 percentage-point decrease in the probability of being incarcerated. We conclude that a $1,000 increase in household income from cash transfers per year would decrease the chance of incarceration by 0.0088 percentage points.

We calculate reduction in costs of crimes using two methods. In the first method, we start with the standardized impact on incarceration and convert it into an impact on the level of crime. We first convert it into an impact on arrests by dividing it by the arrest-incarceration ratio estimated by the Vera Institute (2019): 0.99 incarcerations per arrest.[2] The result is a decrease on arrest probability of 0.0089 percentage points (0.0088/0.99). To be consistent with our crime calculation based on Barr & Smith (2021), we decompose the impact on arrests into impacts on arrest of a specific type of crime. Based on statistics from the FBI (2019),[3] we calculate that 0.2% of all crimes are murder or manslaughter, 1.7% rape, 3.3% robbery, 10% aggravated assault, and 84.8% property crimes. We thus distribute 0.2%, 1.7%, 3.3%, 10%, and 84.8% of the 0.0089 percentage-point reductions in arrests to reductions in arrest of murder (0.00002 percentage points), rape (0.0002 percentage points), robbery (0.0003 percentage points), aggravated assault

[2] This ratio may seem high, but using it has the virtue of giving us an estimate of smaller, more conservative magnitude

[3] According to the FBI (2019), there are 1,245,410 violent crimes and 6,959,072 property crimes, including arson. Among these crimes, 16,425 (0.2%) are murder and manslaughter, 139,815 rape (1.7%), 267,988 (3.3%) robbery, 821,182 (10%) aggravated assault, and 6,959,072(84.8%) property crimes. Among violent crimes, 11.23% (139815/1245410) are rape.

(0.0009 percentage points), and property crimes (0.008 percentage points). Not all crimes lead to arrest and not all crimes are reported to the police. For each type of crime, we further divide the impact on arrests by the percentage of that type of crime that lead to arrest (FBI 2019)[4] and percentage of that type of crime reported to the police (Department of Justice 2022)[5] to arrive at the impact on the level of crime. Having adjusted for the percentage of crime that leads to arrests and is reported, we conclude that there would be a 0.00003 percentage-point reduction in murder, a 0.002 percentage-point reduction in rape, a 0.002 percentage-point reduction in robbery, a 0.003 percentage point reduction in aggravated assault, and a 0.14 percentage-point reduction in property crime. We multiply these percentage-point decrease of crime by the cost of crime calculated above to get the dollar value of reduction in crimes. To calculate the present discounted value, we multiply the dollar value by the distribution of crime from ages 0-78 and discount the benefit with a social discount rate of 3%. We conclude that following a $1,000 increase in household income from cash transfer, the present discounted value of reduced costs of crime over the lifetime (ages 0-78) is $5.

In the second method, we start with the standardized impact on incarceration. We then follow Bailey et al.'s method to monetize such impact. We multiply the standardized impact by the average length of incarceration (2.6 years according to Bailey et al.) and by the cost of incarceration ($33,985 in 2019 dollars according to Bailey et al.) and yield a result of $7.8 (0.000088*2.6*33985). Bailey et al.'s sample for incarceration ranges from 22-54 years old. For simplicity, we assume that the $7.8 reduction in cost of incarceration takes place at age 38 (the midpoint of the age range) and that average child beneficiary is 9 years old. The present discounted value of reduction in incarceration cost is thus $3.3 ($7.8/(1.03)^29). Reduction in the cost of incarceration is only part of the reduction in the cost of crime. As calculated in the previous section, incarceration cost is 30.5% of criminal legal system cost. We thus divide $3.3 by 30.5% to estimate the reduction in criminal legal system cost, a total of $10.8. As calculated in the previous section, victimization cost is 74% of the total cost of crime and criminal legal system cost is 26% of the total cost of crime. We divide $10.8 by 26% to estimate reduction in the total cost of crime and arrive at $41. We multiply $41 of reduction in cost of crime by the distribution of crime from ages 0-78 and discount the benefit with a social discount rate of 3%. We conclude that following a $1,000 increase in household income from cash transfer, the present discounted value of reduced costs of crime over the lifetime (ages 0-78) is $68.

We use the unweighted average of the two present discounted value, $36, as the final result calculated from Bailey et al. (2021). We conclude that following a $1,000 increase in household income from cash transfer, the present discounted value of reduced costs of crime over the lifetime (ages 0-78) is $36.

[4] According to the FBI (2019), 61.4 percent of murder offenses, 52.3 percent of aggravated assault offenses, 30.5 percent of robbery offenses, 32.9 percent of rape offenses, and 17.2 percent of property crimes were cleared by arrest or exceptional means.

[5] FBI statistics are likely underestimates because not all crimes are reported to the police. According to the Department of Justice, in 2021, 27.8 out of 89.1 property victimizations are reported to the police (31%), 1 out of 1.7 robberies are reported to the police (59%), 0.3 out of 1.2 rapes are reported to the police (25%), and 1.7 out of 2.7 aggravated assaults are reported to the police (63%). We assume that 100% of murders are reported to the police.

Barr & Smith (2023)

Authors found that being exposed to Food Stamps in utero through age 5 reduces the probability of any criminal conviction by age 24 by 0.013 (s.e. 0.007), or 1.3 percentage points, reduces probability of violent-crime conviction by 0.005 (s.e. 0.002) or 0.5 percentage points, and reduces the probability of property-crime conviction by 0.003 (s.e. 0.003) or 0.3 percentage points. Being exposed to Food Stamps between ages 0-5 reduces the arrest rate of violent crime between ages 18-24 by 0.151 (s.e. 0.048) or 15.1 percent, and reduces the arrest rate of property crime by 0.128 (s.e. 0.091) or 12.8 percent. Within violent-crime, it reduces arrest rate of murder by 0.032 (s.e. 0.014) or 3.2 percent, rate of aggravated assault by 0.064 (s.e. 0.030) or 6.4 percent, and rate of robbery by 0.042 (s.e. 0.014) or 4.2 percent.

Authors used administrative data from North Carolina on convictions, nationally representative Uniform Crime Reporting (UCR) data on arrests, and linked them with information on Food Stamps availability within a county and month for various birth-month cohorts. The North Carolina data covered all individuals convicted in North Carolina from 1972-2015. UCR data covered individuals arrested in a county (more than counties in North Carolina) and year. The sample on convictions is restricted to those born between 1964-1974 and includes 13,173 observations. The sample on arrests is restricted to those aged 18-24 and the number of observations vary from 30,453 to 96,386 depending on the type of crime. Regressions were conducted via ordinary least squares, exploiting within-county differences in the availability of Food Stamps in the 1960s and 1970s. The dependent variable was the crime rate of individuals born in a certain county and birth-cohort. The main independent variable was Food Stamps exposure in that county and birth-cohort. Other variables included birth county fixed effects, birth cohort fixed effects and interactions between pre-treatment county characteristics and time trends.

We first calculate the per year impact of a $1,000 increase in household income from Food Stamps on convictions. The average conviction rate for any type of crime is 9 percent. Thus, the 1.3 percentage-point decrease in any conviction is a 14.4% decrease (1.3/9). Children in the sample are exposed to Food Stamps for 5.75 years (0.75 year for the nine months in utero, and 5 years between ages 0-5), thus, the per year decrease in any crime conviction is 2.5% (14.4%/5.75). The average annual food stamps value per person in 1972 (near the midpoint of the study period) was $994 in 2019 dollars (Department of Agriculture, 2021); assuming average households have three individuals, the total household food stamps value would be $2,982, on average. A 1,000 increase in Food Stamps would thus cause any crime conviction to decrease by 0.84% (2.5% * 1000/2982). As the paper studies the crime impact of exposure in utero through age 5 (a total of 5.75 years according to the authors), we cautiously assume that child recipient exposure to food stamps is spread over the entirety of childhood (from age -1 to age 17) but only derived benefits for future crime reduction during the first 5.75 years of payments. To measure the impact per year of payments, we multiply results by the 5.75/19 of years in which they are assumed to derive benefits, decreasing the impact to 0.25% (0.84% * 5.75/19). Finally, we adjust for an estimate of the Food Stamps participation rate to obtain the treatment-on-the-treated effect. Using a participation rate of 16%, the treatment-on-the-treated effect is 1.59%. We thus conclude that a one-year increase of household income of $1,000 from the in-kind value of Food Stamps reduces crime conviction by age 24 by 1.59%.

Through the same standardization process, we conclude that a one-year increase of $1,000 from Food stamps reduces violent-crime conviction by 3.68% and reduces property-crime conviction by 0.14%. It reduces the arrest rates of violent crime by 1.67%, property crime by 1.4%, murder by 0.35%, aggravated assault by 0.7%, and robbery by 0.46%. The paper does not provide any estimate on rape. Our calculation based on FBI statistics and statistics from the Department of Justice suggests that 11.23% of violent crimes are rape (for calculation details, see footnote 5). Given the 1.67% reduction in the arrest rate of violent crime we have calculated, we infer that the arrest rate of rape decreased by 0.19%.

To calculate reduction in the costs of crime, we follow the first method of Bailey et al. (2021) converting the impacts on arrests into impacts on levels of crime. To make the conversion, for each type of crime, we divide the impact on arrest by the percentage of that type of crime cleared by arrest, and by the percentage of that type of crime reported to the police. For instance, according to the FBI (2019), 30.5% of robberies lead to arrest and, according to the Department of Justice, 59% of robbery victimizations are reported to the police. We thus divide 0.46% reduction in robbery arrests by 30.5% and again by 58.8% to obtain a reduction in robbery of 2.58%. Then we multiply by cost per crime estimated from Cohen (2005) and by the age-crime relationship from Schulman et al. (2013) to calculate the present discounted value. We conclude that following a $1,000 increase in household income from cash transfer, the present discounted value of reduced costs of crime over the lifetime (ages 0-78) is $2,427.

Appendix C. Summaries and Standardizations of Supplementary Impact Studies

C.1.

C.1.a. Children's Educational Attainment

Barr et al. (2023)

Authors found that exposure to larger child-related tax benefits (primarily EITC) during infancy led to a 0.023 (s.e. 0.011) or 2.3 percentage-point increase in the probability of graduating from high school.

We adjust the 2.3 percentage-point increase by the additional amount of transfers that treated individuals receive relative to a comparison group ($1,385.7 in 2019 dollars), 18 years of exposure, and an EITC take-up rate of 78%. We conclude that a $1,000 increase in household income from cash transfers would increase the likelihood of high school graduation by 0.1 percentage points or 0.2 percent (given an average graduation rate of 75%) per year. Following Garfinkel et al. (2022), we do not further monetize such increases because increased high school graduation rate is an intermediate outcome that is reflected in other outcomes such as higher future earnings.

C.1.b. Parents' Mental Health

Schmidt et al. (2023)

Authors found that a $1,000 increase in potential cash and food benefits would reduce severe psychological distress of single mothers by 0.0032 (s.e. 0.001) or 0.32 percentage points, and reduce moderate or severe psychological distress by 0.0061 (s.e. 0.003) or 0.61 percentage points. When broken down by program, a $1,000 increase in simulated refundable tax credits, TANF cash assistance, or SNAP in-kind benefits would reduce severe psychological distress by 0.0076 (s.e.

0.003), 0.0025 (s.e. 0.001), and 0.0045 (s.e. 0.003), respectively. The same increase by program would reduce moderate or severe psychological distress by 0.0112 (s.e. 0.006), 0.0045 (s.e. 0.004), and 0.0123 (s.e. 0.005), respectively. In terms of health behaviors, authors found that a $1,000 increase in potential cash and food benefits would reduce daily smoking by 0.0027 (s.e. 0.003) and reduce heavy drinking by 0.0018 (s.e. 0.004). Broken down by program, a $1,000 increase in simulated tax credits, TANF, or SNAP would reduce daily smoking by 0.0092 (s.e. 0.007), 0.0030 (s.e. 0.003), and 0.0026 (s.e. 0.005), respectively; or for heavy drinking as the outcome, these increases are associated with reductions of 0.0180 (s.e. 0.007), 0.0011 (s.e. 0.004), and 0.0038 (s.e. 0.007), respectively.

Authors used data from the National Health Interview Survey (NHIS) and CPS-ASEC. The sample was restricted to single mothers aged 18-64. Eligibility and benefits that CPS-ASEC families would receive from refundable tax credits, TANF, SNAP, and Medicaid were imputed by the authors. After eligibility and benefits were imputed for CPS-ASEC families, the authors then calculated the mean eligibility and benefits by state, year, and demographic characteristics. These mean benefits were used as measures of safety net generosity and they varied by state, year, and demographic characteristics. Mental health was assessed using the Kessler Psychological Distress Scale (K6). Indicators for heavy drinking and daily smoking were constructed based on NHIS survey questions. Authors regressed mental health/health behaviors on program generosity. Other controls in the model included individual characteristics (age of mother, number of children in the household, whether there was a child younger than 6, education of mother, race of mother, urban residence), state characteristics (unemployment rate, child support spending per capita, public housing and vouchers per capita), state fixed effects, and year fixed effects.

We use the results on severe psychological distress (rather than on moderate or severe psychological distress) because they are of a smaller magnitude and less likely to overstate benefits. To be consistent with other calculations, we do not use the results on health behaviors. We use the results broken down by specific program where available. Authors found that a $1,000 increase (2016 dollars) in simulated TANF cash assistance would reduce severe psychological distress by 0.25 percentage points. Authors found that a $1,000 increase in simulated TANF would increase actual TANF received by $353 in 2016 dollars, the equivalent of $375.15 in 2019 dollars. Thus, a $1,000 increase in actual TANF benefits in 2019 would reduce distress by 0.67 (0.25*1000/375.15) percentage points. It's unclear how many years of exposure to benefits have led to the reduction in maternal mental health. Given this ambiguity, we do not adjust the estimates for years of exposure. Finally, to obtain a treatment-on-the-treated effect, we divide the estimates by the program take-up rate. According to the authors, take-up rate was 35.3% for TANF. Dividing 0.67 percentage points by 35.3% gives us a 1.89 percentage-point decrease in severe psychological distress. We conclude that a $1,000 increase in TANF benefits would lead to a 1.89 percentage-point decrease in severe psychological distress.

We adopt the same standardization for the effects discovered for SNAP. Authors found that a $1,000 increase in simulated SNAP benefits would increase actual SNAP received by $528 ($561.13 in 2019 dollars). Adjusting the 0.45 percentage-point decrease in distress for the actual SNAP benefits (1000/561.13), and take-up rate (52.8% according to the authors), we conclude that a $1,000 increase in SNAP benefits would lead to a 0.8 percentage-point decrease in severe psychological distress.

Finally, we standardize the effects discovered for tax credit. Authors could not observe receipt of EITC benefits in the dataset so they did not estimate the increase in actual tax credits received from a $1,000 increase in simulated tax credits. To be conservative, we assume that a $1,000 increase in simulated tax credits leads to a $1,000 increase ($1062.75 in 2019 dollars) in actual tax credits received. Authors did not specify the take up rate of tax credits. The tax credits examined were the EITC and Child Tax Credit (CTC). The EITC take-up rate was around 80.53% in 2007 (the middle of the study period) according to Jones (2014). Adjusting the 0.76 percentage-point decrease in distress for the actual SNAP benefits (1000/1062.75) and the 80.53% take-up rate, we conclude that a $1,000 increase in tax credits would lead to a 0.76 percentage-point decrease in severe psychological distress. Following Garfinkel et al. (2022), we do not further monetize such increases because increased mental health is an intermediate outcome that is reflected in other outcomes such as increased self-reported health.

Appendix D. Reasons for Excluding Certain New Studies

D.1.

- Deshpande & Mueller-Smith (2022): This study examines the impact of losing SSI at age 18 on crime outcomes between ages 18 and 38. We exclude this study because unlike other cash transfer studies we have used, where treatment occurs at an early age, treatment occurs at age 18 in this study. Results are also not generalizable to child beneficiaries of a cash transfer because children receiving SSI often have physical or mental disabilities.

- Spencer et al. (2021): This study examines the impact of TANF benefits on child abuse and neglect reported by mothers. We believe the usage of a single difference — comparing children of eligible mothers to children of non-eligible mothers — is not strong enough for causal inference. In addition to including the maximum benefit as an independent variable in the regression, the study also includes a TANF-to-poverty ratio, which is another measure of TANF generosity. This complicates the interpretation of the coefficient for the maximum TANF benefit.

- Jones et al. (2022): This study examines the impact of EITC benefits on women's health. Its analysis sample includes childless women so results may not be generalizable to our group of interest: child beneficiaries of cash transfers and their mothers.

- Jo (2018): This study examines the impact of EITC benefits on children's weight. We exclude this study because weight, unlike self-reported health, is only a partial measure of health.

- East (2020): This study uses variation in immigrant parents' eligibility for Food Stamps to study the impact of Food Stamps on children's health. It's unclear whether results on children of immigrants can be and how to be generalized to all children.

- Batra & Hamad (2021): Both the treatment and the control group in this study receive EITC. The impact discovered is not driven by different amounts of EITC, but when the EITC is received.
- Kovski (2022): The ordinary least squares regression used by this study is not strong enough to uncover causal effects