

This is the appendix to the brief:

Koutavas, Anastasia, Buyi Wang, Irwin Garfinkel, Elizabeth Ananat, Sophie Collyer, Megan Curran, Robert Paul Hartley, and Christopher Wimer. 2025. [The economic costs of cutting SNAP: Every \\$1 in SNAP cuts to families with children costs society \\$14 to \\$20](#). Poverty and Social Policy Brief, vol. 9, no. 6. New York: Center on Poverty and Social Policy, Columbia University.

APPENDIX A. Estimating the impact of rolling back the TFP adjustment to SNAP

Below we describe our methods for estimating changes in SNAP benefits (and subsequently, changes in poverty) that are associated with revoking the 2021 TFP adjustment to SNAP. We utilize data from the 2016-2020 Annual Social and Economic Supplement to the Current Population Survey (CPS-ASEC), reflecting 2015-2019. We augment CPS-ASEC with data on SNAP benefits from the Urban Institute's TRIM3 microdata series, reflective of 2015-2019 to account for underreporting of SNAP benefits. Given that these data are reflective of 2015-2019, we first need to estimate SNAP benefit amounts based on *current* policy parameters in the TRIM3 data, and then again once estimating what SNAP benefits would amount to were the TFP adjustment revoked. The steps taken to produce these estimates are further described below, beginning with how we estimate the change in benefits that could result from the policy change, then how we apply this estimated change in benefits in the TRIM3 data, and finally, how we estimate the effects of this benefit change on the poverty rate.

Step 1: Identify the change in benefits associated with the 2021 TFP adjustment

The 2021 TFP reevaluation led to a 21.03% increase in maximum SNAP benefit levels.¹ However, this does not mean that all families received a 21% increase in benefits, because not all families receive the maximum benefit amount. **Instead, the TFP adjustment can be thought of as having “shifted up” the SNAP benefit calculation model, resulting in a constant dollar change in benefit levels for all recipients of the same unit size.** In other words, regardless of SNAP units' benefit values, SNAP units of the same size experienced the same absolute dollar change in their benefits – equal to the dollar value of the 21% increase to the maximum benefit available to their SNAP unit size (see rightmost column, Table A1).

To estimate the effect of the 2021 TFP adjustment to SNAP benefits, we begin with the June 2023 TFP value of \$973.30 for a family of four, which serves as the basis for maximum monthly SNAP benefits for Fiscal Year 2024.² We assume that this value includes the TFP adjustment; if it did not, the TFP value would be \$804 (as a 21.03% increase to \$804 would give us \$973). We assume that the maximum SNAP value for a four-person unit in 2024 would have been \$804 had the TFP adjustment to SNAP not taken effect. In order to determine the maximum benefits absent the TFP adjustment for households of different sizes, we apply the same adjustment factors as the USDA, such that smaller units receive a greater per-person benefit amount and larger units receive a smaller per-person benefit amount.³

¹ USDA (2021) [Thrifty Food Plan \(2021\)](#). Llobrera, Saenz, and Hall (2021) [USDA announces important SNAP benefit modernization](#).

² USDA FNS (2023) [Official USDA Thrifty Food Plan: U.S. Average, June 2023](#). Fiscal year 2024 defined as October 1, 2023 through September 30, 2024.

³ For more information on the benefit adjustments for different SNAP unit sizes, see the [USDA Food Plans monthly cost of food reports](#).

Table A1 below shares the maximum monthly SNAP benefit allotments in FY2024, and the estimated new maximum had the TFP adjustment to SNAP been revoked in that fiscal year, as described above.⁴

The rightmost column shows the dollar change in the maximum benefit for different unit sizes, which we apply in our simulation, as described in the next section. For a four-person unit in 2024, we estimate that revoking the TFP's SNAP adjustment would have resulted in \$169 in lost monthly SNAP benefits for all units of this size had such a policy gone into effect in FY2024.

Table A1. Estimated dollar change in maximum SNAP benefit levels after revoking the 2021 Thrifty Food Plan (TFP) adjustment to SNAP

<i>SNAP unit size (Number of people)</i>	<i>Maximum monthly SNAP benefit under current policy (FY 2024 includes TFP adjustment)</i>	<i>Maximum monthly benefit if TFP adjustment to SNAP revoked</i>	<i>\$ change in monthly maximum SNAP benefit</i>
1	\$291	\$241	-\$50
2	\$535	\$442	-\$93
3	\$766	\$633	-\$133
4	\$973	\$804	-\$169
5	\$1,155	\$954	-\$201
6	\$1,386	\$1,145	-\$241
7	\$1,532	\$1,266	-\$266
8	\$1,751	\$1,447	-\$304
9+	+\$219	+\$180	<i>*varies per unit size</i>

Source: Authors' calculations. Maximum monthly SNAP benefits levels derived from Fiscal Year 2024.

Note: SNAP units comprise of anyone in a household receiving SNAP benefits. There are cases where all members of a household are SNAP recipients and others where just a subset of household members are SNAP recipients. Additionally, we assume the same dollar change in benefits within SNAP units across all 50 states, including Alaska and Hawaii. This analysis does not account for further adjustments to the TFP in Alaska and Hawaii (see USDA, "[Thrifty Food Plan Cost Estimates for Alaska and Hawaii](#)"). Thus, results for Alaska and Hawaii should be interpreted with some caution.

Step 2: Estimating new SNAP benefits

Notably, the dataset used for this analysis, the 2016-2020 TRIM3 series, adjusts for the underreporting of SNAP benefits, providing more accurate estimates of SNAP benefit levels. However, this dataset precedes the 2021 TFP adjustment to SNAP benefits. For this reason, we use the SNAP benefit levels among recipients in this dataset as an approximation of what SNAP benefits would look like were the 2021 TFP adjustment to SNAP revoked, as they do not include the TFP adjustment.

We then match the changes in SNAP benefits estimated in Table A1 (right-most column) to each SNAP unit in the TRIM3 data based on the size of the SNAP unit in order to estimate how much their benefits would have increased with the TFP adjustment. Since this analysis uses data reflective of years 2015-2019, we deflate the benefit changes in the right-most column of Table A1 from their 2024 dollar value to the dollar value of each respective year of data using the CPI for each year.

We derive annualized estimates of each unit's increase in SNAP benefits with the TFP adjustment by multiplying their inflation-adjusted, monthly benefit change by the number of months that the SNAP unit is reported to have participated in the SNAP program according to the TRIM3 data.

⁴ In determining benefit amounts had the TFP adjustment to SNAP been revoked, we apply the same rounding methods as the USDA (rounding down to the closest integer).

After estimating the annual change in income that SNAP units could receive from the TFP adjustment to SNAP, we prorate the total annual income increase by the number of people in the SNAP unit. We then aggregate the prorated benefit amounts at the family level, or SPM-unit level. To analyze the economic costs of rolling back the TFP adjustment to SNAP, we utilize these estimates for changes in income at the family level, and specifically look at families with children. In all, we estimate that the change in SNAP benefits incurred by recipient families with children totals to \$15.1 billion, in 2024 dollars.

APPENDIX B. Literature on the impact of cash and near-cash transfers

Literature Search Methodology and Selection Criteria

In order to ensure a comprehensive list of literature on the benefits and costs of cash and near-cash transfer, Garfinkel et al., (2022, 2024) followed a meta-analysis approach to gather evidence. The authors used a three-stage screening process to identify relevant studies for each benefit and cost. This search methodology is described in detail in Garfinkel et al., (2022).

Literature on Impacts of Income

In this appendix, we present the detailed summaries and standardization of studies from Garfinkel et al., (2022, 2024), which are used by the authors to calculate the benefits and costs of giving cash and near-cash transfers to families with children. Assuming that giving and taking away cash and near-cash transfers have symmetrical effects, we use the following studies in our analysis to model the opposite scenario of taking cash and near-cash transfers away from families with children. Thus, the benefits of increasing transfers in Garfinkel et al., (2022, 2024) become the costs of reducing transfers in our analysis.

These studies examined the causal effects of cash and near-cash transfers on children's outcomes (future earnings, health in childhood and adulthood, longevity, educational attainment, and involvement in the child welfare system and criminal legal system) and parents' outcomes (health and longevity). Based on the increase in future earnings of children, Garfinkel et al., also calculated the increase in future tax payments of children and decrease in other transfers received by children. Based on the increase in health and longevity of children and adults, Garfinkel et al., calculated the resulting decrease in health expenditures and increase in longevity payments. Garfinkel et al., also estimated the increase in education cost from increased education, and reduction in expenditures on the child welfare and criminal legal system from less involvement in these systems. Garfinkel et al., standardized the findings across studies so they reflected the benefits and costs per \$1,000 increase in household income from cash and near-cash transfers per year. To calculate lifelong benefits and costs, Garfinkel et al., assigned the per-year benefits and costs throughout children's and parents' lives and calculated the present discounted value using a discount rate of 2%. If there were multiple studies for one outcome, Garfinkel et al., calculated the average. Table B1 presents the studies selected for the benefit-cost analysis. Only the impacts in Column A are used for the estimation of benefits and costs. Those listed in panel B and labeled supplementary studies are not used as that would involve double counting. The primary benefit of education is higher earnings, which are already counted. Similarly, the primary benefits of low birth weight are better health and eventually higher earnings, which are already counted. Improvements in mental health are encompassed by improvements in health.

Table B1. Impact studies used in Garfinkel et al., (2022,2024)

Panel A: Impact studies used for the calculation of benefits and costs	Panel B: Supplementary Impact studies
Children's earnings	Birthweight
Bailey et al. (2020)	Hoynes et al. (2015)
Bastian and Micheltmore (2018)	Kehrer and Wolin (1979)
Aizer et al. (2016)	Almond et al. (2011)
Hoynes et al. (2016)	Markowitz et al. (2017)
Price and Song (2018)	Children's educational attainment
Children's health during childhood	Thompson (2019)
Averett and Wang (2018)	Bastian and Micheltmore (2018)
Children's health during adulthood	Maxfield (2015)
Bailey et al. (2020)	Akee et al. (2010)
Hoynes et al. (2016)	Micheltmore (2013)
Price and Song (2018)	Aizer et al. (2016)
Braga et al., (2020)	Child receiving high school diploma
Song (2019)	Thompson (2019)
Neonatal mortality	Akee et al. (2010)
Almond et al. (2011)	Bastian and Micheltmore (2018)
Child longevity	Micheltmore (2013)
Bailey et al. (2020)	Maxfield (2015)
Aizer et al. (2016)	Parents' and other adults' mental health
Crime	Gangopadhyaya et al. (2020)
Bailey et al. (2020)	Boyd-Swan et al. (2016)
Barr & Smith (2023)	
Child protection	
Berger et al. (2017)	
Rittenhouse (2022)	
Parents' and other adults' health	
Larrimore (2011)	
Morgan et al. (2020)	
Evans and Garthwaite (2014)	
Price and Song (2018)	
Parents' and other adults' longevity	
Price and Song (2018)	
Aizer et al. (2020)	
Chetty et al. (2016)	

Children's Future Earnings

Aizer et al. (2016)

Aizer et al. (2016) found that in adulthood, sons whose mothers had received Mothers' Pensions between 1911 and 1935 experienced an increase in annual income of \$90.93 (s.e. 35.976), a 14% increase. As discussed in sections on children's longevity and children's educational attainment below, the authors also found an increase in longevity of 0.0158 (s.e. 0.007) or 1.16 years and an increase in educational attainment of 0.316 (s.e. 0.262) years. The authors matched administrative records, census records, and death records from 11 states to examine the long-term outcomes of male children who were raised in households who applied for the Mothers' Pensions between 1911 and 1935 (n=1,960). The authors compared the outcomes of children of accepted and rejected applicants using linear regressions. Rejected applicants were deemed to be an appropriate comparison group because like the accepted mothers, the rejected mothers were also economically constrained and sought aid, but they were somewhat better off (which is why they were rejected). So, in the absence of aid, their sons would have been expected to do somewhat better than the accepted sons, which implies that these estimates may somewhat understate the impact.

According to Aizer et al. (2016), Mothers' Pensions were \$3,684 (2019\$) annually and received for three years on average. A \$1,000 transfer for one year would thus increase children's future earnings by 1.27%⁵ ($0.14 \times ((1000/3684)/3)$). We believe that the level of future earnings of children whose mothers received Mothers' Pensions during Aizer et al.'s study period approximates the 25th percentile income in 2019. According to the Current Population Survey, in 2019, annual earnings were on average \$10,000 at the 25th percentile of the working-aged⁶ earnings distribution (authors' calculations). Multiplying \$10,000 by 1.27% yields an annual increase in earnings of \$127. We calculate the present discounted value using equation 1 below. We assume a discount rate of $i=0.02$. According to our calculation above, the early benefit $B=\$127$. The average child beneficiary is assumed to be age 9. We use this assumption in the calculation of all child benefits. Increased earnings are assumed to begin at age 22 ($a=22$) and end at age 64 ($A=64$). We use this assumption for all estimates on children's future earnings. We conclude that the present discounted value of increased earnings in adulthood is \$2,863 as a result of a \$1,000 cash transfer during childhood.

$$PDV = \sum_{t=a}^A \frac{B}{(1+i)^{t-9}} = B \left(\frac{(1+i)^{9-(a-1)} - (1+i)^{9-A}}{i} \right) \quad (1)$$

Hoynes et al. (2016)

Hoynes et al. (2016) examine the long-term health and economic impact of exposure to food stamps between conception and age 5 using the Panel Study of Income Dynamics (PSID). They found that among individuals whose parents were without a high school diploma, exposure to food stamps from conception to age 5 increased earnings by \$3,610 (s.e. 5,064). \$3,610 (measured in 1995 dollars) is the equivalent of \$6,063 in 2019 dollars⁷. As discussed in the section on children's health, they also found that among the full sample, exposure to food stamps from conception to age 5 decreased the probability of having metabolic syndrome by 0.438 (s.e. 0.204) standard deviations and increased the probability of reporting good health by 0.292 (s.e. 0.133) or 30 percentage points. The authors conducted difference-in-differences analyses taking advantage of variation in the introduction of the Food Stamp Program by county. The intent-to-treat group included individuals whose parents were without a high school diploma and who did not receive food stamps as well as those whose parents were without a high school diploma but did receive food stamps. Models controlled for county, year of birth fixed-effects, year of interview, whether child was born to a female-headed household, education of head of household, family income, the child's gender, child's marital status, child's race, quadratic in age of child, state linear time trends, and 1960 county characteristics.

⁵ Note that 1.27% is a rounded number. Even though in calculations we use the unrounded number, in the text we present the rounded number.

⁶ By working-aged, we refer to ages 25 to 64.

⁷ The paper starts measuring economic outcomes such as earnings in adulthood when individuals reach age 25. Since the sample includes individuals born between 1956-1981, this means that earnings in adulthood are first measured in 1981. The last wave of PSID data used by the paper is 2009. Thus, we assume that \$3610 is measured in 1995 dollars (the middle of the period 1981-2009).

Hoynes et al. (2016) estimate that among families where heads had less than a high school degree, 43 percent participated in food stamps. Thus, in order to adjust results to reflect the impact on treated individuals we divide their results by 0.43, resulting in an estimate of \$14,100 ($\$6063/0.43$). Since individuals in the sample were exposed to food stamps for 7 years (from conception (age -1) to age 5), the estimate decreases to \$2,014. Average annual food stamps values per person in 1972 (near the midpoint of the study period) were \$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. Thus, the impact decreases to \$675 ($\$2014 \times (1000/2982)$). As the paper studies the impact of exposure from conception (age -1) to age 5, we (conservatively) assume that individuals were exposed to food stamps through the entirety of childhood (from age -1 to age 17) but only derived benefits for future earnings during the first 7 years of payments. To measure the impact per year of payments, we multiply results by the 7/19 of years in which they derive benefits, yielding an estimate of \$249. Using equation 1, we conclude that the present discounted value of increased earnings in adulthood is \$5,624 as a result of a \$1,000 cash transfer during childhood.

Bailey et al. (2020)

Bailey et al. (2020) found that exposure to food stamps from conception to age 5 increased future earnings by 0.0114 (s.e. 0.0034) or 1.14 percent. The authors find no additional effects for exposure at ages 6-18. As discussed in the sections on children's health, children's longevity, and on crime reduction, they also discovered that as a result of exposure to food stamps, children's physical ability and health increased by 0.0013 standard deviations (s.e. 0.0013), children's longevity increased by 0.176 years (s.e. 0.030), children's future earnings increased by 1.14 percent (s.e. 0.34 percent), adult economic self-sufficiency increased by 0.0043 standard deviations (s.e. 0.0016), and the probability of being incarcerated decreased 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.

Since children in the sample were exposed to food stamps for 7 years (conception to age 5), we divide 1.14 percent by 7, arriving at 0.16 percent. Average annual food stamps values per person in 1972 (near the midpoint of the study period) were \$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. Thus a \$1,000 cash transfer would increase earnings by 0.055 percent ($0.0016 \times (1000/2982)$). Then, we convert the intent-to-treat estimate to an estimate of the treatment effect on the treated. Using the Panel Study of Income Dynamics, the authors estimate that 16 percent of children participated in food stamps between 1975 and 1977. Thus, we divide 0.055 percent by 0.16, yielding 0.34 percent. The authors report that the natural log of the average labor income of the full samples is 10.57, which equals \$38,948.67. Income data spans from year 2000 to 2013 so the midpoint is year 2006. \$38,948.67 in 2006 dollars equals \$49,169 in 2019 dollars. Thus, the estimate becomes \$168 (0.0034×49169) increase in income per year. As the paper studies the impact of exposure from conception (age -1) to age 5, we (conservatively) assume that child recipients were exposed to food stamps through the entirety of childhood (from age -1 to 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 \$62. Using equation 1, we conclude that the present discounted value of increased earnings in adulthood is \$1,397.

Bastian and Micheltmore (2018)

Bastian and Micheltmore (2018) found that an additional \$1,097 in EITC (2019 dollars) exposure during childhood was associated with an increase in earnings of \$646.1 (s.e. 818.3) among children exposed between ages 0 and 5, an increase in earnings of \$42.4 (s.e. 415.1) among children exposed between ages 6 and 12, and an increase in earnings of \$564.0 (s.e. 244.9), among children exposed between ages 13 and 18. As discussed in the section on children's educational attainment, the exposure was also associated with a 0.012 (s.e. 0.003) or 1.2 percentage-point higher probability of completing high school, a 0.013 (s.e. 0.005) or 1.3 percentage-point higher probability of completing college and a 0.008 (s.e. 0.004) or 0.8 percentage-point higher chance of being employed in young adulthood among children

exposed between ages 13-18. The 1968-2013 waves of the Panel Study of Income Dynamics (PSID) were used to examine the impact of exposure to the federal and state EITC between 1967 and 1995 (n=3,495). The authors measured EITC exposure using the maximum potential federal and state credit a household could receive based on the year, state, and number of children in the household. F-statistics using this maximum credit to predict increased family income were well above the critical value for weak instruments.

To simplify our calculations, we first determined an average impact across all ages by multiplying each of Bastian and Micheltore's estimates for the three age groups times the proportion of children in that age group. According to Bastian and Micheltore (2018), children exposed to EITC from ages 0-5, from ages 6-12 and from ages 13-18 make up 21.6%, 40.4% and 38% of their samples, respectively. Thus, the weighted average impact is \$371 ($[646.1 \times 0.216] + [42.4 \times 0.404] + [564.0 \times 0.38]$). Bastian and Micheltore (2018) measure earnings in 2013 dollars. \$371 in 2013 dollars is \$407 in 2019 dollars. We find that \$1,000 of EITC, in 2019 dollars, increased children's earnings in adulthood by \$371 ($407 \times (1000/1097)$). However, these results are for multiple years of exposure to the EITC and include all children in states in which the maximum EITC increased, not just recipient children. We assume the child was exposed to the EITC from age 0-17 (a total of 18 years), yielding a \$21 ($\$371/18$) increase in earnings per year of exposure. To convert this intent-to-treat estimate to an estimate of the effects on the treated, we divide \$21 by the percentage of EITC-eligible households that received the EITC in 1990 (the middle of the study period), which was 83% (Scholz 1994)⁸, resulting in a \$25 increase in earnings for a \$1000 transfer. Using equation 1, we conclude that the present discounted value of increased earnings in adulthood is \$561, as a result of a \$1,000 cash transfer during childhood.

Price and Song (2018)

Price and Song (2018) found that an additional \$2,962 (2019 dollars) in cash transfers annually for three to five years decreased children's future earnings by \$356 (s.e. 601). As elaborated in the sections on children's health, adult health and adult parent longevity, in consequence of the transfer, the probability of children applying for disability benefits (either means-tested and non-means-tested) in adulthood increased by 0.537 percentage points (s.e. 1.25), disability benefits application rate increased among parents by 0.063 (s.e. 0.0199) or 6.3 percentage points, and the likelihood of death rose among parents by 0.0138 (s.e. 0.0196) or 1.38 percentage points. They used long-term outcomes of the Seattle-Denver Income Maintenance Experiment (SIME/DIME) to examine the impact on families (n=52,867) who were randomized to receive cash transfers. On average, the treatment group received \$2,962 (2019 dollars) more in transfers annually than the control group for either three or five years, depending on treatment group. Long-term outcomes were measured by matching experimental data with data from the Social Security Administration and Washington State Department of Health. Regressions were conducted via least square, with the main independent variable being a dummy on treatment status. Other controls in the model included indicators for treatment location, race, family type, gender, manpower treatment status, birth date/age and year fixed effects.

\$356 is measured in 2013 dollars and in 2019 dollars it would be \$391. Adjusting for years of exposure, we divide -\$391 by 4 (the unweighted average of 3 and 5) and derive -\$98. Finally, to estimate the impact of a 1,000 transfer, we multiply -\$98 by (1000/2962). The final estimate is a \$33 decrease in earnings per year, or \$746 decrease in the lifetime.

Children's Health

Monetizing the Value of Life and Health

We follow the standard practice to measure the monetary value of improvements in health using quality-adjusted life-years (QALY). QALY quantifies the impact of disease burden on a person's life expectancy as well as quality of life. In our analysis, we use a QALY value of \$126,628 for perfect health and \$0 for death, meaning that a year of living in perfect health has a monetary value of \$126,628. This value falls within the value of a QALY in the US recommended by the Institute for Clinical and Economic

⁸ Scholz (1994) estimated an EITC participation rate of 80.5-86.4 percent. We use the average of this range of values, which is approximately 83%.

Review (Institute for Clinical and Economic Review 2020). We assume that the change in the value of a year of life as one moves from perfect health to death is linear.

It is also worth noting here that we use mother-reported measures of their own and their child's overall health status as our key measure of health impacts. Other measures available are consistent with the mother-reported measures, but mothers' reports are the only measures that are common to all of the studies we use. Self-reports of health status such as we are using have also been documented to be a good predictor of longevity (McGee et al. 1999; Miilunpalo et al. 1997). Overall health status is reported as either excellent, very good, good, fair, or poor, with excellent health having a rating of 5 and poor health a rating of 1. We add another status, "death", with a rating of 0, for self-reported health to fully capture the value of QALY. Excellent health corresponds to a full QALY value of \$126,628 and death corresponds to a QALY value of \$0.⁹

Birthweight

-Kehrer & Wolin (1979)

Kehrer & Wolin (1979) found that participation in the NIT through the Gary Income Maintenance Experiment (GIME) among the low-income Black population changed birthweight by between

-0.26 (s.e. 0.07) and 1.17 (s.e. 0.41) pounds. The GIME was conducted in Gary, Indiana between 1970 and 1974 and consisted of a negative income tax designed to replace welfare programs in place at the time (n= 1,799). Guarantees provided to families differed by family size— participants were randomly assigned to four treatment groups with a combination of tax rates (40% or 60%) and guarantee levels (\$4,300, approximately the 1971 poverty line, or \$3,300). The experiment was limited to the number of children born during the experiment. Tobin's maximum likelihood method (Tobit) was conducted on four treatment groups and controlled for numerous household characteristics.

We use Kehrer and Wolin (1979)'s results to measure the impact of a \$1,000 increase in household income in utero on birthweight. Using the midpoint of results, we find that participation in the NIT increased birthweight by 0.455 pounds, or 6.5 percent on average (out of an average birthweight of 7 pounds of the control group). The paper doesn't specify the exact amount of payment received by an average treated family, but according to the report by U.S Senate and Congress, Welfare Research and Experiment (1978), by the end of 1973, average payment to a treated, female-headed family in the Gary experiment was \$258 a month, the equivalent of \$17,942 per year in 2019 dollars. Since the majority of participants in the Gary experiment were female-headed families, we take the \$17,942 as the amount of payment received by an average participating family. Thus, \$1,000 in an income transfer results in 0.36 percent ($0.065 \times 1000 / 17942$) increase in birthweight.

-Almond et al. (2011)

Almond et al (2011) found that having adjusted for program participation rate, receipt of income transfers from food stamps during the third trimester resulted in an 0.52 percent increased birthweight for White infants, 0.91 percent increased birthweight for Black infants, a 7.63 percent lower fraction of low-birth-weight infants (<2,500 grams) among White infants, and an 8.7 percent lower fraction of low-birth-weight infants among Black infants. The authors combined annual reports of food stamp caseloads from the USDA, county population data, and birth and death data from the National Center for Health Statistics between 1968 and 1977 (n=125,159). Treatment is measured as whether food stamps were introduced during the quarter prior to birth as a proxy for the third trimester. They used variation in the introduction of the food stamp program by county and year to examine the effects of program participation on birth outcomes and infant mortality using a difference-in-difference design.

⁹ Ideally, valuing quality of life is also done with a more detailed measure of current health but such data were not available in most studies and self reported health is considered to be very reliable. The National Center for Health Statistics has used similar measures of self-reported health (paired with physical limitations) to measure quality of life using a scale in which zero is death and 1 is excellent health (Gold et al., 1996).

We use Almond et al. (2011)'s results to measure the impact of a \$1,000 increase in household income in utero on birthweight. White infants make up 78% of the sample while Black infants make up 22% of the sample. Average annual food stamps values per person in 1972 (near the midpoint of the study period) were \$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. Taking a weighted average of the results for Black and White recipients, we find that a \$1,000 income transfer in the form of food stamps yields an increase in birthweight of 0.2 percent $((0.52*0.78+0.91*0.22)*(1000/2982))$ and a decrease in the probability of low birthweight of 2.64 percent $(7.63*0.78+8.7*0.22)*(1000/2982))$.

-Hoynes et al. (2015)

Hoynes et al. (2015) found that the 1993 expansion of the federal EITC during the third trimester of pregnancy decreased the rate of low birthweight by 0.132 percentage points (s.e. 0.072) relative to an average rate of 8.1 percent among White participants, and 0.728 percentage points (s.e. 0.143) relative to an average rate of 14.4 percent among Black participants. White and Black participants make up 46 percent and 29 percent of the sample, respectively. The weighted average is thus 2.2 percent $(0.46*0.132/8.1 + 0.29*0.728/14.4)$. The authors used the U.S. Vital Statistics Natality Data, which includes all births from 1983-1999, and the March Current Population Survey (CPS), focusing on single mothers 18 years or older with a high school education or less ($n=76,444$) because single filers with children made up about three-quarters of EITC payments and because less-educated parents are more likely to be eligible for the EITC.

The authors found that the impact of the EITC expansion on after-tax income was approximately \$1,850 in 2019 dollars. Thus, a \$1,000 increase in income as a result of a cash transfer decreases the rate of low birthweight by 1.2 percent $(0.02*1000/1850)$.

-Markowitz et al. (2017)

Markowitz, Komro, Livingston, Lenhart, & Wagenaar (2017) found that exposure to EITC increased birth weight by between 16.845 (s.e. 6.883) and 27.307 (s.e. 6.083) grams among states with a refundable credit, and between 9.441 (s.e. 3.605) and 12.681 (s.e. 3.680) grams among states with a non-refundable credit. The authors use U.S. National Vital Statistics System birth data, limiting to mothers with a high school education or less ($n= 20,206,601$), paired with characteristics of state EITCs, including generosity and refundability, from 1994-2013 to examine the impact of state EITC income on birthweight. Supplementary analyses were further conducted separately by marital status, but results did not differ significantly from the primary findings.

We use Markowitz et al. (2017)'s results to measure the impact of a \$1,000 increase in household income during childhood on birthweight. Using the midpoint of results, EITC exposure increases birth weight by 22.076 grams, or 0.67 percent (the average birthweight of the sample is 3280.36 grams), in states with a refundable credit and 11.06 grams, or 0.34 percent, in states with nonrefundable credits. The median state EITC was 10 percent of the federal EITC over the period, representing approximately \$248 in 2019 dollars (Internal Revenue Service, 2019). Rescaled to estimate the effect of \$1,000 in income transfer, the study's results indicate that birth weight would increase by 2.71 percent $(0.0067*1000/248)$ in states with a refundable credit and 1.36 percent $(0.0034*1000/248)$ in states with a nonrefundable credit. Adjusting these results to apply only to the 75 percent of EITC-eligible households that are "treated" through actual receipt of an income transfer in 2005 (near the middle of the study period 2004) (Internal Revenue Service, 2009), our estimates indicate an increase in birthweight of 3.62 percent among states with a refundable credit and 1.81 percent among states with a nonrefundable credit as a result of a \$1,000 cash transfer.

Child Neonatal Mortality

Our literature search yielded one quasi-experimental study examining the relationship between cash or near-cash transfers and neonatal mortality (death in first 28 days), by Almond et al. (2011). The authors' estimates relied on a dataset that combined annual reports of food stamp caseloads from the USDA, county population data, and birth and death data from the National Center for Health Statistics between 1968 and 1977 (n=125,159). Treatment was measured as whether food stamps were introduced during the quarter prior to birth (as a proxy for the third trimester). The authors used variation in the introduction of the Food Stamp Program by county and year to examine the effects of program participation on birth outcomes and infant mortality using a difference-in-difference design. They found that receipt of income transfers from food stamps during the third trimester resulted in a decrease in the neonatal mortality rate among White infants by between 0.0158 (s.e. 0.1194) and 0.0806 (s.e. 0.1242) per 1,000 live births, and among Black infants by between 0.0067 (s.e. 0.4610) and 0.6551 (s.e. 0.4793) per 1,000 live births. Adjusted for program participation rates, the treatment on the treated effect is a 3.4 percent lower neonatal mortality rate for White infants and a 4.02 percent lower rate for Black infants.

White infants make up 78% of the sample while Black infants make up 22% of the sample. Taking a weighted average of the results of Black and White infants results yields a decrease in neonatal mortality of 3.53 percent ($3.4 \text{ percent} \times 0.78 + 4.02 \text{ percent} \times 0.22$) at the time of food stamps rolling out. Average annual food stamps values per person in 1972 (near the midpoint of the study period) were \$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. Therefore, we extrapolate that a \$1,000 increase in annual food stamps would decrease neonatal mortality by 1.19 percent ($0.0353 \times (1000/2982)$). According to UNICEF (2020), in 2019 the neonatal mortality rate in the United States was 0.37 percent. Therefore, the estimated change in neonatal mortality is 0.0044 percentage points (0.0119×0.0037).

We monetize changes in mortality using a \$9.88 million VSL. To calculate the value of the declines in neonatal fatalities, we multiply the VSL by the 0.0044 percentage-point reduction in mortality. Because the life saved by reducing neonatal fatalities comes during the first year of life rather than in a future year, there is no need to discount the value to the present. We conclude a \$1,000 increase in household income as a result of a cash transfer decreases neonatal mortality by a value of \$433 (9876998×0.000044). Lastly, to account for the 19 years of exposure (from conception through age 17), during which time this benefit is only received in the first year, we divide results by 19, decreasing our final estimate of the effects of an annual \$1,000 transfer during childhood on neonatal mortality to \$23.

Children's Health from One Month of Age Onward

Many studies measuring improvements in health rely upon a self-rated health measure. Self-rated health, in most cases, includes five categories (poor, fair, good, very good, or excellent). We use the self-rated health scale to measure the quality component of QALY. However, self-rated health may not fully capture QALY as there is still some potential value in having poor health as opposed to death. Therefore, we include "death" as an additional category to all self-rated health measures. We assume the distance between each point is equal, ranging from zero (death) to five (excellent health).

-Averett and Wang (2018)

Averett and Wang (2018) found that increased income under the 1993 federal EITC expansion had the following effects among households with two or more children relative to one-child households with smaller EITC transfers: increased mother-rated reports of children's health by 0.2294 points (s.e. 0.2000) on a scale from 1 to 4 (with 1 being *poor*, 2 being *fair*, 3 being *good* and 4 being *excellent*), decreased accident rates by 0.0546 (s.e. 0.0275) or 5.46 percentage points, increased the frequency with which mothers sought medical attention for a child's illness by 0.0274 (s.e. 0.0410) or 2.74 percentage points, and increased reports of behavioral problems (measured by a standardized z-score) by 0.2435 standard deviations (s.e. 1.1146). The study used the 1979 National Longitudinal Survey of Youth (NLSY79) and the NLSY79 Child and Young Adult (NLSCYA) data and focused on mothers with fewer than 13 years of

education as a proxy EITC eligibility ($n=12,686$). Difference-in-difference and mother fixed effects frameworks were employed to measure the increase in mothers' report of overall child health. Models controlled for characteristics of mothers and children and for state fixed effects.

We first use the result on mother-rated health for calculation. In order to examine the average impact of a \$1,000 cash transfer we first establish that as a result of the EITC expansion, families with two or more children received an increase in EITC benefits that are \$1,226 (2019\$) greater than families with one child.¹⁰ Therefore, we estimate that mother-rated health of children would increase by 0.19 points ($0.2294 \times 1000 / 1226$) as a result of a \$1,000 cash transfer. Next, we divide the impact by years of exposure. We assume children were exposed to the EITC through the entirety of childhood or 18 years (from age 0-17), decreasing the impact to 0.01 points per year. We value the benefit of improved health by utilizing the QALY value of \$126,628, described in greater detail in the children's health section in the main text. To make sure that mother-rated health captures the full value of QALY, we add a category of "death" to the scale and give it a value of zero. Thus, death represents \$0 of QALY while excellent health (value of 4) represents the full value of \$126,628. A 0.01-point increase in absolute value of the scale thus represents a 0.26 percent improvement in health ($0.01/4$). We therefore estimate that a \$1,000 cash transfer increases quality of life by a value of \$329 every year ($\$126,628 \times 0.0026$) during childhood.

We then use the result on the frequency with which children suffer from accidents or injuries for the calculation. Having adjusted for \$1,226 EITC benefits in 2019 dollars and 18 years of exposure, we obtain a decrease in frequency of 0.25 percentage points per year. To keep the calculation consistent throughout the children's health section, we assume that moving from having no accidents or injuries to having accidents or injuries captures one-sixth of the value of QALY (this assumption is tied to the calculation of metabolic syndrome index in Hoynes et al. 2016, as discussed later). We estimate that a 0.25 percentage points decrease in frequency of accident and injuries per year translates into a \$52 increase in children's health per year ($(\$126,628/6) \times 0.0025$) during childhood.

The result on the frequency of illness that requires medical attention could suggest a decline in children's health. Having adjusted for \$1,226 EITC benefits in 2019 dollars and 18 years of exposure, we obtain a 0.12 percentage-point increase in the frequency per year. Assuming that having an illness that requires medical attention captures one-sixth of the value of QALY, we estimate that children's health decreased by \$26 per year during childhood.

The result on children's behavioral problems also suggests a decline in children's health. Having adjusted for \$1,226 EITC benefits in 2019 dollars and 18 years of exposure, the increase in behavioral problems becomes 0.01 standard deviation per year. Assuming that one standard-deviation of the behavioral health measure represents one-sixth of \$126,628, a 0.011 standard-deviation increase in behavioral problems per year represents a loss of \$233 per year.

We calculate the present discounted value using equation (1). We assume a discount rate of $i=0.02$. We do not discount the yearly benefit at age 9 and start discounting the yearly benefit from age $a=10$ to $A=21$. Giving all four results equal weight, we obtain a mean present discounted value of \$354.

-Hoynes et al. (2016)

Hoynes et al. (2016) examine the long-term health and economic impact of exposure to food stamps between conception and age 5 using the Panel Study of Income Dynamics (PSID). They found that among the full sample, exposure to food stamps from conception to age 5 decreased the probability of having metabolic syndrome by 0.438 (s.e. 0.204) standard deviations and increased the probability of reporting good health by 0.292 (s.e. 0.133) or 29.2 percentage points. Metabolic syndrome is measured using an average standardized z-score of five binary components (obesity, high blood pressure, diabetes, heart disease, and heart attack). Report of good health is based on a self-reported health measure, with scale

¹⁰ According to Averett and Wang (2018), families with one eligible child receive an average EITC benefit of \$822 in 1992 dollars pre-expansion and \$1374 post-expansion. Families with two or more eligible children receive an average EITC benefit of \$747 pre-expansion and \$1970 post expansion. The increase for families with two or more eligible children is \$671 in 1992 dollars greater than the increase for families with only one child.

from 1 to 5 (with 1 being excellent, 2 being very good, 3 being good, 4 being fair, and 5 being poor). Both results on metabolic syndrome and report of good health are treatment-to-treated effects and suggest improvement in health.

We first calculate an estimate using the result on metabolic syndrome. As discussed above, average annual food stamps values per person in 1972 (near the midpoint of the study period) were \$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. Children in the sample were exposed to food stamps for 7 years (from conception (age -1) to age 5). As a result, a \$1000 cash transfer would lead the probability of metabolic syndrome to decrease by 0.021 standard deviations ($0.438 \times (1000 / (2982 \times 7))$). As the paper studies the health impact of exposure from conception (age -1) to age 5, we (conservatively) assume that child recipients were exposed to food stamps through the entirety of childhood (from age -1 to age 17) but only derived benefits for future health during the first 7 years of payments. To measure the impact per year of payments, we multiply results by the 7/19 of years in which they derive benefits, decreasing the impact to 0.0077 ($0.021 \times 7/19$) standard deviations per year. We assume that six standard deviations of the metabolic syndrome index approximately capture the full range of quality of life: a standard deviation of -3 would equate to a QALY value of \$0 and a standard deviation of 3 would equate to a QALY value of \$126,628. We assume the distance between each standard deviation (an absolute value of 6) is equal so one standard deviation captures 1/6 of the value of \$126,628. If a \$1000 increase in household income during childhood from a cash transfer decreases the probability of having metabolic syndrome by 0.0077 standard deviations per year, the benefit is then \$163 ($0.0077 \times (126628/6)$) per year.

An estimate can also be calculated based on the result on probability of reporting good health. A \$1,000 cash transfer would lead the probability of reporting good health to increase by 1.4 percentage points ($0.292 \times (1000 / (2982 \times 7))$). To measure the per year impact, we assume that children are exposed to food stamps during the entire childhood (age -1 to 17) but only derive health benefits for 7 years (age -1 to age 5). Thus, we multiply 1.4 percentage points by (7/19) and obtain a per year impact of 0.52 percentage points. We measure improved health using QALYs. We measure quality of life using a scale that includes death and the five categories in the self-rated health measure (poor, fair, good, very good, or excellent). With death having a value of 0 and excellent health having a value of 5, the maximum increase in health would be an increase of 5 points. We equate death to a QALY value of \$0 and equate excellent health to a QALY value of \$126,628. Therefore, an increase of one unit of health quality for one year would be valued at $(126,628/5)$. A 0.52 percentage points per year increase in probability of good health would result in a benefit of \$131 ($0.0052 \times (126,628/5)$) per year.

We assume the average age of child beneficiaries to be 9 and the average age of death to be 78 and that the increase in physical health occurred from age 22 to age 78. Giving results on metabolic syndrome and probability of good health equal weight, we conclude that the present discounted value of improved health is \$3,917.

-Bailey et al. (2020)

Bailey et al. (2020) found that exposure to food stamps from conception to age five increased physical ability and health, measured between the ages of 25 and 46 using a comprehensive index, by 0.0013 standard deviations (s.e. 0.0013).

The health index used by Bailey et al. (2020) is a standardized z-score and measures whether the respondent has a work disability, ambulatory difficulty, cognitive difficulty, independent living difficulty, vision or hearing difficulties, and/or self-care difficulty. The estimate of 0.0013 standard deviations improvement in physical health was derived from a sample that included all children who were exposed to food stamps rollout and was not limited to recipients. To adjust for this, we divide 0.0013 by the percentage of children in this age group who received food stamps, 16% (calculated by Bailey et al. using the PSID), increasing the impact to 0.008 standard deviations. Since children in the sample were exposed to food stamps for 7 years (conception to age 5), we divide 0.008 standard deviations by 7 and yield 0.001 standard deviations.

Again, the typical household food stamps value in 2019 dollars would be \$2,982. The impact of a \$1,000 benefit in 2019 dollars is thus 0.001 times the ratio of \$1000/\$2982, or 0.0004. As the paper studies the health impact of exposure from conception (age -1) to age 5, we (conservatively) assume that child recipients were exposed to food stamps through the entirety of childhood (from age -1 to age 17) but only derived benefits for future health during the first 7 years of payments. To measure the impact per year of payments, we multiply results by the 7/19 of years in which they derive benefits, decreasing the impact to 0.0001 ($0.0005 \times 7/19$) standard deviations per year.

Assuming that one standard-deviation of the physical health measure represents one-sixth of \$126,628, a 0.0001 standard-deviation increase in physical health per year is equivalent to \$3 ($0.000143 \times 126628/6$) per year. Using equation (1), we conclude that the present discounted value of increased health in adulthood is \$81 as a result of a \$1,000 cash transfer during childhood.

-Price & Song (2018)

Price and Song (2018) found that a transfer of \$2,962 (2019 dollars) for three to five years increased the probability of children applying for disability benefits (either means-tested and non-means-tested) in adulthood by 0.537 percentage points (s.e. 1.25).

Given that a treated family received an average of \$2,962 (2019 dollars) more transfer income for 3 to 5 years, we adjust the 0.537 percentage point impact on future disability assistance participation based on the unweighted average of 4 years of exposure. A cash transfer of \$1,000 would imply an impact of 0.181 percentage point ($0.537 \times 1000/2962$) for 4 years of exposure, or 0.0453 percentage points ($0.181/4$) higher disability assistance participation per year of childhood receipt. Assuming that moving from not applying for disability benefits to applying for disability benefits reflects a decline in one-sixth of value in health, we estimate that a \$1,000 cash transfer decreases quality of life by a value of \$10 every year ($-0.000453 \times 126628/6$). Using equation (1), we conclude that a \$1,000 transfer is associated with a present discounted value of -\$255 in children's health in adulthood.

-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 ($1.7 \times 1000/104.57$). 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 \$7,351.

-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 \$1,557 in increased adulthood health, following a \$1,000 increase in household income from cash transfer per year.

Child Longevity

Aizer et al. (2016)

Aizer et al. (2016) found that in adulthood, sons whose mothers had received Mothers' Pensions experienced an increase in longevity of 0.0158 (s.e. 0.007) or 1.16 years.

The \$20 monthly transfer in 1922 would be worth \$307 in 2019, or \$3,684 annually for on average three years. Therefore, a \$1,000 transfer for one year would increase children's life by 0.10496 years (1.16*(1000/3684)/3). Applying the QALY value, an increase in longevity of 0.105 years would be valued at \$13,291 (0.10496*\$126,628). Using assumptions described above, we calculate the present discounted value as $B/(1+i)^{t-9}$, with B=13291, i=0.02 and t=78. We conclude that the present discounted value of increased longevity in adulthood is \$3,390 as a result of a \$1,000 cash transfer during childhood.

Bailey et al. (2020)

Bailey et al. (2020) found that exposure to food stamps from conception to age 5 increased longevity by 0.176 years (s.e. 0.030). This estimate includes all children who were exposed to food stamps and is not limited to recipients. To adjust for this, we divide 0.176 by the percentage of children in this age group who received food stamps, 16% (calculated by Bailey et al 2020 using the PSID). Thus, the treatment-on-the-treated outcome is 1.1 years ($0.176/0.16$). Children in the sample were exposed to food stamps for 7 years (conception to age 5), so the impact decreases to 0.16 ($1.1/7$) years in longevity. As discussed above, family food stamps value in 2019 dollars was \$2,982 on average. Thus, the impact becomes 0.05 years ($0.16 \times 1000/2982$). As the paper studies the impact of exposure from conception (age -1) to age 5, we (conservatively) assume that child recipients were exposed to food stamps through the entirety of childhood (from age -1 to age 17) but only derived benefits for future health during the first 7 years of payments. To measure the impact per year of payments, we multiply results by the 7/19 of years, decreasing the impact to 0.0194 years in longevity per year. We value this increase in life expectancy using QALY. The increase in longevity is thus worth \$2458 ($0.0194 \times \$126,628$). Assuming that the extension of life occurred at age 78 (conservative, given that the mortality improvements in this study occurred at ages 25-64 so with our assumption we are discounting mortality improvements by more years), we calculate the present discounted value of increased longevity in adulthood as $2458/(1.02)^{69}$, which implies a benefit of \$627 as a result of a \$1,000 cash transfer during childhood.

Avoided Health Expenditures for Children

Beam et al. (2020)- Decline in Healthcare Expenditures in First Six Months of Life

Beam et al. (2020) examine healthcare expenditures among low-birthweight infants for the first six months of life. The study used data on approximately 45 million individuals with a private insurance plan through Aetna from January 2008 through February 2016. Healthcare expenditures include the total amount paid to providers of medical services from both insurer and patient. The authors descriptively find that in 2019 dollars, low-birthweight infants had a median healthcare cost of \$51,975 ($n=32,508$) compared to a median cost of \$4,066 for normal birthweight infants ($n=727,538$). The authors further conducted a generalized linear regression with a logarithmic link function and a gamma distribution to examine the association between birthweight and spending. Spending was measured in the regression analysis as a “spending multiplier,” which represents the multiplicative increase in average spending on a log scale. Regressions controlled for sex, gestational age in weeks, and the occurrence of adverse birth events. Compared to infants greater than 2000 grams, infants of 1750-1999 grams experience the smallest increase in expenditure, by a multiple of 1.34 [1.26, 1.43] (95-percent confidence intervals in brackets) and infants of 500-749 grams experience the largest increase in expenditure, by a multiple of 2.81 [2.27, 3.48]. The increased healthcare expenditures implied by these estimates ranges from \$5,449 to \$11,426 in 2019 dollars (\$4,066 multiplied by 1.34 or 2.81)

As stated above, through estimates of Almond et al. (2011), we calculate the impact of a \$1,000 cash transfer on the probability of low birthweight. In 2017, 8.3 percent of live births were low birthweight (Beam et al., 2020). Based on these results and the lower and upper-bound health expenditures of Beam et al., (2020), we calculate the mean savings in healthcare expenditures from decreased probability of low birthweight to be \$18.

Healthcare Expenditure Elasticity

We rely on the results of three studies to determine the rate at which healthcare expenditures decrease in relation to increases in health status. Although the studies are not causal, no quasi-experimental study exists, to our knowledge, examining this relationship.

Chern, Wan, and Begun (2002) found that a one percent increase in SF-36 score was associated with 0.19 percent ($p < 0.001$; s.e. not available) decrease in health expenditures. The study sample included 4,255

randomly selected Trigon BlueCross/BlueShield policyholders in Virginia. The sample was limited to adults between the ages of 18 and 64. Health status was measured in 1994 using the MOS 36-Item Short-Form Health Survey (SF-36). The SF-36 measure used included five dimensions of health and ranged from 0-100 points (physical functioning, role limitations due to physical health problems, body pain, general health, and social functioning). Healthcare expenditures were measured in 1995 and include out-of-pocket expenditures and expenditures covered by insurance. Using a structural equation modeling framework, the authors examined the association between health status and healthcare expenditures, controlling for age, gender, marital status, educational attainment, occupation, race, smoking behavior, high cholesterol, high blood pressure, diabetes, household income, point-of-service (POS) health plans, and Preferred Provider Organization (PPO) health plans. Since their estimate indicates that a one percent increase in health leads to a 0.19 percent decrease in health expenditures, we infer an elasticity of 0.19.

Lima and Kopec (2005) use the 1994-1998 Canadian National Population Health Survey (n=2,084) to examine the impact of health status on health care expenditures. Health status was measured using the Health Utilities Index (HUI). Using a multivariate log-linear model, controlling for sociodemographic characteristics, they found that a 0.1 improvement in HUI is associated with a 10% reduction in annual health care costs (s.e. not available). We infer an elasticity of one.

Desalvo et al. (2009) examine healthcare expenditures by self-rated health status using the 2003-2005 Medical Expenditure Panel Survey (n=7,948). The authors descriptively find that the average healthcare expenditures for individuals with excellent, very good, good, fair, and poor health were \$1,654, \$2,640, \$4,228, \$9,831, and \$12,709, respectively. To estimate the elasticity of healthcare expenditures in relation to health status we determine the change in healthcare expenditures associated with a one unit increase in health status; We measure the elasticity associated with moving from good to very good health because the average respondent in the sample reported their health to be good. We use DCG/HCC score to measure percentage change in health as it performs the best in predicting health expenditure according to the paper. Moving from good to very good health involves a 25 percent increase in health (good health corresponds to a DCG/HCC score of 1.66 and very good health corresponds to a score of 1.24). Improving health from good to very good is associated with a \$1,588 or 38%, decrease in healthcare expenditures. The results imply that the elasticity of health expenditures in relation to health status is 1.48 (38% /25%). In conclusion, the results indicate that the elasticity of healthcare expenditures in relation to health status ranges from 0.19 to 1.48, for an average elasticity of 0.84.

Decline in Healthcare Expenditures from 6 Months of Age Onwards

We rely on estimates from the Centers for Medicare & Medicaid Services (CMS, 2019) on average healthcare spending by age to estimate the value of decreased child healthcare expenditures. The CMS's most recent estimate of healthcare spending by age was from 2010. Age was divided into five categories: 0-18, 19-44, 45-64, 65-84, and 85 or older. Healthcare expenditures include costs to insurer and patient but exclude non-personal health care spending (government administration and the net cost of private health insurance, noncommercial research, investment in structures and equipment, and government public health activities). Average per capita spending was \$3,628 among children, \$4,422 among adults 19-44, \$8,370 among adults 45-64, \$15,857 among adults 65-84, and \$34,783 among adults 85 and older. CMS (2020) additionally estimates per capita healthcare expenditures projections for 2019. However, the projections were not disaggregated by age. In 2019, per capita healthcare expenditures were \$9,825.¹¹ This represents a 38% increase from 2010. Assuming growth in healthcare expenses was consistent by age group, we conclude that 2019 per capita health care spending was \$5,007 ($3628 + (0.38 \times 3628)$) among children, \$6,102 among adults 19-44, \$11,551 among adults 45-64, \$21,883 among adults 65-84, and \$48,001 among adults 85 and older.

¹¹ Centers for Medicare & Medicaid Services (2020) estimate per capita spending using both person and non-personal health expenses (\$11,559). Results further indicate that aggregate personal healthcare expenses make up 85% of total healthcare spending. As a result, we assume that per capita personal healthcare spending is 85% of total per capital healthcare spending, providing a final per capita spending of \$9,825.

In the section on children's health, we find that children's health in childhood (ages 9-21) would increase by 0.02 percent of QALY per year and children's health in adulthood (ages 22-78) would increase by -0.008 percent, 0.002 percent, 0.116 percent, 0.05 percent, or 0.2 percent of QALY per year as a result of \$1,000 cash transfer. We also find that one percent increase/decrease in health would lead to 0.84 percent decrease/increase in health expenditures. To calculate the monetary value of change in health at a certain age, we multiply the percentage change in health by the healthcare expenditure elasticity and then by per capita health care spending of that age. To calculate the present discounted value, we assume children experience avoided health expenditures from ages 9-21 as a result of increase in health during childhood and experience avoided health expenditures from ages 22-78 as a result of increase in health in adulthood. We conclude that a \$1,000 transfer is associated with a \$12 decrease in healthcare expenditures from ages 9-21 and an average of \$170 decrease in healthcare expenditures from ages 22-78.

Parents' and Other Adults' health

Larrimore (2011)

Larrimore (2011) found that a \$1,541 (2019\$) increase in income led to a 0.0032 (s.e. 0.0028) or 0.32 percentage-point increase in the likelihood of having excellent health, a 0.0013 (s.e. 0.0011) or 0.13 percentage-point decrease in the probability of being in poor health and a 0.0328 (s.e. 0.01659) or 3.28 percentage-point decrease in the probability of having any functional limitation. The author examined the impact of income on health among parents 22-62 years-old with incomes below 200% of the federal poverty line using the maximum state plus federal EITC as an instrumental variable for income. Results were examined using the 1992-2005 Survey of Income and Program Participation (SIPP) panels (n=85,397). F-statistic results indicated the maximum EITC was a strong predictor of post-tax income. Health was measured using self-reported health status. The two-stage least squares regressions controlled for state of residence, whether the 1996 welfare reform had been enacted at the time of the observation, year, age, age-squared, race/ethnicity, gender, education, marital status, health insurance status, number of children in the household, and whether the respondent lives in a metropolitan area.

To stay consistent with other studies cited in the adult health section, we use the result on probability of excellent health for calculation. The midpoint of the study period is 1999 and the author was estimating the average marginal effect of a \$1000 increase. A \$1,000 increase in household income in 1999 is equivalent to an increase of \$1,541 in 2019. Thus, we find a 0.21 percentage point ($0.32 \times (1000/1541)$) increase in the likelihood of having excellent health. Larrimore measures self-rated health the same year as the transfer was received so no adjustment for years of exposure is needed. We measure improved health using QALYs valued at \$126,628, described in greater detail in the children's health section in the main text. We measure quality of life using a scale that includes death and the five categories in the self-rated health measure (poor, fair, good, very good, or excellent). With death having a value of 0 and excellent health having a value of 5, the maximum increase in health would be an increase of 5 points. Therefore, an increase of one unit of health quality for one year would be valued at \$25,326 ($\$126,628/5$). A 0.21 percentage point increase in the likelihood of having excellent health would then result in a benefit of \$53 ($0.0021 \times \$126,628/5$) per year.

We calculate the present discounted value assuming the adult is 38 at the first transfer and that adult recipients receive health benefits for the remainder of their life. We conclude that a \$1,000 transfer improves the present discounted value of adult health by \$1,491.

Evans and Garthwaite (2014)

Evans and Garthwaite (2014) found that the 1994 EITC expansion increased the probability of mothers' reporting very good or excellent health by 0.0135 (s.e. 0.0075) or 1.35 percentage points, increased mothers' poor physical health days in the past month by 0.0105 (s.e. 0.039) or 1.05% (out of an average of 2.65 days among the treatment group), decreased mothers' poor mental health days in the past month by 0.0754 (s.e. 0.0328) or 7.54% (out of an average of 4.52 days among the treatment group), and decreased the total number of risky health conditions (i.e., total cholesterol, systolic blood pressure, any

risky inflammatory condition) by 0.235 (s.e. 0.095) or 23.5% (out of an average of 1.108 conditions among the treatment group). The authors use a difference-in-difference framework, exploiting the 1994 EITC increase in the relative benefit for families with two or more children relative to those with one child. Analyses were conducted using the 1993-2001 Behavioral Risk Surveillance Survey (BRFSS) and the sample was restricted to mothers with a high school education or less ($n=82,907$). Models control for individual characteristics, state level fixed effects, and time fixed effects.

We use the 1.35 percentage-point increase in the probability of reporting very good or excellent health for the calculation. However, this result is not limited to EITC beneficiaries. In 1999 (near the midpoint of the study period of 1997), 75% of eligible households received the EITC (U.S. Government Accountability Office, 2001). Thus, we divide 1.35 percentage points by 75%, determining that the additional EITC cash transfer to larger families increased the probability of mothers having very good or excellent health by 1.8 percentage points among recipients. The authors find that conditional on receipt, on average, households with two or more children receive \$864 (2019\$) more in EITC benefits than families with one child, which suggests that a \$1,000 increase in EITC payments would increase the likelihood of having very good or excellent health by 2.08 percentage points ($1.8 \times (1000/864)$). The authors measure improved health for 6 years after the increase in transfers. Therefore, per year of exposure the probability of having excellent health increases by 0.35 percentage points ($2.08/6$). We measure the monetary value of improvements in health using QALYs of \$126,628. QALYs are measured using a scale which includes death and the five self-rated health categories. Evans and Garthwaite (2014) examine the probability of having very good or excellent health, so we measure the benefit of moving up one unit, from good to very good health. An increase of one unit of quality would be valued at ($\$126,628/5$). A 0.35 percentage point increase in the likelihood of having very good health then results in a benefit of \$88 ($0.0035 \times 126,628/5$) per year.

We also use the 1.05 percent increase in the number of bad physical health days for the calculation, because unlike other results, it reflects a decline in mother's health. To obtain the effect among recipients only, we divide 1.05 percent by 75% (the percent of eligible households that received EITC in 1999), yielding 1.4 percentage points. Adjusting the impact for a \$1,000 increase, we increase the impact to 1.62 percentage points ($1.4 \times (1000/864)$). Lastly, to obtain the impact of an exposure of one year, we divide 1.62 percentage points by 6, yielding 0.27 percentage points. The increase in the number of bad physical health days can be considered as an increase of the probability of having bad health. We measure the loss of moving down one unit, from fair to poor health. Multiplying 0.27 percentage points by ($\$126,628/5$), we yield a loss of \$68 per year.

We do not use the decrease in total number of risky conditions for the calculation because we are unsure whether such bio-marker measures the continuous health degradation or the probability of future health risks. We do not use the decrease in the number of poor mental health days for the calculation because it is a partial measure of overall health and we remain consistent in not counting the mental health outcome equally with the more comprehensive outcome (in this case the probability of reporting very good or excellent health).

We calculate the present discounted value assuming the adult is 38 at the first transfer and that adult recipients receive health benefits for the remainder of their life. Since the paper has four results on health, three of which suggest improvement in health and one suggests a deterioration in health, we give the result on probability of good/excellent health a weight of 3/4 and the result on bad physical health day a weight of 1/4. The weighted present discount value is \$1,385.

Morgan et al. (2020)

Morgan et al. (2020) found that a 10-percentage point higher state EITC (relative to the federal EITC) was associated with a decrease in the prevalence of individuals having frequent poor mental health by 97 [-237.2, 42.6] individuals per 100,000 and a decrease in the prevalence of individuals with frequent poor physical health by 150 [-284.4, -14.9] individuals per 100,000, with 95-percent confidence intervals shown in brackets. The prevalence of having suboptimal overall health increased by 31 per 100,000 individuals [-123.3, 185.9]. The authors use a difference-in-difference framework to examine the impact of increased state EITC transfers on health using state and year variation in the EITC. Analyses were conducted using

the 1993-2016 Behavioral Risk Factor Surveillance System survey. The sample was limited to adults with a high school education or GED equivalent or less ($n=2,884,790$). Frequent poor physical health is measured as whether the respondent reported having had 14 or more days in the past month in which they would describe their physical health as “not good.” Overall health is measured by a self-reported health scale from 1 to 5 (with 1 being excellent, 2 being very good, 3 being good, 4 being fair, and 5 being poor). Respondents with fair or poor health are regarded as having suboptimal health. States with non-refundable EITC’s were considered to not have an EITC and were lumped with non-EITC states. Models control for state minimum wage, state GDP, adoption of Medicaid expansion, state fixed effects, and year fixed effects.

Results indicated that a 10-percent higher state EITC (relative to the federal EITC) was associated with a decrease in the number of people reporting frequent poor physical health of 150 per 100,000 individuals, or 0.15 percentage points. In 2004 (the approximate midpoint of the study period), the average federal EITC was \$1,834 (Kneebone, 2007). Therefore, a 10 percent increase in the state EITC, relative to the federal EITC, would be \$183.4, the equivalent of \$248 in 2019 dollars. Thus, we estimate that a \$1,000 increase in cash transfers would decrease frequent poor physical health by 605 ($(1000/248)*150$) per 100,000 individuals, or by 0.605 percentage points. However, these results include all households with a high school education or less and are not limited to treated individuals. According to Internal Revenue Service (2013), 20% of households with a high school education or less are eligible for the EITC. To estimate the effect of the treatment on the treated, we divide 0.605 by 0.2, yielding 3.03 percentage points. Lastly, we adjust results for years of exposure. The authors do not describe the average years of exposure. We assume state EITC programs were implemented or expanded at the midpoint of the study period on average, 2004. This would indicate the average years of exposure was 12. Thus, we conclude that per year, a \$1,000 state EITC decreases the prevalence of frequent poor physical health by 0.25 ($3.03/12$) percentage points. To remain consistent with the valuing procedures used in the remainder of adult health estimates, we assume the frequent poor physical health measure captures the equivalent of moving one-fifth of a QALY. Thus, results indicate a 0.25 percentage-point decrease would result in a benefit of \$64 ($0.0025*126628/5$) per year.

Following the same process, we monetize the result on suboptimal health, which indicates a decline in adult health. Results indicate that a 10-percent higher state EITC was associated with a 0.031 percentage-point increase in the prevalence of suboptimal health. A \$1,000 transfer would increase the prevalence by 0.125 percentage points ($0.031*(1000/248)$). The treatment on the treated effect would be 0.625 percentage point ($0.125/0.2$). Lastly, to adjust for years of exposure, we divide 0.625 by 12, yielding 0.05 percentage points per year. Multiplying -0.05 percentage point by (\$126628/5), we arrive at a loss of -\$13 in adult health per year.

We do not use the result on poor mental health for the calculation because it is a partial measure of overall health and we remain consistent in not counting the mental health outcome equally with the more comprehensive outcome (in this case the prevalence of having suboptimal overall health).

We calculate the present discounted value assuming the adult is 38 at the first transfer and that adult recipients receive health benefits for the remainder of their life. Since the paper reports three results on health, two of which suggest an improvement of health and one of which suggests a decline, we give the result on physical health a weight of 2/3 and the result on suboptimal health a weight of 1/3. The weighted present discounted value is \$1,082.

Price and Song (2018)

Price and Song (2018) found that a \$2,962 (2019 dollars) transfer for three to five years resulted in a 6.28 percentage-point increase in disability benefits application rate among parents (s.e. 0.0199).

Having adjusted the result to reflect the impact of a \$1,000 dollars cash transfer, the impact decreases to 2.12 percentage points ($6.28*(1000/2962)$). Having adjusted for 4 years (an unweighted average of 3 and 5) of exposure the impact further decreases to 0.53 percentage points ($2.12/4$). We value the benefit of improved health by utilizing QALY, valued at \$126,628. To remain consistent with other impact studies in

this section, we assume that moving from not applying for disability benefits to applying for disability benefits reflects a decline in one-fifth of the value of QALY. We multiply \$126628/5 by 0.53%, yielding a loss of \$134 in adult health per year. We calculate the present discounted value assuming the adult is 38 at the first transfer and that adult recipients receive health benefits for the remainder of their life. We conclude that a \$1,000 transfer is associated with a present discounted value of -\$3,806 in adult's health.

Parents' or Other Adults' Longevity

Price and Song (2018)

Price and Song (2018) found that an additional \$2,962 (2019 dollars) in cash transfers annually for three to five years increased the likelihood of death among adults by 0.0138 (s.e. 0.0196) or 1.38 percentage points.

When we adjust their estimate to measure the impact of a \$1,000 transfer, the impact decreases to 0.47 percentage points ($1.38 \times (1000/2962)$). To account for years of exposure, we divide by 4 (an unweighted average of 3 and 5), decreasing our estimate to 0.12 percentage points ($0.47/4$). We value the change in mortality by utilizing QALY, valued at \$126,628. As a result, a 0.12 percentage point increase in the probability of death represents a QALY decrease of \$147 (126628×0.0012). We calculate the present discounted value assuming that adults received the first transfer benefit at age 38 (based on the assumption that a parent is 29 at their child's birth (based on the mean age of mothers at birth as of 2019 according to CDC Vital Statistics)) and that the extension of life occurred at age 78 (life expectancy in the U.S. in 2018). We plug zero into the equation from ages 38-77 and -\$147 for age 78. We conclude that \$1,000 transfer is associated with a present discounted value of -\$67 in adult longevity.

Aizer et al. (2020)

Aizer et al. (2020) found that the Mothers Pension Program increased mother's longevity by 0.247 years (s.e. 0.494). Sample was restricted to mothers who had applied for the program only once no later than 1930 (n=16,228). The causal impact of the program was evaluated through OLS regressions that controlled for county fixed effect, application year fixed effect, individual control, county control and state control.

Mothers participated in the program for an average of three years. The \$20 monthly transfer in 1922 would be worth \$307 in 2019, or \$3,684 annually for on average three years. Adjusting the impact for a \$1000 transfer, mother's longevity would rise by 0.07 years ($0.247 \times (1000/3684)$). Adjusting for years of exposure, mother's longevity would rise by 0.02 years ($0.07/3$). We value the change in mortality using QALYs, valued at \$126,628. Therefore, a 0.02-year of increase in longevity is equivalent of \$2,830 (0.02×126628) (\$2,830 per year is around 2.23% of QALY per year) and the present discounted value is \$1,282.

Chetty et al. (2016)

Chetty et al. (2016) found that an increase in income from \$14,000 to \$20,000 (moving from the 10th to the 15th income percentile) was associated with an increase in longevity of 0.7-0.9 years (s.e. not available). The authors used population-level tax records and Social Security death records between 1999 and 2014 to examine the relationship between pre-tax income and life expectancy. The study included all individuals with incomes above zero between the ages of 40 and 76 with a valid Social Security Number in the specified years, and measured income using tax records. The authors defined income as adjusted gross income plus tax-exempt interest income minus taxable Social Security and disability benefits. Respondents were assigned a percentile rank from 1 to 100 based on their income relative to all other individuals with the same sex and age during this period. The relationship between income percentile and life expectancy was approximately linear. Life expectancy was measured using the expected length of life for a hypothetical individual who faced a mortality rate at each age that matched those in the cross-section during a given year. Results were analyzed separately for men and women. To help mitigate concerns regarding reverse causality, mortality was measured two years after income (2001-2014). Their estimate of increased longevity implies that per \$1,000 increase in household income, the present

discounted value of longevity is \$234. Even though the paper is not causal, its results do assist in establishing an upper-bound estimate.

Chetty et al. found that an increase in income from \$14,000 to \$20,000 (moving from the 10th to the 15th income percentile) was associated with an increase in longevity of 0.7-0.9 years (s.e. not available). Income was measured in 2012 dollars. The \$6,000 increase is the equivalent of \$6697 increase in 2019. Extrapolating from these results, a \$1,000 increase in income was associated with between a 0.1 ($0.7 \times (1000/6697)$) and 0.13 ($0.9 \times (1000/6697)$) year increase in life expectancy. We use the approximate midpoint of this range for our final estimate, 0.12 years. A QALY is valued at \$126,628 (described in greater detail in children's health section in the main text). As a result, a 0.12-year increase in life represents a QALY increase of \$15,127. To account for years of exposure, we divide results by 21.5 (assuming that on average parents will have 2 children. Through CPS data we found that in two-children families, siblings are spaced 3.5 years apart on average, leading to parent's eligibility to receive a transfer for 21.5 years), decreasing our estimate to \$704. We calculate the present discounted value assuming that adults received the first transfer benefit at age 38 (based on the assumption that a parent is 29 at their child's birth (based on the mean age of mothers at births as of 2019 according to CDC Vital Statistics)) and that the extension of life occurred at age 78 (life expectancy in the U.S. in 2018). We conclude that \$1,000 transfer is associated with a present discounted value of \$319 in increased longevity.

Using three studies above, we conclude that the average present discounted value of increased adult longevity is \$511.

Avoided Health Expenditures for Parents and Other Adults

We rely on the Centers for Medicare & Medicaid Services (2019) to estimate average health expenditures. As explained above, using the Centers for Medicare & Medicaid Services (2019)'s results, we estimate that 2019 per capita health care spending averaged \$6,102 among adults 19-44, \$11,551 among adults 45-64, and \$21,883 among adults 65-84.

According to table 2, a \$1,000 cash or near-cash transfer increases an adult's health by -0.106 percent, 0.03 percent, 0.039 percent or 0.042 percent of QALY per year. We use the same calculation method in the section on children's health expenditures to convert this percentage change in health into monetary value of change in healthcare expenditures. We calculate the present discounted value of health expenditures, assuming that parents experience benefits in avoided health expenditures from ages 38-78. We conclude that a \$1,000 transfer is associated with an average present discounted value of \$3.24 in reduced health expenditures.

Children's Educational Attainment

Based on six studies below, we found that a \$1,000 cash transfer would increase children's years of schooling by 0.002-0.03 years. The mean increase is 0.01 years. We do not count increased education as a benefit because any benefit from increased education is already counted in the benefit of increased earnings. However, as detailed later, we do use the results of these studies to calculate the increased cost posed by increased educational attainment.

Akee et al. (2010)

Akee et al. (2010) found among American Cherokee children, receiving tribal casino payments led to an increase in years of education of 0.379 (s.e. 0.447) and 0.117 (s.e. 0.304) years among the age 9 and age 11 cohorts, respectively, and an increase in the probability of graduating high school by age 19 of 0.156 (s.e. 0.073) or 15.6 percent for the age 9 cohort and 0.042 (s.e. 0.066) or 4.2 percent for the age 11 cohort. The authors used data from the Great Smoky Mountains Study (GSMS), which began in 1993 and included a representative sample of children aged 9, 11, and 13 in 11 counties in North Carolina (n=1,185). American Cherokee children within the included counties were oversampled (350). In 1996, the Eastern Band of Cherokees opened a casino. Each tribal member received a proportion of the casino's profits. The two youngest age cohorts (ages 9 and 11) were identified as "after-treatment" cases and the

oldest cohort (age 13) functioned as the “before-treatment” case. Casino payments began in 1997, when children were 13, 15, and 17; therefore, each age cohort lived in homes in which the parent(s) received payments for 6, 4, and 2 years, respectively. Linear regression models controlled for the number of adults in the household eligible for the casino payments, the age cohort of the child, an interaction term of the age cohort and number of adults, household poverty status prior to the opening of the casino, sex of child, race of child, and education levels of both parents. Outcomes were measured at ages 19 or 21.

According to Akee et al. (2010), annual payments were an average of \$4,000 starting in 1996, which is the equivalent of \$6,538 in 2019. Therefore, to determine the change in educational attainment associated with a \$1,000 cash transfer, we divide results by $(1000/6538)$. Age 9 cohort experienced a 0.06-year $(0.379 \times (1000/6538))$ increase in years of education and a 2.39 percent $(15.6 \text{ percent} \times (1000/6538))$ increase in the probability of graduating high school. Age 11 cohort experienced a 0.02-year $(0.117 \times (1000/6538))$ increase in years of education and a 0.64 percent $(4.2 \text{ percent} \times (1000/6538))$ increase in the probability of high school graduation. The age 9 cohort was exposed to transfers for a total of 6 years and the age 11 cohort was exposed for 4 years. A one year \$1,000 transfer increased the probability of graduating high school by between 0.16 percent $(0.64 \text{ percent}/4)$ and 0.4 percent $(2.39 \text{ percent}/6)$. It increased years of education by between 0.004-year $(0.02/4)$ and 0.01-year $(0.06/6)$. Since age 9-cohort makes up 54 percent of the post-treatment group and age-11 cohort makes up of 46 percent of the post-treatment group, the weighted increase in high school graduation is 0.29 percent $(0.16 \text{ percent} \times 0.46 + 0.4 \text{ percent} \times 0.54)$ and the weighted increase in educational attainment is 0.007 years $(0.004 \times 0.46 + 0.01 \times 0.54)$. If we want to express the increase in years of education in percentage, then given that the control group (households with no American Indian parent) has an average of 11.96 years of education, a one year \$1,000 transfer increased years of education by between 0.04 percent $(0.004/11.96)$ and 0.08 percent $(0.01/11.96)$. The weighted increase in years of education is 0.06 percent $(0.04 \text{ percent} \times 0.46 + 0.08 \text{ percent} \times 0.54)$.

Maxfield (2015)

Maxfield (2015) found that a \$1,000 increase in maximum EITC led to a 0.0139 (s.e. 0.0078) or 1.39 percentage-point increase in the probability of completing one or more years of college at age 19, a 0.0207 (s.e. 0.0099), or 2.07 percentage-point increase in the probability of receiving a high school diploma or GED at age 19 and a 0.0295 (s.e. 0.0301) increase in years of schooling at age 19. The author used the 1979 National Longitudinal Survey of Youth (NLSY) and corresponding child file. The data included children of all ages linked to their mother between 1988 and 2000, covering all major federal EITC expansions, and long-term outcomes for the children as young adults between 1994 and 2010. The sample was limited to children whose family was ever eligible to receive the EITC and to children who have a sibling in the sample ($n=2,720$). EITC exposure is measured based on the maximum federal and state EITC the household was eligible for by year, number of children, and state. Ordinary least squares (OLS) analyses controlled for child age and age squared, mother’s score on the Armed Forces Qualification Test (AFQT), indicators for race, sex, birth order, and birth year, mother’s age and age squared, mother’s marital status, age of mother at birth of child, mother’s educational attainment, the age the child would be expected to graduate high school, number of children in the household, maximum welfare benefit by state and year for a family of three, per pupil spending on K-12 public education in state and year, and state, year, and family fixed effects.

The author found that the average probability of obtaining a high school diploma or GED at age 19 is 75 percent, the average probability of completing one or more years of college at age 19 is 25 percent, and the years of schooling completed at age 19 on average is 12.07 years. Therefore, a 2.07 percentage-point increase in the probability of obtaining a high school diploma or GED represents a 2.76 percent increase, a 1.39 percentage-point increase in the probability of completing one or more years of college represents a 5.56 percent increase, and a 0.0295-year increase in years of schooling represents a 0.24 percent increase. The author states that a \$1,000 increase in maximum EITC benefit increased average estimated EITC payments by \$328 in 2008 dollars, the equivalent of \$384 in 2019 dollars. Therefore, a \$1,000 increase in real EITC payments increases the probability of receiving a high school diploma or GED by 7.19 percent $(2.76 \text{ percent} \times (1000/384))$, increases the probability of completing one or more years of

college by 14.48 percent ($5.56 \text{ percent} \times (1000/384)$) and increases years of schooling by 0.64 percent ($0.24 \text{ percent} \times (1000/384)$). Children in the sample were an average of 8 years old, meaning they were exposed to the increased EITC for an average of 10 years (age 8-17). Thus, a one-year, \$1,000 increase in EITC payments increases the probability of receiving a high school diploma or GED by 0.72 percent, increases the probability of completing one or more years of college by 1.45 percent, and increases years of schooling by 0.06 percent. Lastly, since the sample includes children whose families were ever eligible for EITC, not those whose families have actually received EITC, we divide all impacts by 75 percent (U.S. Government Accountability Office, 2001), which is the percentage of eligible households that claimed EITC in 1999 (near the middle of the study period of 1994). The impact on receiving a high school diploma or GED becomes 0.96 percent, on completing one or more years of college becomes 1.93 percent, and on years of schooling becomes 0.08 percent. If we express the increase in schooling in terms of years, then the increase is 0.01 years ($((0.0295 \times (1000/384))/10)/0.75$).

Micheltmore (2013)

Micheltmore (2013) found that a \$1,000 increase in the maximum state EITC increased the likelihood of being enrolled in college by 0.015 (s.e. 0.012), increased the likelihood of ever being enrolled in college by 0.027 (0.012), increased years of educational attainment by 0.107 years (s.e. 0.051) or 0.89 percent (0.107 years out of an average of 11.97 years), and increased the probability of high school completion by 0.023 (s.e. 0.012) or 3.29 percent (2.3 percentage points out of an average of 70 percent). Data was derived from the Survey of Income and Program Participation (SIPP), pooling panels from 1990 through 2008. Data when individuals were 18-23 years old was used for this analysis, with parental educational attainment as a proxy for EITC eligibility. Participants living with parents who had no schooling beyond a high school degree were considered EITC-eligible ($n=25,337$). The study employed a difference-in-differences analysis with variation in treatment dosage to determine the impact of state EITCs on educational attainment. Analyses examined the impact of within state EITC expansions on educational attainment relative to changes in outcomes among individuals in untreated states. Models controlled for demographic characteristics and year and state fixed effects.

To remain consistent with other literature, we focus on results for high school completion and years of education. The author does not describe the change in dollars received associated with a \$1,000 increase in the maximum EITC. We assume the increase is \$384 in 2019 dollars, as found by Maxfield (2015). This results in a 8.57 percent ($0.0329 \times (1000/384)$) increase in the likelihood of completing high school and a 2.32 percent ($0.0089 \times (1000/384)$) increase in years of education. Individuals were exposed to the EITC for between 7 and 18 years (individuals in the sample were younger than 12 years old). We take the midpoint of the range of exposure, 12.5 years. Thus, a one-year, \$1,000 increase in EITC benefits increased the likelihood of completing high school by 0.69 percent ($8.57 \text{ percent}/12.5$) and increased years of education by 0.19 percent ($2.32 \text{ percent}/12.5$). Next, we adjust results to apply only to the 75 percent of EITC-eligible households that are “treated” through actual receipt of an income transfer (U.S. Government Accountability Office, 2001). We find that per \$1,000 cash transfer the probability of completing high school increased by 0.91 percent and increased years of education by 0.25 percent. If we express the increase in education in terms of years, then the increase is 0.03 years ($((0.107 \times (1000/384))/12.5)/0.75$).

Hoynes et al. (2016)

Hoynes et al. (2016) found that exposure to food stamps in early childhood increased the probability of receiving more than a high school education by 0.184 standard deviations (s.e. 0.108). We do not use this result to measure the impact of a \$1,000 transfer on educational attainment because the outcome differs slightly from remaining literature and we are unable to convert results presented in z-scores to percentage terms due to absence of the standard deviation of the mean.

Aizer et al. (2016)

Aizer et al. (2016) found that in adulthood, sons whose mothers had received Mothers’ Pensions experienced an increase in years of schooling of 0.316 years (s.e. 0.262), a 3.4 percent increase.

As previously stated, the \$20 monthly transfer in 1922 would be worth \$307 today, or \$3,684 annually for on average three years. Therefore, a \$1000 transfer for one year would increase years of education by 0.31 percent [$0.034 * ((1000/3684)/3)$]. If we express the increase in education in terms of years, then the increase is 0.03 years ($((0.316 * (1000/3684))/3)$).

Bastian and Micheltore (2018)

Bastian and Micheltore (2018) found that an exposure of \$1,097 in EITC benefit (2019 dollars): prior to age five, decreased the probability of graduating high school by 0.005 (s.e. 0.005) or -0.5 percent and decreased educational attainment by 0.024 years (s.e. 0.071) or -0.18 percent (based on an average of 13.7 years); between the ages of 6 and 12, decreased the probability of graduating high school by 0.003 (s.e. 0.003) or -0.3 percent, and increased schooling by 0.008 years (s.e. 0.022) or 0.06 percent (based on an average of 13.7 years); and between the ages of 13 and 18, increased the probability of graduating high school by 0.012 (s.e. 0.003) or 1.2 percent and increased schooling by 0.081 years (s.e. 0.025) or 0.59 percent (based on an average of 13.7 years).

To simplify calculations, we first calculate an average impact across all ages by multiplying each of Bastian and Micheltore's estimates for the three age groups times the proportion of children currently in that age group. According to Bastian and Micheltore (2018), children exposed to EITC from ages 0-5, from ages 6-12 and from ages 13-18 make up 21.6%, 40.4% and 38% of their samples, respectively. This results in an increase in the probability of graduating high school by 0.23 percent and increase the average years of schooling by 0.21 percent. However, these results are for multiple years of exposure to EITC and include all children in states in which the maximum EITC increased, not just recipient children. We assume the child was exposed to the EITC in all 18 years, yielding a 0.01 percent increase in the probability of graduating high school and a 0.01 percent increase in the average years of schooling. To convert this intent-to-treat estimate to an estimate of the effects on the treated, we divide each estimate by 83 percent (Scholz 1994), which was the EITC participation rate in 1990 (the middle of the study period). It results in a 0.02 percent increase in the probability of graduating high school and a 0.01 percent increase in schooling for a \$1000 transfer. Finally, to obtain the impact of a \$1,000 increase, we multiply the estimate by $(1000/1097)$, resulting in a 0.01 percent increase in the probability of graduating high school and a 0.01 percent increase in years of schooling. If we express the increase in schooling in terms of years, then the increase is 0.002 years, calculated as the following: $((((-0.024 * 0.216) + (0.008 * 0.404) + (0.081 * 0.38)) / 18) / 0.83) * (1000 / 1097)$.

Thompson (2019)

Thompson (2019) found that exposure to an average-sized casino operation over the entirety of childhood increased the probability of receiving an associate's degree by 0.057 (s.e. 0.027) or 5.7 percentage points, increased the probability of receiving a bachelor's degree by 0.010 (s.e. 0.009) or 1 percentage point, increased educational attainment by 0.328 years (s.e. 0.070), and increased the probability of high school graduation by 0.041 (s.e. 0.011) or 4.1 percentage points. The author examined educational attainment among self-identified American Indians in 36 counties where a tribal casino was opened during respondents' childhood. Analyses were conducted using the 2000 Decennial Census IPUMS samples and American Communities Survey (ACS). A difference-in-differences framework was used to compare the educational attainment of American Indian individuals from the same county with differing levels of exposure to tribal casino payments. The within-county differences were then compared to determine whether results differed based on the size of the county's casino operations. The sample was limited to self-identified American Indian individuals from counties that opened a casino between 1987 and 2004. The author was able to identify respondents' current county of residence (during adulthood) and state of birth but was unable to identify what county the individual resided in throughout childhood. As selective migration might bias findings, the author limited the sample to individuals currently living in a county in the same state as they were born ($n=11,647$). Casino exposure was measured by dividing the number of slot machines operated by the American Indian casino in the county by the size of the American Indian population per county and year. The casino exposure measure was then scaled so that a one-unit increase corresponded to an individual spending their full childhood in a

county with an average-sized gaming operation and American Indian population. Outcomes were measured between the ages of 22 and 40. Analyses controlled for county and cohort fixed effects, age at time of survey, tribal identity, and gender.

Transfer income increased by \$304.9 (s.e. 47.1) in the average American Indian household. Hourly wage increased by \$1.56 (s.e. 0.093) and unemployment decreased by 0.020 (s.e. 0.004) or 2 percentage points. Results indicate that increased educational attainment of children was likely a result of both improved labor market opportunities and transfer payments for the family. Of the total \$3,548 increase in income among American Indian families, 8.6 percent (\$305 in 2016 dollars or \$325 in 2019 dollars) was a result of transfer income. We assume the same proportion of increased educational attainment was a result of transfer income. Therefore, the income transfer increased educational attainment by 0.03 (0.086×0.328) years or 0.23 percent (out of the control group mean of 12.33 years) and increased the probability of high school graduation by 0.35 (0.086×0.041) percentage points or 0.46 percent (out of the control group mean of 76 percent). A \$1,000 transfer would then increase educational attainment by 0.7 percent ($0.0023 \times (1000/325)$) and the probability of high school graduation by 1.43 percent ($0.0046 \times (1000/325)$). Results represent the impact of exposure to the transfer for 18 years, so we adjust results for years of exposure. We find that a \$1,000 cash transfer increased educational attainment by 0.04 percent ($0.007/18$) and the probability of high school graduation by 0.08% ($0.0143/18$). If we express the increase in educational attainment in terms of years, then the increase is 0.005 years ($((0.328 \times 0.086) \times (1000/325))/18$).

Child Welfare

Berger et al. (2017)

Berger et al. (2017) found that \$1,000 in potential EITC is associated with a decrease in the probability of neglecting a child, a decrease in the probability of abusing a child, and a 0.0027 (s.e. 0.0038) or 0.27 percentage-point decrease in the probability of being investigated by Child Protective Services (CPS). Using the Fragile Families and Child Wellbeing Study (4,040 family-wave observations), the authors use an instrumental variable strategy to examine the effect of income on child maltreatment. Income is instrumented using state and national variation in EITC generosity. The sample is limited to unmarried families with AGIs of no more than \$45,000 per year (nominal dollars). EITC generosity is measured using TAXSIM based on year, income, filing status, number of dependents, and state of residence. F-statistic results indicated the EITC was a strong predictor of post-tax income. Child maltreatment is measured using mothers' self-reports of having been investigated by CPS, indicators of physical violence, and indicators of neglect. Analyses control for race/ethnicity, maternal education, number of biological children in household, family structure, age of youngest child, mother's age, whether the mother reported no household income, average of lagged and current household income, census tract unemployment rate, census tract public assistance receipt rates, wave of observation, and state of observation.

The authors find that a \$1,000 increase in potential EITC benefits is associated with a \$936 to \$1,030 increase in income in 2009 dollars; We use the average of this range of earnings, \$983, which is the equivalent of \$1,167 in 2019 dollars. Thus, the impact on the probability of CPS investigation becomes 0.23 percentage points ($0.27 \times (1000/1167)$). Fang et al. (2012), based on federal, state, and local expenditures on child welfare activities (CPS investigations and foster care) and the number of CPS-involved children, estimate that the average per-year cost per investigated child is \$7,728 (2010 dollars), the equivalent of \$9,082 (2019 dollars). Therefore, we estimate that a \$1,000 transfer is associated with \$21 (9082×0.0023) in decreased spending on child welfare investigations. Berger et al. (2017)'s sample is limited to unmarried mothers. However, based on correspondence with Berger, who reported finding similar, but much less precisely estimated, effects for married mothers, we assume the impact of a \$1,000 transfer on CPS involvement does not differ among married mothers. We conclude that a \$1,000 transfer decreased the present discounted value of expenditures on child welfare by \$37.

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 \$2,151 using a 2% discount rate. We contribute the effects discovered by the paper to the difference between \$3,012.59 and \$2,151, around \$861. If \$861 led to a 0.547 percentage-point decrease in the likelihood of having CPS investigations, then a \$1,000 benefit would lead to a 0.64 ($0.547 \times 1000 / 861$) 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 0.64 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 0.81 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 0.81 percentage-point decrease in CPS investigation is thus worth \$73. We conclude that a \$1,000 increase in household income from cash transfers would bring \$73 worth of benefits in reduced expenditures on child welfare per year.

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. The calculation below is documented in Garfinkel et al., (2024), published on the website of Columbia University Center on Poverty and Social Policy. It is based on Garfinkel et al., (2022), published in the Journal of Benefit and Cost Analysis, but improves it further by using more accurate estimates of cost per crime and the age distribution of crime and also including new quasi-experimental evidence on the impact of cash transfers on crime.

Quasi-experimental research indicates that cash transfers to children, especially children in poverty, reduce crime, including both property crimes and violent crimes. We use the result of quasi-experimental

research on crime reduction per year and studies that examine the age distribution of crime to calculate reduction in crimes throughout children's lifetimes. We monetize the lifetime decrease in crime using standard literature estimates on the cost of crime.

Cost per crime

Cost of crime includes both victim cost and criminal legal system costs (ex: police, incarceration, court). We use Cohen (2020)'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 (2020) 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 (2020), 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 the 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. The criminal legal system cost is thus 6.1% of total cost for violent crime. Per non-violent crime, the criminal legal system cost is \$707 (\$274+\$433), and total cost minus perpetrator work loss is \$2,250. The 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 victim cost, our calculation based on Miller et al. (2021) suggests that victim cost is 73.6% of the total cost of all crimes.¹²

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

¹² An alternative calculation based on Cohen (2020) suggests that criminal legal system cost is 10.1% of total cost of crime. Table 6.2 of Cohen (2020) 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 the 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.

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, 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% ($9\% \times 0.7\%$) 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.

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.¹³ The result is a decrease in arrest probability of 0.0089 percentage points (0.0088/0.99). To be consistent with our crime calculation based on Barr & Smith (2023), we decompose the impact on arrests into impacts on arrest of a specific type of crime. Based on statistics from the FBI (2019),¹⁴ 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 (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)¹⁵ and percentage of that type of crime reported to the police (Department of Justice 2022)¹⁶ 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 discount rate of 2%. 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 \$6.

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 the average child beneficiary is 9 years old. The present discounted value of reduction in incarceration cost is thus \$3.3

¹³ This ratio may seem high, but using it has the virtue of giving us an estimate of smaller, more conservative magnitude.

¹⁴ 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.

¹⁵ 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.

¹⁶ 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.

$(\$7.8/(1.03)^{29})$. 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, victim 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 discount rate of 2%. 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 \$104.

We use the unweighted average of the two present discounted value, \$55, 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 \$55.

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. (2020) in 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 (2020) 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 \$2,808.

Other Transfers

As there were not published findings appropriate to our question, we conducted our own analyses on the relationship between earnings and other transfers using the 2014 Survey of Income and Program Participation. Respondents were interviewed annually between 2013-2016. Transfers are measured as the sum of annual EITC, housing subsidies, disability, workers compensation, WIC, unemployment compensation, TANF, SSI, general assistance, and food stamps. SIPP respondents report the amount received for each transfer excluding the EITC and housing subsidies. EITC transfers are estimated using the NBER's Taxsim. Respondents report receipt of housing subsidies but not the amount received. The amount of housing subsidies received is estimated based on the difference between the amount of rent paid and the fair market rent in the state (estimated separately for urban and rural areas) for the corresponding household size. The sample includes individuals between the ages of 18 and 64. The sample is limited to individuals with a high school education or less, a proxy for eligibility for mean-tested programs. Linear regressions were conducted controlling for race, the number of children in the household, and marital status ($n=634,678$). Further analyses were conducted expanding the sample to include individuals with less than a college degree; results, as expected, are smaller, increasing our confidence in the findings (Regression results presented in table A4.1 and A4.2 below).

In the children's earnings section in the main text, we find that a \$1,000 cash transfer during childhood increases earnings in adulthood by -\$33, \$25, \$62, \$127, and \$249 per year. We estimate that \$1,000 in earnings reduces transfers by \$13.61. Therefore, we find that the corresponding decrease in transfers is $-\$0.45$ ($13.61*(-33/1000)$), $\$0.34$ ($13.61*(25/1000)$), $\$0.84$ ($13.61*(62/1000)$), $\$1.72$ ($13.61*(127/1000)$), and $\$3.39$ ($13.61*(249/1000)$). We estimate the present discounted value of the decrease in other transfers, assuming to begin at age 22, and end at age 64. The average child beneficiary is assumed to be age 9. Using the mean estimate, we conclude that the present discounted value of decreased transfers is \$26 in adulthood as a result of a \$1,000 cash transfer during childhood.

Increased Payments Due to Increased Children's and Adult's Longevity

With the increased children's longevity comes a cost. Two major components of the cost are Social Security and Medicare payments. According to the Social Security Administration (2019), retired workers received an average of \$1,461 in Social Security per month in 2018. This means that the annual Social Security payment was \$17,532 in 2018, the equivalent of \$17,821 in 2019 dollars. According to the Kaiser Family Foundation, Medicare spending per enrollee was \$10,536 in 2019. We thus assume that one year of increase in longevity requires \$28,357 of payments from Social Security and Medicare. To estimate the total increase in Social Security and Medicare payments, we turn to our previous estimates on longevity.

Our estimates indicate that a \$1,000 increase in cash transfer for one year would increase children's longevity by 0.0194 (Bailey et al., 2020) or 0.105 years (Aizer et al., 2016). A 0.0194-year increase in longevity would thus require \$551 (0.0194×28357) more Social Security and Medicare payments. Since we assume that the extension of longevity occurs at age 78, we assume that payments are made to children at age 78 as well. The present discounted value of increased payments is \$140. A 0.105-year increase in longevity would require \$2976 (0.105×28357) more Social Security and Medicare payments. The present discounted value is \$759. Using the mean of these two present discounted values, we conclude that as a result of the impact of a \$1,000 cash transfer on children's longevity, there would be a \$450 increase in Social Security and Medicare payments to children once in adulthood.

For adults' longevity, the average increase in longevity based on three studies is 0.0089-year. A 0.0089-year increased longevity would require \$253 in increased payments (0.0089×28357). The present discounted value is \$114. We conclude that due to the impact of the \$1,000 cash transfer on adults' longevity, there would be a \$114 increase in Social Security and Medicare payments made to parents.

Increased Costs Due to Increased Education of Children

Increased schooling poses direct costs to child beneficiaries in the form of tuition and fees and to taxpayers in the form of tax payments used to support national and local educational systems. Our estimates on increased schooling suggest that a \$1,000 dollar increase in household income from a child allowance for one year would increase years of schooling by 0.0018-0.0297 years. Since for most of our impact studies, an average child in the sample has 12 years of education, we regard the 0.0018-0.0297 increase as an increase in postsecondary education. We use data provided by Abel and Deitz (2014) to calculate the increased direct costs. The study estimated that for a 4-year bachelor degree, the price charged for one year was \$14,750 but students paid only \$6550, with \$8,200 offset by grants, scholarships and tax benefits to students. For a 2-year associate degree, the price charged for one year was approximately \$3,000, but was completely offset by grants, scholarships and tax benefits to students that summed up to \$4,300, implying that students gained \$1,300 in tuition and fees. Taking an average of \$6,550 and -\$1,300, the average direct costs to child beneficiaries in the form of tuition and fees are worth \$2,625, the equivalent of \$2,880 in 2019 dollars. Taking an average of \$8,200 and \$4,300, the direct costs to taxpayers in the form of tax payments used for grants and scholarship are worth \$6,250, the equivalent of \$6,856 in 2019 dollars. Multiplying 0.0018-0.0297 years of schooling by \$2,880 yields an increase in yearly cost for child beneficiaries of \$5-\$86. Multiplying 0.0018-0.0297 years of schooling by \$6,856 yields an increase in yearly taxpayers cost of \$12-\$204. Assuming that an increase in schooling takes place at age 18, the average of the present discounted values of child beneficiaries' and taxpayers' costs would be \$33 and \$79 respectively.

Increased schooling also poses opportunity cost for child beneficiaries in the form of lost wages while attending school. We again use the opportunity cost of college estimated by Abel and Deitz (2014). The study found that students would forgo \$96,000 in annual earnings (in 2013 dollars) over a 4-year bachelor degree and \$46,000 in annual earnings over a 2-year associate degree. Thus, per year, students would forgo \$24,000 in annual earnings for a bachelor degree and \$23,000 for an associate degree, yielding an average of \$23,500, the equivalent of \$25,778 in 2019 dollars. We thus assume that individuals would give up \$25,778 in earnings in the labor market for every one-year increase in postsecondary education. Multiplying our estimates on increased schooling by \$25,778 gives us \$45-\$766 of opportunity cost. Assuming that child beneficiaries are age 9 and increase in schoolings happen at age 18, the present discounted values of the opportunity cost of schooling range from \$38-\$641, with an average of \$296.

Thus, for child beneficiaries, total costs of increased schooling amounts to an average of \$329. For taxpayers, total costs of increased schooling amounts to an average of \$79.

Standardized benefits and costs per \$1,000 increase in household income from cash and near-cash transfers

Table B2 below is built upon Table 1.3. of Garfinkel et al., (2024) and summarizes the calculations explained above. Displayed in the table is the present discounted value of monetary benefits and costs for single child, single parent low-income families per \$1,000 increase in household income, using a discount rate of 2%. The three columns represent benefits and costs for participants (in this case, children and parents who experience changes in household income from the policy), taxpayers, and the society respectively. A positive number indicates a benefit while a negative number indicates a cost. For children, the biggest benefit lies in health and longevity. The present discounted value of increased lifelong health and longevity is \$4,892 per child, over four times the \$1,000 increase in household income. The benefit in increased lifelong earnings is also substantial, with a present discounted value of \$1,940. There are costs for children as well. With higher earnings comes more tax payments (-\$407) and less transfers (-\$26). With more education comes more expenditures on education (-\$329). For parents, the largest benefit is increased health and longevity, valued at \$549. Increased household income also benefits taxpayers in various ways. For taxpayers, the biggest gain comes from the saved expenditures on the criminal legal system and reduced victim costs of crime, valued at \$1,432. The improved health of children will reduce taxpayers' share of healthcare expenditures by \$170. The increased earnings of children will generate \$407 more payments to taxpayers. The biggest cost for taxpayers is increased longevity payment (ex: social security) to children due to children's increased longevity, amounting to -\$450.

We assume that taking cash and near-cash transfers away from families is symmetrical to giving families cash. In using the estimates presented below to model the opposite effect of cutting cash and near-cash assistance, we simply reverse each benefit and cost category. For instance, while a \$1,000 increase in cash and near-cash transfers generates \$1,940 of benefits in increased future earnings of children, a \$1,000 decrease in transfers results in decreased future earnings of children (-\$1,940).

Table B2. Present discounted value of monetary benefits and costs for one child and one parent in low-income families per \$1,000 increase in household income: Using a social discount rate of 2%

	Direct + Participants	Indirect = Taxpayers	Total Society
Total transfer	\$ 1,000	\$ -1,000	\$ 0
Increased future earnings of children	\$ 1,940	\$ 0	\$ 1,940
Increased future tax payments by children	\$ -407	\$ 407	\$ 0
Decreased neonatal mortality ^a	\$ 23	\$ 0	\$ 23
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 ^b	\$ 0	\$ 47	\$ 47
Avoided criminal legal system expenditures	\$ 0	\$ 372	\$ 372
Reduced victim costs of crime	\$ 0	\$ 1,060	\$ 1,060
Increased costs of children's education	\$ -329	\$ -79	\$ -408
Avoided expenditures on children's health care costs ^a	\$ 22	\$ 179	\$ 201
Avoided expenditures on parents' health care costs	\$ 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

Source: Center on Poverty and Social Policy at Columbia University.

^a These are slightly larger than the estimates presented in Table 1.3. of Garfinkel et al., (2024) because Garfinkel et al., (2024) analyze child allowances and the birth-related benefits of child allowances only apply to non-first born. In contrast, the birth-related benefits of SNAP apply to both first born and non-first born.

^b This is slightly larger than the estimate presented in Table 1.3. Of Garfinkel et al., (2024). In one of the two child protection estimates, Garfinkel et al., (2024) didn't use the updated social discount rate of 2%, but instead used the outdated 3%. Here we correct the calculation error, leading to a slightly higher estimate.

Adjustment of benefits by number of children and family income

To calculate the national economic costs of rolling back the TFP, we combine the impact estimates from the literature with our microsimulation estimate on the amount of SNAP spending cut for families with children under the TFP rollback. During the calculation, we make two further adjustments. First, we adjust the economic costs by the number of children in the families of our CPS-ASEC sample since the estimate from the literature represents average impacts per child. However, we do not adjust the economic costs by the number of parents as most literature examines the impact on mothers. Second, we reduce the economic costs by family income under the assumption that higher-income families have less to lose from a reduction in cash and near-cash transfers. This assumption mirrors that of Garfinkel et al., (2022), who given a quasi-experimental study in Norway (Loken et al., 2022), assumes that benefits of receiving transfers start to decrease as family income reaches above \$50,000 (2019 dollars) and become zero as family income reaches \$100,000. In our opposite analysis of the economic costs of losing transfers, we assume that the economic costs decrease linearly as family income goes above \$50k and that families with \$100k of income and above incur zero economic costs from reduced transfers.

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