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The EITC and Linking Data for Examining Multigenerational Effects

Randall Akee, Maggie R. Jones, and Emilia Simeonova

18.1 Introduction

The Earned Income Tax Credit (EITC) is the best-known and most widely utilized provision of the federal income tax code that targets families of low-income tax filers. As opposed to welfare programs, such as food stamps, the EITC is available only to working adults and is administered through the Internal Revenue Service as an addition to a refund on filed earned income taxes. The EITC was first adopted in 1975 as a modest transfer to working families. It has expanded substantially and is currently the largest government cash transfer program. In 2018, 22 million working families and individuals received EITC, with an average refund of $3,191 for a family with children. Maximum credit dollars reached $5,828 for a family of four earning around $20,000 in 2019. Refunds for families and individuals without children are much smaller, with an average of $298 in 2018 (CBPP 2019).

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Researchers credit the EITC with lifting families out of poverty, encouraging employment, and improving the long-term well-being of families and children. Very little is known about the potential effects of EITC on the long-term outcomes of children from affected households, but recent research has examined late childhood and early adult outcomes (Bastian and Michelmore 2018; Dahl and Lochner 2012). At the same time, a large and growing literature has shown that family financial conditions during childhood, and in particular family income, have strong and persistent effects on children's well-being as young adults and beyond (Akee et al. 2013, 2018; Almond, Currie, and Duque 2018; Currie 2009; Hoynes, Schanzenbach, and Almond 2016). Further, research has shown that parental use of welfare benefits and government programs affects children's utilization of these programs (Dahl, Kostøl, and Mogstad 2014); if the same is true of intergenerational EITC use, this may result in additional positive effects on labor force attachment and earnings.

Another strand of the literature has found that programs that enable families to "move to opportunity" have lasting impacts on the outcomes of low-income children (Chetty and Hendren 2018a, 2018b; Chetty, Hendren, and Katz 2016). In light of the fact that the EITC is often used to forestall eviction or improve a family's housing situation (Pilkauskas and Michelmore 2019), an important and unexplored question in EITC research is how the EITC compares to other public assistant programs, such as housing voucher programs, in improving children's opportunities and outcomes. By using the same analysis data and similar cohort years as a recent, large-scale study of intergenerational mobility, we are in a position to assess the impact of EITC dollars on the next generation.

There are several reasons why the EITC could affect children's long-term outcomes. Prior research has demonstrated that the EITC increased household incomes and reduced the incidence of poverty among at-risk families (Dahl and Lochner 2012; Hoynes, Miller, and Simon 2015). It also affected labor force participation and attachment, especially for single mothers (Bastian 2017; Bastian and Michelmore 2018; Eissa and Liebman 1996), and reduced levels of maternal stress, potentially leading to gains in long-term health status (Evans and Garthwaite 2014). Theoretically, these findings about households' response to EITC could have opposite effects on children's long-term labor market outcomes. On the one hand, increased household incomes, parental labor force attachment, and better parental health should have positive effects on children's long-term labor market success. On the other hand, increased labor force participation, especially by single mothers, is often associated with less parental supervision, which could lead to undesirable social behaviors (Dave et al. 2019).

The immediate effects of public policies aimed at reducing poverty are relatively well researched and evaluated. The long-term and intergenerational effects are not well understood, and may run contrary to initial expectations because of the many different choices involved in deriving maximum individual benefit from the policy for the generation immediately affected by it. In light of the recent surge in interest in the determinants of intergenerational economic and social mobility, it is crucial that we understand better how the most expensive US tax policy intended to promote work has impacted the long-term well-being of the next generation.

In this study we use individual-level panel data from linked Internal Revenue Service tax data and Census Bureau demographic data to evaluate whether changes in the generosity of the EITC affected the intergenerational transmission of socioeconomic status (SES). We make several contributions to the literature. First, to our knowledge, this is the first study to examine how a large federal antipoverty program in the United States affects intergenerational income mobility. Second, because we have access to individual data, we test for important heterogeneities in effects across sociodemographic characteristics of the parents and the children at the time of EITC expansion, such as single parenthood and child gender. Importantly, because we use variation in the age at which increased EITC generosity affects children residing in the same state, our estimates are not affected by other entitlements and government programs (such as Medicaid expansions), which applied to children of all ages at the time of implementation.

We find strong positive correlations between parental income and child income rank for those born in households whose income, on average, is within the qualifying range for EITC. The correlation is stable around 0.27. Consistent with some of the other literature on the effects of positive socioeconomic changes to households on children's long-term outcomes, we find a positive impact of greater EITC generosity on outcomes measured at ages 25–26, including improved rank in the child income distribution, lower EITC claiming in adulthood by children, and higher probabilities of having gainful employment. We also find positive effects on the probability of children being married in their mid-20s. Results vary by childhood family type and child gender, with children from married families showing stronger labor force attachment and rank improvement than children of single mothers. Girls from single-mother families improve more in income rank than do boys of single families, and girls from married-parent families display stronger labor-force attachment in response to greater EITC generosity than boys from a similar background.

18.2 Background

18.2.1 The Earned Income Tax Credit

The EITC was developed in the 1970s as a way to compensate low-wage workers for regressive payroll taxes. The EITC refunded 10 cents of every earned dollar, up to an earnings maximum level of $5,000, at which point the credit phased out at a rate of 12.5 percent of income. The maximum credit a tax filer could be eligible for was between $400 and $500 between 1975 and 1986 (about $1,200 in 2019 dollars). The tax credit required some positive earnings and the filer had to have a qualified child in the household; there was no childless household EITC during the initial phase of the program.

During the decade of the 1990s, EITC qualifying rules and generosity underwent dramatic changes. Tax code amendments included a more generous benefit schedule for all families, gradually implemented from 1991 to 1996, that increased the phase-in rate from 14 percent per dollar of earned income in 1990 to 34 and 40 percent in 1996 for households with one and two or more children. A new credit schedule for childless earners was added in 1994. Meanwhile, rules over eligibility tightened, including a new cap on investment income.

18.2.2 Related Research

This work is related to several strands of the existing literature. First, we contribute to the work on differences in economic opportunity for children growing up across the US and how exposure to improved opportunity affects the next generation, pioneered by Chetty and Hendren (2018a, 2018b). We adopt many of the definitions of that literature, including employing income ranks in our analysis. A second strand of emerging related research is dedicated to the intergenerational effects of public policies. Some of this work has focused on the intergenerational effects of fertility policies (e.g., Ananat and Hungerman 2012; Madestam and Simeonova 2012); others have investigated large public assistance programs such as food stamps (e.g., Hoynes, McGranahan, and Schanzenbach 2015) and the expansion of public health clinics and Title X (Bailey, Malkova, and McLaren 2019). This work is also related to the large literature on household SES and children's adult outcomes, ranging from socioeconomic success to long-term health. This literature has demonstrated strong associations between parents' resources and children's success. As the EITC expansion created exogenous positive variation in some families' resources (but not others'), our findings contribute to the small but growing branch of this literature exploiting natural and social experiments to identify the mechanism of SES transmission across generations net of selection and omitted variable biases. Last, and most directly, this work is related to the many strands of research on the effects of EITC and EITC expansions on the individuals directly affected by the policy (in our case, parents of multiple children) and their dependents.

18.2.3 EITC and Effects on Parents' Outcomes and Own Employment

Eissa and Liebman (1996) investigate the role of the 1986 EITC expansion on mothers' labor force participation and hours worked; they find that there is an almost 3 percentage point increase in labor force participation rates for single mothers with children. Subsequent analysis by Eissa and

Hoynes (2004) finds that later expansions of EITC to married couples effectively reduces total family labor supply. Their analysis finds that while males increase their labor force participation, their female spouses tend to more than proportionately reduce their labor force participation rates. On net, this leads to a reduction in total family labor in the market; the authors characterize the expansion as subsidizing married mothers to stay at home. On the other hand, Hotz and Scholz (2006) find that EITC increases labor force participation for single-parent families. Chetty, Friedman, and Saez (2013) find that the EITC provides significant incentives for individuals to increase the number of hours worked so as to maximize their EITC refunds on the initial phase-in portion of benefits. The prevailing analysis for EITC impact shows that the EITC has an effect on hours worked as well as on labor force participation—both on intensive and extensive margins.

18.2.4 The EITC and Children's Outcomes

The most closely related literature is that on EITC and children's educational outcomes—in the period during and right after EITC exposure, and also the college years. Dahl and Lochner (2012) utilize the same variation in EITC as we do—the federal expansion for households with two or more children—and data from the National Longitudinal Survey of Youth (NLSY) to investigate the effect of increased household resources on children's test scores. They find that a $1,000 increase in income improved math and reading test scores by 6 percent of a standard deviation. This improvement is contemporaneous with EITC receipt by the mothers, and echoes findings on reduced maternal stress by Evans and Garthwaite (2014), and findings in Akee et al. (2013, 2018) demonstrating that extra income reduces parental stress and improves children's schooling outcomes and emotional and behavioral health.

A contemporaneous paper by Chetty, Friedman, and Rockoff (2011) examines how the EITC affects long-run outcomes through its impact on childhood test scores. Dahl and Lochner (2017) rely on the NLSY, which while representative does not contain a large number of individuals. Chetty, Friedman, and Rockoff (2011) combine data from a large urban school district with administrative tax records. Importantly, they also find that a $1,000 increase in tax credits leads to a 6 percent of a standard deviation increase in childhood test scores. This increase in childhood test scores results in a 0.3 percentage point increase in college going by age 20.

Bastian and Michelmore (2018) consider exposure to EITC throughout childhood and across all children from potentially affected cohorts that are surveyed by the Panel Study of Income Dynamics. They sum the total amount of EITC credits that the child could potentially be eligible for during her time in her parents' household, regardless of whether the child's household was ever actually eligible for EITC receipts. Both single children and children from multiple sibship pairs are included in the analysis, and the identifying variation comes from changes in EITC exposure by birth cohort and state of residence. Thus, the estimated results are interpretable as the average effects of EITC exposure by state and birth cohort across all children. Bastian and Michelmore use all EITC expansions, and thus are utilizing changes in household refunds starting as early as 1975; relatively few children, and thus a very small fraction of the identifying variation, come from cohorts born after 1990. The most substantial changes in EITC generosity happened in the period 1991–94.

18.3 Data

18.3.1 Data Sources

Our data reflect the same intergenerational relationships as described in Chetty et al. (2020) (hereinafter CHJP). The online appendixes to that paper provide the details on the sources of variables and their descriptions. In brief, the data comprise information from several Census-held data sets: the decennial 2000 and 2010 short forms; the decennial 2000 long form; the 2005–17 American Community Surveys (ACS); IRS Form 1040 returns from 1994, 1995, and 1998–2017; and IRS Form W-2 data from 2005 to 2017. The decennial short forms cover the entire population of the US, while the long form and ACSs are stratified random samples covering one-sixth and 2.5 percent of US households.

These records are linked using a unique person identifier called a Protected Identification Key (PIK) that the Census Bureau assigns using personally identifiable information such as a social security number (SSN), name, address, and date of birth. The algorithm used for record linkage is described in Layne, Wagner, and Rothaas (2014). CHJP, both in their text and online appendixes, provide evidence on the quality of the PIK placement and data match. The population frame for the linked data is the 2016 Census Numident, which is the universe of SSNs issued up to that year.

18.3.1.1 Sample and Variable Definition

Our target sample comprises all children in the 1979–91 birth cohorts who were born in the US or who came to the US in childhood. Both children and their parents must be authorized immigrants to be included in the sample. We identify all children who were claimed as a child dependent on a Form 1040 at any time between 1994 and 2017 using the child's unique identifier, which is assigned to the Form 1040 data beginning in 1994. The identifier of the person who first claims the child is the invariant "parent," but we restrict parents to adults who appear in the 2016 Numident and who were between the ages of 15 and 50 when the child was born. The linking to an invariant parent captures approximately 93 percent of all children who appear in the Numident.

In assigning siblings, we collect children by the mother's identifier, regardless of whether the mother's filing status changed between sibling births. For example, a child claimed in 1994 by two parents may have a sibling born after 1994 who was claimed only by the mother. In each child's case, the mother's filing status is captured at the time of the focal child's claiming—in the example considered here, the mother would be considered married throughout. When the mother's identifier is absent, we use the father's identifier. In later iterations of this work, this choice will be examined. Although we are following CHJP in keeping the claiming parent(s) invariant vis-à-vis the individual child, this choice may be less defensible when the analysis relies on the correct identification of siblings. While the target sample includes birth cohorts 1979–91, we capture siblings claimed on parents' 1040s who were born between 1978 and 1999.

Our key outcome of interest is the child's rank in the cohort income distribution averaged over ages 25 and 26. For children born in 1991, this value is captured in 2016/17, the last year we use in our analysis. This choice of cohort range and the timing of the outcome "sandwiches" our sample between two events: our youngest cohort was two to three years old at the time of the major EITC policy changes in the 1990s and were 17–18 (aging out of eligibility) at the time of the 2009 expansion. Rank definitions for both parents and children are based on family income reported in the adjusted gross income field of the 1040. Parents' income is averaged over years 1994–2000 and is measured within the focal child's cohort.

A second outcome of interest is whether the child is working at ages 25–26. Working is defined as having nonzero individual earnings. Our third outcome of interest is whether the children themselves, as adults, claim EITC for their own family. We define a binary outcome variable for any EITC claiming. We also examine the average amount of EITC paid.

We define child's and parent's race based on the most recent race reported for them on a decennial census or an ACS. Gender is also defined using the available demographic data. The filing status of parents, used to identify our sample of single mothers, is derived directly from the Form 1040 on which the child was first claimed. We define single mothers as those who file as "single" or "head of household" and married families as those who file jointly.

Figure 18.1 shows available age ranges for the parent/child link for data held at the Census Bureau, where the first year of data used for the child's adult earnings is 2004. We consider households below the 35th percentile of the income distribution because these households could qualify for EITC. Several features of this time frame should be noted. First, all of the children in our sample were still claimable by parents under different EITC regimes, with major EITC changes taking place in 1985 (children ages one to six) and over 1991–96 (children ages 1–18). Each cohort in our sample spent at least some of their childhood after the one-versus-two-child split in the

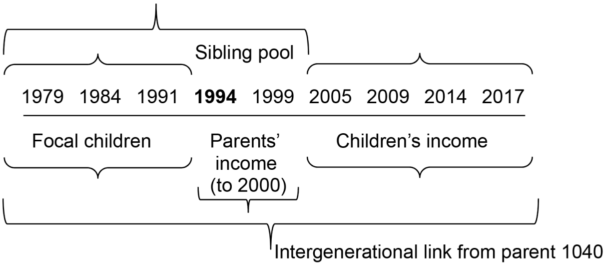

Fig. 18.1 Years used in analysis

Notes: Focal children were born between 1979 and 1991. This age range allows us to find 1040 income and W-2 earnings for children between 2005 and 2017, when each cohort was between the ages of 25 and 26. To find siblings, we use a larger span of child cohorts: 1978 to 1999. All intergenerational links rely on the parents' claiming of children on 1994, 1995, and 1998–2017 Form 1040s. We calculate the parent income rank averaged over 1994 to 2000 income reported on Form 1040s.

EITC schedule, which provides the source of variation in lifetime EITC within a cohort.

18.3.2 Sample Description

Table 18.1 presents the means for the main outcomes and explanatory variables for children residing in households below the 35th percentile of the parental income distribution averaged over the period 1994 to 2000. We also report means for the two subsamples that we consider—children who grew up in single-mother families or in married-parent families. The category that is not shown comprises children who were first claimed by an unmarried father. Children of single mothers are exposed to slightly less potential EITC compared to children from married families, which is likely a function of higher fertility rates for married mothers at this income range, as seen by the greater number of siblings for children of married families.

Demographic characteristics are in line with expectations, with a higher proportion of Black children growing up in single mother families compared with White, Asian, or Hispanic children. Single mothers also have a lower average income rank compared with married families.

18.4 Empirical Methodology

The cohorts we examine grew up over a period of expanding EITC generosity that rolled out between tax years 1991 and 1995. Throughout our analysis, we follow the standard procedure of treating EITC policy changes as exogenous in terms of family structure. We apply broad eligibility by family size over the lower third of the parental income distribution, rather than calculating it directly using income or earnings, which may be endog-

Table 18.1 **Summary statistics**

	All families (1)	Single mothers (2)	Married families (3)
Childhood eligible EITC (10,000s)	5.86	5.73	5.97
Average child income rank at ages 25–26	0.41	0.39	0.45
Average EITC claimed at ages 25–26	84.71	93.52	70.85
Probability child claims EITC at ages 25–26	0.04	0.04	0.03
Child works at ages 25–26	0.80	0.82	0.82
Child married at 25–26	0.21	0.17	0.28
Child cohort	1985.00	1985.00	1985.00
Number of siblings	2.39	2.13	2.70
Years between closest sibling	2.44	2.43	2.55
Order of siblings	1.52	1.44	1.63
First child	0.62	0.66	0.56
Male	0.51	0.50	0.51
White	0.43	0.36	0.56
Black	0.26	0.38	0.09
Asian	0.04	0.02	0.07
Hispanic	0.23	0.20	0.23
AIAN	0.01	0.01	0.01
Other	0.03	0.03	0.03
Parent income rank	0.17	0.16	0.20
Single mother	0.43	1.00	0.00
Married family	0.38	0.00	1.00
Observations	17,700,000	7,568,000	6,786,000

Sources: Linked parent-child data derived from Numident, 2000 and 2010 decennial; American Community Survey; Forms 1040, W-2, and 1099 tax records. The Census Bureau's Disclosure Review Board has approved all statistics and estimates presented today for public release under approval numbers list approvals here, e.g., CBDRB-FY2019-CES005-039.

enously determined by households' adapting their labor supply to changes in EITC generosity. Our estimates are thus interpretable in an intention-to-treat framework.

In 1991, the two-child credit schedule was added, although in this year the difference between it and the one-child credit was only $43 at the maximum credit value. This maximum credit difference changed little between 1991 and 1993. Then, between 1993 and 1994, the credit difference expanded from $77 to $490, the largest single increase in percentage terms over the policy roll-out (a 36 percent change versus 8–18 percent in all other years). Figure 18.2 shows the changes in generosity in the EITC schedule by number of children over time.

For each child, we calculate the year-by-year maximum EITC, adjusted to 2015 dollars, that a child's household would be eligible for based on the number of children in the household for that year. This annual value is calculated independent of parental income, although we focus on families whose

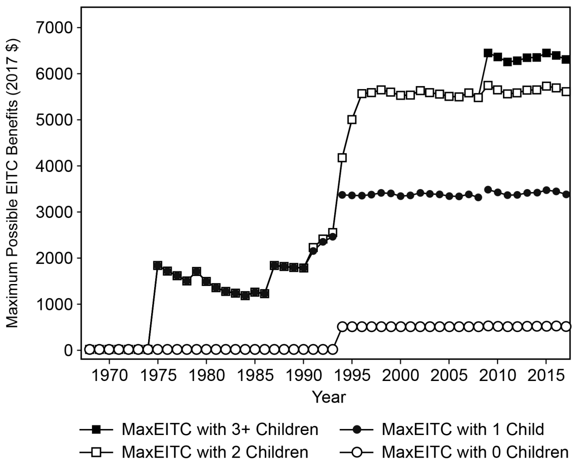

Fig. 18.2 Changes in EITC eligibility over time

average parental income rank was below the 35th percentile to guarantee that, on average, we are including only low-income families. These annual values are then summed to generate a "childhood total EITC," expressed in \$10,000s. This value implicitly nests variation in EITC "treatment" based on three characteristics: the cohort of the child, which captures variation over time in EITC generosity; the child's order in the family, which determines the persistence of the two-child versus one-child treatment based on whether the child is an only, middle, first, or last child; and the difference in age between the child and their older/younger sibling, which determines the duration of the two-child versus the one-child treatment. Because of the time frame of our data, we use the age of 18 as the last year of eligibility, even though full-time students may remain eligible until age 24.

For example, focal children with both an older and a younger sibling live in a family that was eligible for the two-child credit for the portion of the child's 18 years after 1991 and are assigned the maximum possible lifetime value for their cohort. A child in the same cohort with just an older sibling would, in contrast, be in an eligible family only for the years after 1991 during which their sibling was under 18 ("aging out"). Meanwhile, those with just younger siblings are only in two-child-eligible families if their sibling is born after 1991. Single children are assigned the maximum possible value for the one-child credit.

All of the siblings we capture were claimed on parents' 1040s between 1978 and 1999, but we focus on a subset of these children in the analysis born between 1979 and 1991 to capture earnings and EITC claiming for all children when they are 25/26 years old. The latest data on earnings are from the year 2017, which restricts the age and the cohort range.

The main estimating equation is

$$(18.1)\quad Y_i = \alpha + \beta \times ParentRank_i + \delta \times LifetimeEITC + \nu_i + \theta_i + \gamma_i + \mu_i$$
$$+ \omega_i + \pi_i + \chi_i + \varepsilon_i,$$

where the outcome is the child's income rank in her cohort's income distribution averaged between 25 and 26, the dollar amount of EITC claimed by the child as an adult (ages 25–26), or a binary outcome variable indicating receipt of EITC as an adult, whether the child is currently working or marital status of the child. The variable $ParentRank_i$ is the income rank of the claiming parent averaged within parental birth cohort over 1994 through 2000. We include a measure for the lifetime EITC receipt (during childhood) that a child is eligible for given the family structure, birth cohort, and family type: this variable is *LifetimeEITC*. The additional control variables are cohort fixed effects, ν_i; also birth-order fixed effects, θ_i; a gender dummy variable, γ_i; single-mother family type, μ_i; race fixed effects ω_i; total number of siblings fixed effects, π_i; and state of residence fixed effect, χ_i. Family type (married vs. single) is assigned based on the first year that a child is claimed. The state fixed effects account for differences in state-level economic conditions and social program generosity.

Differences in outcome variables, conditional on parental income rank, are thus identified through differences in the total childhood EITC amount eligible for children born in the same cohort, having the same birth order, family type, gender, race, and total sibship size, and residing in the same state at the time they are first claimed. The cohort years we examine allow us to calculate our main outcome—child income rank averaged over ages 25 and 26—for all children from the same birth cohort.

A potential threat to identification could arise from endogenous fertility in response to the increased EITC generosity for families with two or more children. If some families responded to the policy by acquiring more children, then a specification comparing families of different sizes over time would produce biased estimates affected by selection. This is not a concern for us for two reasons. First, there is no evidence that the EITC affected fertility (e.g., Baugman and Dickert-Conlin 2009) or marriage formation. Second, our identification is based on differences between children treated at different ages, with variation in treatment within a cohort depending on the timing of sibling births and the focal child's order in the family rather than general fertility.

18.5 Results: Intention to Treat Estimates of Childhood EITC on Adult Outcomes

Table 18.2 shows the results from estimating equation (18.1), where the odd-numbered models in each case include only parental income rank and childhood total EITC, and the even-numbered models include the full set

Table 18.2 **Effect of childhood total EITC on child outcomes, conditional on parent rank**

	Child rank		EITC claiming		Claiming probability		Child working		Child married	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				Panel A: All families						
Parent income rank	0.33	0.27	−75.73	−76.97	−0.02	−0.02	0.33	0.26	0.23	0.10
	(0.02)	(0.01)	(6.00)	(2.81)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
Childhood eligible EITC	0.001	0.003	1.734	0.948	0.002	0.0001	−0.0001	0.003	−0.011	0.0001
(10,000s)	(0.0007)	(0.0004)	(0.2476)	(0.3085)	(0.0001)	(0.0002)	(0.0005)	(0.0005)	(0.0008)	0.0004)
Observations	17,700,000									
				Panel B: Single mothers						
Parent income rank	0.31	0.29	−78.81	−83.80	−0.02	−0.02	0.32	0.29	0.10	0.09
	(0.01)	(0.01)	(3.96)	(2.64)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Childhood eligible EITC	−0.001	0.002	3.288	1.876	0.003	0.000	0.001	0.003	−0.014	0.002
(10,000s)	(0.0006)	(0.0003)	(0.3929)	(0.4366)	(0.0001)	(0.0002)	(0.0004)	(0.0005)	(0.0007)	(0.0005)
Observations	7,568,000									
				Panel C: Married families						
Parent income rank	0.28	0.23	−50.64	−65.53	−0.01	−0.02	0.32	0.23	0.18	0.07
	(0.02)	(0.01)	(8.83)	(5.04)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.02)
Childhood eligible EITC	0.001	0.006	0.910	1.595	0.002	0.000	−0.001	0.008	−0.015	0.004
(10,000s)	(0.0008)	(0.0004)	(0.2428)	(0.6464)	(0.0001)	(0.0003)	(0.0005)	(0.0006)	(0.0010)	0.0006)
Observations	6,786,000									

Notes: Columns 1, 3, 5, and 7 include only the covariates of interest as shown. Columns 2, 4, 6, and 8 include all additional covariates outlined in the text for equation (18.1).

Sources: Linked parent-child data derived from Numident, 2000 and 2010 decennial; American Community Survey; Forms 1040, W-2, and 1099 tax records. The Census Bureau's Disclosure Review Board has approved all statistics and estimates presented today for public release under approval numbers list approvals here, e.g., CBDRB-FY2019-CES005-039.

of child, family, and sib-ship variables and state fixed effects. The treatment variable of interest is childhood total EITC, constructed as described earlier. The child's rank in the child-specific household income distribution is calculated as the child's average rank over ages 25 and 26. EITC claiming is the dollar value of EITC claimed by the child in adulthood (averaged over ages 25 and 26) and claiming probability is the probability that the child claimed any EITC at age 25 or 26.[1] We use the presence of Forms W-2, 1099, and SE to measure the child's probability of working at some time while aged 25 and 26. Finally, we use information on the 1040 to identify whether the child is married at age 25 or 26.

In each case, we report the association between parent household income rank and the outcome variable, finding an overall child income rank association of 0.27 for the full model, which is close to the values calculated in CHJP. Higher parental income is associated with lower EITC amounts claimed by children, lower probability of claiming any EITC, and a higher probability that children work and are married in early adulthood.

Meanwhile, higher values of childhood EITC lead to an increased rank in the child income distribution, with $10,000 more childhood EITC associated with a 0.3 percentage point higher rank. More childhood EITC also leads to a 0.3 percentage point increase in the probability of working at ages 25 and 26. For the full sample, impacts on claiming probability and whether the child is married at 25 or 26 are not statistically different from zero in the full model.

In the next two panels, we present the results for single-mother households and married households separately. Higher values of childhood EITC increase the child's own rank in the child household income distribution for single-mother and married households: a $10,000 increase in EITC leads to a 0.6 percentage point increase in child rank for children brought up in married households and a 0.2 percentage point increase in income rank for children from single mother households. While statistically significant, this overall impact is modest in absolute dollar terms, amounting to between $400 to $1,800 more in annual income as a young adult. As a comparison, CHJP find that moving to a neighborhood with 1 percent better outcomes in childhood is associated with a few thousand dollars per year more in young adult income. However, if we consider the amount of EITC received annually per household per child, the effects we find are not trivial. The average household received around $3,000 and had about 2.4 children. The amount received per child per year is thus about $1,250. We find that this transfer results in $400 to $1,800 in extra income per child per year in young adulthood, implying a basic rate of return of 30 to 140 percent.

1. The variables at our disposal are the number of children claimed for EITC and the dollar amount of earnings on which the EITC claim is based. This is a simple calculation of what the child claimed, on average, between the ages of 25 and 26.

For the full sample and both subsamples, a $10,000 increase in lifetime EITC receipt increased the probability of working in a child's mid-20s by 0.3 to 0.8 percentage points and the probability of marriage by 0.2 to 0.4 percentage points.

The effects on child income rank and whether a child works are stronger for children growing up in married households, while the dollar value of EITC claimed as an adult is higher for children from single-mother households. Taken together, these results provide suggestive evidence that the EITC confers differential benefits to children who grew up in married households.

In table 18.3, we examine differences by gender and by the two-family types: single mothers and married families. For single-mother families, the improvement in income rank is driven by girls, who show a 0.4 percentage point increase in income rank for every $10,000 of childhood EITC. The effect for boys is about four times smaller and not statistically significant. Girls from single-mother households also show an increased response in labor force participation, which is the same size as the effect on boys. For boys raised in single-mother households, the only significant effect from a $10,000 increase in childhood receipts of EITC is the increase in labor force participation in their mid-20s.

For married families, both boys and girls appear to benefit in child income rank of 0.7 and 0.6 percentage points, respectively, in response to an additional $10,000 in EITC. Both genders are more likely to be gainfully employed in their mid-20s in response to increased EITC generosity, and boys are significantly less likely to claim EITC in young adulthood.

18.6 Discussion

The research presented in this chapter is work in progress. Several other pieces of information will be useful in assessing what we find, including an examination of the impact of the EITC expansion on the labor force participation of mothers in our data, which may go far in explaining some of the differences we see by family structure and child gender. We also are in a position to examine how the EITC expansion we consider may have changed the rank of single mothers through their own labor force participation, which may lead to an overestimate of the gains children make in terms of their own rank.

Other parameters we intend to explore are differences by child race. As we do find some results which indicate that children from married households realize larger benefits (in the child income distribution) as adults, this may exacerbate existing racial income inequality. Specifically, if the positive impact of EITC receipt as a child has a more than proportionate effect on children from married households, then to the extent that marital rates differ across race and ethnic groups, this may play a role in increasing racial income

Table 18.3 **Effect of childhood total EITC on child outcomes by child gender, conditional on parent rank**

	Child rank		EITC claiming		Claiming probability		Child working		Child single parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Single mothers										
Girls										
Parent income rank	0.30	0.29	−120.9	−126.1	−0.02	−0.03	0.28	0.25	0.10	0.09
	(0.01)	(0.01)	(7.16)	(4.45)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Childhood eligible EITC, in 10,000s	−0.002	0.004	5.346	2.648	0.003	0.001	0.001	0.004	−0.016	0.003
	(0.0007)	(0.0006)	(0.7120)	(0.9357)	(0.0001)	(0.0003)	(0.0005)	(0.0005)	(0.0009)	(0.0008)
observations	8,697,000									
Boys										
Parent income rank	0.31	0.30	−41.00	−39.97	−0.01	−0.01	0.35	0.32	0.09	0.08
	(0.02)	(0.01)	(1.87)	(1.85)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Childhood eligible EITC, in 10,000s	0.000	0.001	1.650	1.672	0.002	0.000	0.002	0.003	−0.012	0.002
	(0.0007)	(0.0005)	(0.2313)	(0.5210)	(0.0001)	(0.0002)	(0.0006)	(0.0008)	(0.0005)	(0.0005)
observations	3,762,000									
Panel B: Married families										
Girls										
Parent income rank	0.27	0.21	−64.91	−85.31	−0.01	−0.02	0.30	0.21	0.19	0.07
	(0.02)	(0.01)	(12.21)	(5.45)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.02)
Childhood eligible EITC, in 10,000s	−0.002	0.006	1.129	1.899	0.002	0.000	−0.002	0.007	−0.017	0.005
	(0.0008)	(0.0006)	(0.332)	(0.8578)	(0.0001)	(0.0003)	(0.0005)	(0.0007)	(0.0011)	(0.0009)
observations	3,312,000									
Boys										
Parent income rank	0.29	0.24	−37.57	−46.20	−0.01	−0.01	0.34	0.25	0.16	0.07
	(0.02)	(0.02)	(6.85)	(5.40)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.02)
Childhood eligible EITC, in 10,000s	0.003	0.007	0.552	1.354	0.002	−0.000	0.001	0.008	−0.014	0.002
	(0.0008)	(0.0006)	(0.2599)	(0.6057)	(0.0001)	(0.0003)	(0.0006)	(0.0008)	(0.0009)	(0.0006)
observations	3,473,000									

Notes: Columns 1, 3, 5, and 7 include only the covariates of interest as shown. Columns 2, 4, 6, and 8 include all additional covariates outlined in the text for equation 18.1.

Sources: Linked parent-child data derived from Numident, 2000 and 2010 decennial; American Community Survey; Forms 1040, W-2, and 1099 tax records. The Census Bureau's Disclosure Review Board has approved all statistics and estimates presented today for public release under approval numbers list approvals here, e.g., CBDRB-FY2019-CES005-039.

inequality. This certainly merits additional analysis. Further data linkage to available ACS data will allow us to examine other child outcomes, such as education, childbearing, occupation, and home ownership.

Finally, one inspiration for this work is the "movers" literature, which estimates how a family's move from a low-opportunity area to a high-opportunity area influences children's outcomes. An extension of this work will examine the influence of EITC dollars on family mobility and whether there is an association between exposure to EITC dollars and moves to better neighborhoods.

Results so far indicate that greater EITC generosity improves child outcomes in terms of rank in the child income distribution and labor market participation, and that the magnitude of these outcomes varies by gender and the type of family a child grows up in.

18.7 Conclusion

This study examines how changes in EITC generosity implemented in the 1980s and 1990s affected children's economic outcomes relative to their parents'. Using the universe of IRS records for parents of children born between 1979 and 1991, linked to census demographic data, we find that conditional on parent income rank, more generous EITC improved children's ranks in their cohort distribution. Family type and gender also matter—children from single-mother households respond more strongly to higher EITC dollars than do children from married families, and girls tend to experience stronger effects than boys in these families. Meanwhile, the reverse is true for children from married families, with boys responding more strongly than girls.

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