

From Better Neighborhoods to Better Futures: Tax Credits and Intergenerational Opportunity

Jacob Bastian (Rutgers University and NBER)
Leah Clark (U.S. Census Bureau)

NBER Children and Families, Spring 2026
April 30, 2026

Disclaimer: Any opinions and conclusions expressed herein are those of the author(s) and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7505725: CBDRB-FY25-0313, CBDRB-FY26-0162).

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.
- Some evidence of positive long-run impacts; based on smaller survey datasets (Hoynes et al., 2016; Bastian and Michelmore, 2018)

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.
- Some evidence of positive long-run impacts; based on smaller survey datasets (Hoynes et al., 2016; Bastian and Michelmore, 2018)
- Larger-sample evidence of positive long-run effects reflects treatment from 1960s or earlier (Aizer et al., 2016; Bailey, Hoynes, et al., 2024)
 - Unclear if these results have implications for policy today

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.
- Some evidence of positive long-run impacts; based on smaller survey datasets (Hoynes et al., 2016; Bastian and Michelmore, 2018)
- Larger-sample evidence of positive long-run effects reflects treatment from 1960s or earlier (Aizer et al., 2016; Bailey, Hoynes, et al., 2024)
 - Unclear if these results have implications for policy today
- Recently: a few experiments have found null effects of cash on children (Gennetian et al., 2025; Bartik et al., 2025)
 - Caveats: sample size, short-run, during Covid & multiple cash transfers

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.
- Some evidence of positive long-run impacts; based on smaller survey datasets (Hoynes et al., 2016; Bastian and Michelmore, 2018)
- Larger-sample evidence of positive long-run effects reflects treatment from 1960s or earlier (Aizer et al., 2016; Bailey, Hoynes, et al., 2024)
 - Unclear if these results have implications for policy today
- Recently: a few experiments have found null effects of cash on children (Gennetian et al., 2025; Bartik et al., 2025)
 - Caveats: sample size, short-run, during Covid & multiple cash transfers
- This raises an important open question: Do modern transfer programs meaningfully improve long-run outcomes for children and families?

Motivation and Research Question

- Do income transfers have long-run effects on children's outcomes?
 - If so, why? Parental earnings and time, neighborhoods, health, etc.
- Some evidence of positive long-run impacts; based on smaller survey datasets (Hoynes et al., 2016; Bastian and Michelmore, 2018)
- Larger-sample evidence of positive long-run effects reflects treatment from 1960s or earlier (Aizer et al., 2016; Bailey, Hoynes, et al., 2024)
 - Unclear if these results have implications for policy today
- Recently: a few experiments have found null effects of cash on children (Gennetian et al., 2025; Bartik et al., 2025)
 - Caveats: sample size, short-run, during Covid & multiple cash transfers
- This raises an important open question: Do modern transfer programs meaningfully improve long-run outcomes for children and families?
- We test this question using linked administrative IRS-Census data covering millions of children over 3+ decades
 - Outcomes: employment, earnings, mortality, family structure, neighborhood quality

Determinants of Children's Outcomes

- Two (of many) key determinants of children's long-run outcomes are parental financial resources and neighborhoods they grow up in

Determinants of Children's Outcomes

- Two (of many) key determinants of children's long-run outcomes are parental financial resources and neighborhoods they grow up in
- Abundant research on how transfers like the EITC affect parental income & employment (e.g., Bastian, 2021; Hoynes and Patel, 2023)

Determinants of Children's Outcomes

- Two (of many) key determinants of children's long-run outcomes are parental financial resources and neighborhoods they grow up in
- Abundant research on how transfers like the EITC affect parental income & employment (e.g., Bastian, 2021; Hoynes and Patel, 2023)
- Mixed evidence on whether increased resources lead families to move to higher quality neighborhoods
 - Positive effects: Bailey, Hoynes, et al., (2024); Bastian & Black, (2024)
 - Null effects: Chetty et al., (2016 and 2023); Golosov et al., (2024)

Determinants of Children's Outcomes

- Two (of many) key determinants of children's long-run outcomes are parental financial resources and neighborhoods they grow up in
- Abundant research on how transfers like the EITC affect parental income & employment (e.g., Bastian, 2021; Hoynes and Patel, 2023)
- Mixed evidence on whether increased resources lead families to move to higher quality neighborhoods
 - Positive effects: Bailey, Hoynes, et al., (2024); Bastian & Black, (2024)
 - Null effects: Chetty et al., (2016 and 2023); Golosov et al., (2024)
- We test whether the EITC leads low-income families to move to higher-quality neighborhoods; a powerful—but expensive and often elusive—pathway to upward intergenerational mobility

EITC Policy Variation and Research Design

- We exploit rich policy variation by year, state, and number of children
 - Federal EITC expansions in the 1970s–2000s; largest changes in 1990s
 - Dozens of changes to state EITC that top-up federal EITC

EITC Policy Variation and Research Design

- We exploit rich policy variation by year, state, and number of children
 - Federal EITC expansions in the 1970s–2000s; largest changes in 1990s
 - Dozens of changes to state EITC that top-up federal EITC
- We capture these changes with a measure of the average annual maximum potential benefits during childhood (**MaxEITC**)
 - Unrelated to household income or actually receiving EITC

EITC Policy Variation and Research Design

- We exploit rich policy variation by year, state, and number of children
 - Federal EITC expansions in the 1970s–2000s; largest changes in 1990s
 - Dozens of changes to state EITC that top-up federal EITC
- We capture these changes with a measure of the average annual maximum potential benefits during childhood (**MaxEITC**)
 - Unrelated to household income or actually receiving EITC
- We then create a childhood average *MaxEITC* (ages 0–18), as well as values for ages 0–5, 6–12, and 13–18
- We estimate the impact of *MaxEITC* on long-run outcomes with and without family fixed effects to account for unobserved family traits

EITC Policy Variation and Research Design

- We exploit rich policy variation by year, state, and number of children
 - Federal EITC expansions in the 1970s–2000s; largest changes in 1990s
 - Dozens of changes to state EITC that top-up federal EITC
- We capture these changes with a measure of the average annual maximum potential benefits during childhood (**MaxEITC**)
 - Unrelated to household income or actually receiving EITC
- We then create a childhood average *MaxEITC* (ages 0–18), as well as values for ages 0–5, 6–12, and 13–18
- We estimate the impact of *MaxEITC* on long-run outcomes with and without family fixed effects to account for unobserved family traits
- We also carry out a mediation analysis to decompose the channels behind the EITC's long-run effects, considering parental earnings, EITC transfer income, childhood neighborhood quality, health, etc.
 - Using estimates from this paper as well as previous EITC research

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.
 - Neighborhood quality: ranked 1.1–1.4 p.p. higher in various traits (e.g., household income, education, share non-poor & married-parents)

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.
 - Neighborhood quality: ranked 1.1–1.4 p.p. higher in various traits (e.g., household income, education, share non-poor & married-parents)
 - Small negative impact on marriage at younger ages and a growing small positive effect after age 28 or so

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.
 - Neighborhood quality: ranked 1.1–1.4 p.p. higher in various traits (e.g., household income, education, share non-poor & married-parents)
 - Small negative impact on marriage at younger ages and a growing small positive effect after age 28 or so
- Similar effects by gender; largest effects for kids from lower-income families and kids with unmarried parents

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.
 - Neighborhood quality: ranked 1.1–1.4 p.p. higher in various traits (e.g., household income, education, share non-poor & married-parents)
 - Small negative impact on marriage at younger ages and a growing small positive effect after age 28 or so
- Similar effects by gender; largest effects for kids from lower-income families and kids with unmarried parents
 - Positive effects for children of married parents show transfer income itself—not just earnings—has long-run benefits for children

Summary of Results

- Each \$1,000 increase in average annual childhood EITC exposure:
 - Annual earnings: \$300–\$400 at 19–25; \$2600–\$2700 at 26–34
 - Employment: 1.3–1.6 p.p. (similar at ages 19–34)
 - Lower poverty: 0.7–0.8 p.p. at 19–25; 2.0–2.5 p.p. at 26–34
 - Lower mortality (by age 20, 25, 30): 0.2–0.4 p.p.
 - Neighborhood quality: ranked 1.1–1.4 p.p. higher in various traits (e.g., household income, education, share non-poor & married-parents)
 - Small negative impact on marriage at younger ages and a growing small positive effect after age 28 or so
- Similar effects by gender; largest effects for kids from lower-income families and kids with unmarried parents
 - Positive effects for children of married parents show transfer income itself—not just earnings—has long-run benefits for children
 - Teenage exposure leads to the largest effects; smaller and still strongly positive at younger ages

Roadmap

- Discuss EITC policy changes and creation of *MaxEITC*
- Discuss data (linked IRS, Census, ACS, Opportunity Atlas)
- Empirical strategy and results for long-run outcomes
- Decompose longer-run effects on earnings into channels by estimating EITC's short-run effects and carrying out a mediation analysis

The EITC

- The EITC is one of the U.S.'s most important anti-poverty programs
- The EITC is an earnings subsidy, requires work, distributes \$65 billion to 28 million families each year (average of \$4,000, often > \$8,000)
- EITC increases income via an annual tax refund & increased earnings

The EITC

- The EITC is one of the U.S.'s most important anti-poverty programs
- The EITC is an earnings subsidy, requires work, distributes \$65 billion to 28 million families each year (average of \$4,000, often > \$8,000)
- EITC increases income via an annual tax refund & increased earnings
- Abundant research on the EITC and labor supply, income, poverty
- Growing research on short- and longer-run effects on children: infant health, behavior, test scores, educational attainment, adult health
 - Bastian and Michelmore (2018): emp. & earnings with PSID data

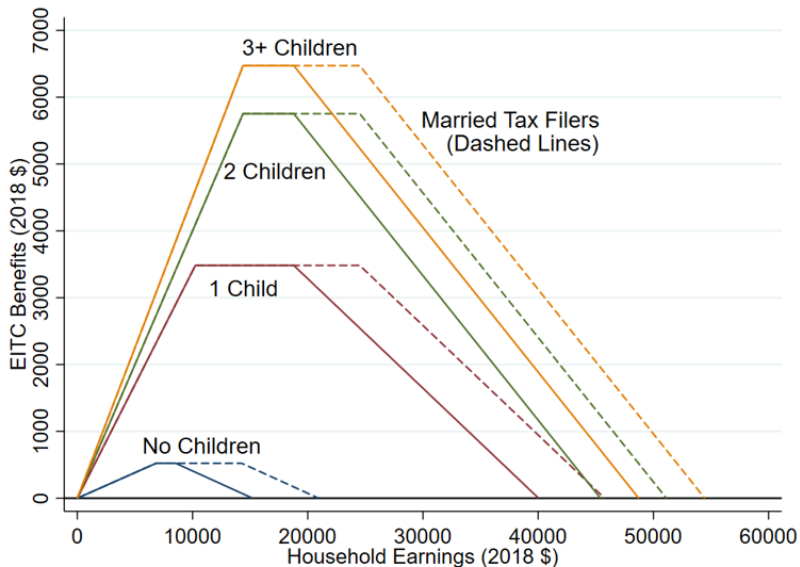
The EITC

- The EITC is one of the U.S.'s most important anti-poverty programs
- The EITC is an earnings subsidy, requires work, distributes \$65 billion to 28 million families each year (average of \$4,000, often > \$8,000)
- EITC increases income via an annual tax refund & increased earnings
- Abundant research on the EITC and labor supply, income, poverty
- Growing research on short- and longer-run effects on children: infant health, behavior, test scores, educational attainment, adult health
 - Bastian and Michelmore (2018): emp. & earnings with PSID data
- Lump-sum payments (often > \$5,000) increase savings and credit access (Jones & Michelmore, 2018); spending on larger items, e.g., vehicles and durable goods (Goodman-Bacon & McGranahan, 2008)

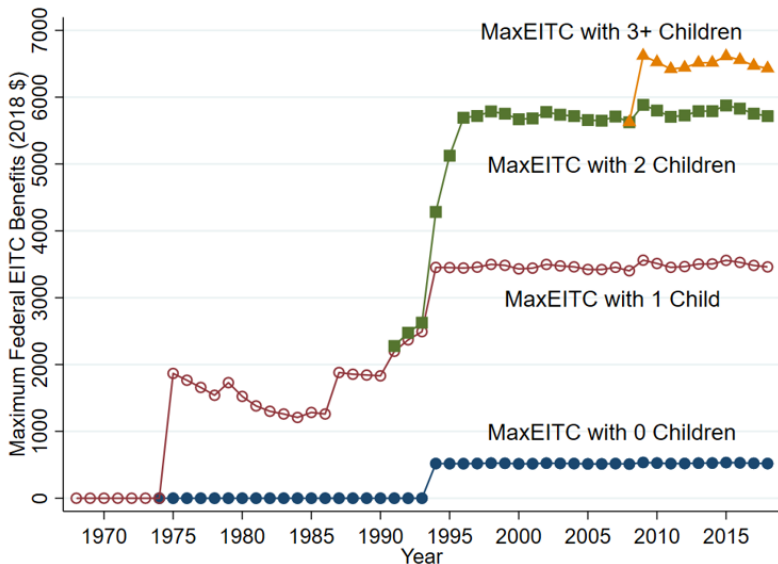
The EITC

- The EITC is one of the U.S.'s most important anti-poverty programs
- The EITC is an earnings subsidy, requires work, distributes \$65 billion to 28 million families each year (average of \$4,000, often > \$8,000)
- EITC increases income via an annual tax refund & increased earnings
- Abundant research on the EITC and labor supply, income, poverty
- Growing research on short- and longer-run effects on children: infant health, behavior, test scores, educational attainment, adult health
 - Bastian and Michelmore (2018): emp. & earnings with PSID data
- Lump-sum payments (often > \$5,000) increase savings and credit access (Jones & Michelmore, 2018); spending on larger items, e.g., vehicles and durable goods (Goodman-Bacon & McGranahan, 2008)
- EITC's impact on housing stability and migration:
 - Bastian and Black (2024) show EITC increases migration out of rural and distressed places—public ACS data, limited geography measures
 - Michelmore and Pilkauskas (2022) show EITC decreases housing instability and living doubled-up with other families

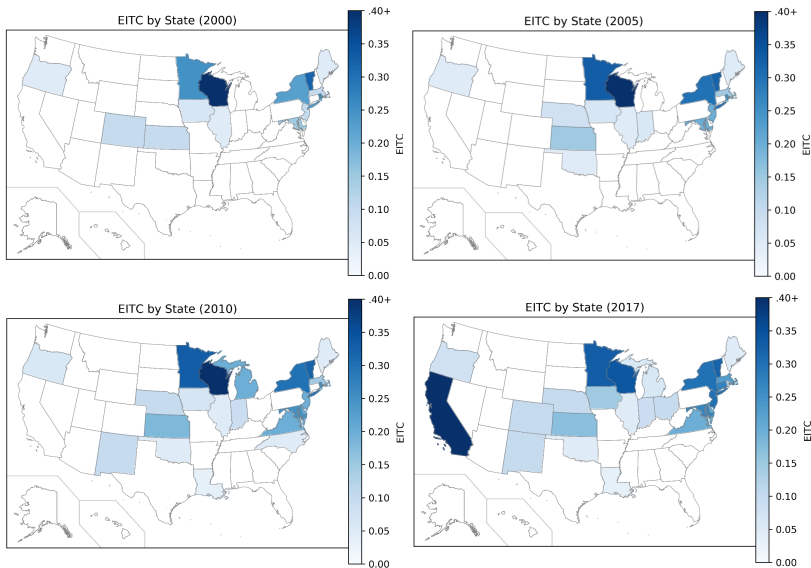
Federal EITC Structure



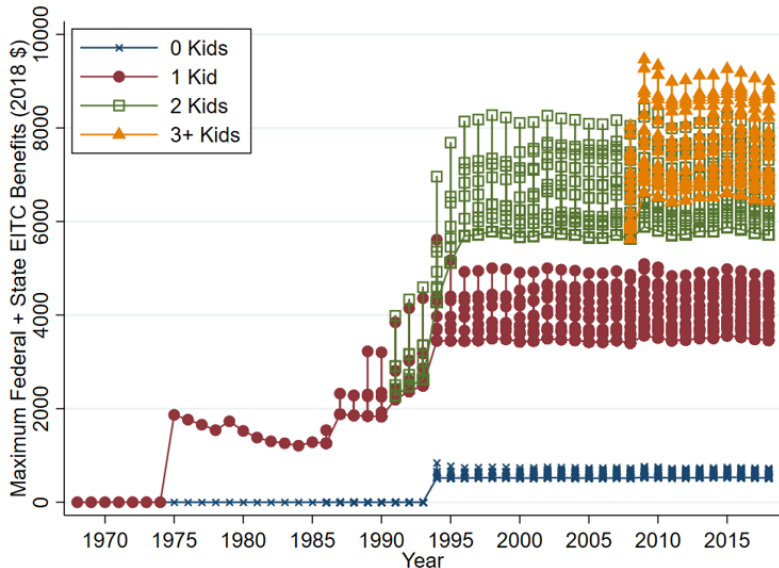
Federal *MaxEITC* Over Time



State EITCs Over Time



Federal+State *MaxEITC* Over Time



Overview of the Setting: EITC Policy Expansions

- Quasi-experimental research design exploiting several policy changes:
 - Several state and federal EITC expansions
 - EITC policy variation by year, state, number of kids, marital status

Overview of the Setting: EITC Policy Expansions

- Quasi-experimental research design exploiting several policy changes:
 - Several state and federal EITC expansions
 - EITC policy variation by year, state, number of kids, marital status
- Empirical strategy: capture EITC policy changes with continuous DD
 - Main approach: use family's *MaxEITC* during childhood
 - *MaxEITC*: $f(\text{number of kids, age of children, year, state})$

Overview of the Setting: EITC Policy Expansions

- Quasi-experimental research design exploiting several policy changes:
 - Several state and federal EITC expansions
 - EITC policy variation by year, state, number of kids, marital status
- Empirical strategy: capture EITC policy changes with continuous DD
 - Main approach: use family's *MaxEITC* during childhood
 - *MaxEITC*: $f(\text{number of kids, age of children, year, state})$
 - Reflects plausibly exogenous policy variation
 - Alternate approaches: EITC phase-in rate; state vs federal EITC; IV; simulated IV

Overview of the Setting: EITC Policy Expansions

- Quasi-experimental research design exploiting several policy changes:
 - Several state and federal EITC expansions
 - EITC policy variation by year, state, number of kids, marital status
- Empirical strategy: capture EITC policy changes with continuous DD
 - Main approach: use family's *MaxEITC* during childhood
 - *MaxEITC*: $f(\text{number of kids, age of children, year, state})$
 - Reflects plausibly exogenous policy variation
 - Alternate approaches: EITC phase-in rate; state vs federal EITC; IV; simulated IV
- To look at long-run effects, we average *MaxEITC* over ages 0–18
- We also estimate effects of *MaxEITC* at ages 0–5, 6–12, and 13–18
- *MaxEITC* interpreted as average annual *MaxEITC* within each childhood age range
- Outcomes measured in adulthood from ages 19 to 34

Linked Tax and Census Admin Panel Data

- Core data come from the Census Bureau's internal Opportunity Project Databank, which links 1994–2022 IRS Form 1040 and W-2 records to the Census Numident and demographic traits from the ACS and 2000 and 2010 decennial censuses

Linked Tax and Census Admin Panel Data

- Core data come from the Census Bureau's internal Opportunity Project Databank, which links 1994–2022 IRS Form 1040 and W-2 records to the Census Numident and demographic traits from the ACS and 2000 and 2010 decennial censuses
- We begin with a 1% random sample of PIKs; if a sampled PIK has ever claimed children, we pull all years of records for that PIK, any spouse PIK, and any children claimed by either
- Over 50 million person-year observations; about 7 million unique obs

Linked Tax and Census Admin Panel Data

- Core data come from the Census Bureau's internal Opportunity Project Databank, which links 1994–2022 IRS Form 1040 and W-2 records to the Census Numident and demographic traits from the ACS and 2000 and 2010 decennial censuses
- We begin with a 1% random sample of PIKs; if a sampled PIK has ever claimed children, we pull all years of records for that PIK, any spouse PIK, and any children claimed by either
- Over 50 million person-year observations; about 7 million unique obs
- Sample limited to people observed at least once between ages 0–5, 6–12, and 13–18, and age 19+
- Outcomes defined at particular ages; some regressions run separately by gender

Linked Tax and Census Admin Panel Data

- Core data come from the Census Bureau's internal Opportunity Project Databank, which links 1994–2022 IRS Form 1040 and W-2 records to the Census Numident and demographic traits from the ACS and 2000 and 2010 decennial censuses
- We begin with a 1% random sample of PIKs; if a sampled PIK has ever claimed children, we pull all years of records for that PIK, any spouse PIK, and any children claimed by either
- Over 50 million person-year observations; about 7 million unique obs
- Sample limited to people observed at least once between ages 0–5, 6–12, and 13–18, and age 19+
- Outcomes defined at particular ages; some regressions run separately by gender
- Geographic identifiers (MAFIDs) from IRS-reported addresses and mapped to census tracts via the Census Bureau's MAFX file

Opportunity Atlas Data

- We link annual Census tracts to the *Opportunity Atlas* (Chetty et al., 2018), which contains rich measures of neighborhood quality
- Measures include: average household income; employment rates; college completion rates; test scores; poverty rates; fraction married parents; demographic traits; etc.

Opportunity Atlas Data

- We link annual Census tracts to the *Opportunity Atlas* (Chetty et al., 2018), which contains rich measures of neighborhood quality
- Measures include: average household income; employment rates; college completion rates; test scores; poverty rates; fraction married parents; demographic traits; etc.
 - Captured in specific years—generally 2000 or 2010
 - Measured in levels or percentiles

Opportunity Atlas Data

- We link annual Census tracts to the *Opportunity Atlas* (Chetty et al., 2018), which contains rich measures of neighborhood quality
- Measures include: average household income; employment rates; college completion rates; test scores; poverty rates; fraction married parents; demographic traits; etc.
 - Captured in specific years—generally 2000 or 2010
 - Measured in levels or percentiles
- We merge data to individuals' annual location
- Census tracts are small geographic units—on average containing about 4,000 residents and covering just a few square miles
 - U.S. has 84,414 tracts; NYC has over 2,100; Chicago has 866

Opportunity Atlas Data

- We link annual Census tracts to the *Opportunity Atlas* (Chetty et al., 2018), which contains rich measures of neighborhood quality
- Measures include: average household income; employment rates; college completion rates; test scores; poverty rates; fraction married parents; demographic traits; etc.
 - Captured in specific years—generally 2000 or 2010
 - Measured in levels or percentiles
- We merge data to individuals' annual location
- Census tracts are small geographic units—on average containing about 4,000 residents and covering just a few square miles
 - U.S. has 84,414 tracts; NYC has over 2,100; Chicago has 866
- Tracts capture changes in neighborhood quality, even for short moves
 - In contrast, public Census/ACS survey data identifies 19 PUMAs in Chicago

Empirical Strategy: Longer-Run Outcomes

- We estimate long-run effects using average annual childhood EITC exposure ($MaxEITC$) between ages 0 and 18:

$$Y_{ist} = \beta_1 MaxEITC_{ist}^{0-18} + X'_{ist} \gamma_1 + \epsilon_{ist}$$

Empirical Strategy: Longer-Run Outcomes

- We estimate long-run effects using average annual childhood EITC exposure ($MaxEITC$) between ages 0 and 18:

$$Y_{ist} = \beta_1 MaxEITC_{ist}^{0-18} + X'_{ist}\gamma_1 + \epsilon_{ist}$$

- Treatment effect captured by β_1 and reflects a \$1,000 increase in $MaxEITC$ in 2022 \$

Empirical Strategy: Longer-Run Outcomes

- We estimate long-run effects using average annual childhood EITC exposure ($MaxEITC$) between ages 0 and 18:

$$Y_{ist} = \beta_1 MaxEITC_{ist}^{0-18} + X'_{ist} \gamma_1 + \epsilon_{ist}$$

- Treatment effect captured by β_1 and reflects a \$1,000 increase in $MaxEITC$ in 2022 \$
- X_{ist} includes FE for state, year, and #children ($MaxEITC$ components); state-year FE; annual state factors interacted with demographic traits
- We run everything with and without family FE

Empirical Strategy: Longer-Run Outcomes

- We estimate long-run effects using average annual childhood EITC exposure ($MaxEITC$) between ages 0 and 18:

$$Y_{ist} = \beta_1 MaxEITC_{ist}^{0-18} + X'_{ist} \gamma_1 + \epsilon_{ist}$$

- Treatment effect captured by β_1 and reflects a \$1,000 increase in $MaxEITC$ in 2022 \$
- X_{ist} includes FE for state, year, and #children ($MaxEITC$ components); state-year FE; annual state factors interacted with demographic traits
- We run everything with and without family FE
- Standard errors robust to heteroskedasticity, clustered at state level
- No weights used (since it is a random sample of population data)

Empirical Strategy: Longer-Run Outcomes

- We also estimate subgroup effects (e.g., by race, parents married):

$$Y_{ist} = \sum_g \beta_2^g \text{MaxEITC}_{ist}^{0-18} + X'_{ist} \gamma_2 + \epsilon_{ist}$$

Empirical Strategy: Longer-Run Outcomes

- We also estimate subgroup effects (e.g., by race, parents married):

$$Y_{ist} = \sum_g \beta_2^g \text{MaxEITC}_{ist}^{0-18} + X'_{ist} \gamma_2 + \epsilon_{ist}$$

- We also estimate effects by childhood age of exposure:

$$Y_{ist} = \beta_3 \text{MaxEITC}_{ist}^{0-5} + \beta_4 \text{MaxEITC}_{ist}^{6-12} + \beta_5 \text{MaxEITC}_{ist}^{13-18} + X'_{ist} \gamma_3 + \epsilon_{ist}$$

Childhood *MaxEITC* on Adult Male Outcomes

Childhood *MaxEITC* on Adult Male Outcomes

	Real Earnings	Real AGI	Employed	Poverty <100%	Poverty <150%
Panel A: Men Ages 19–25					
MaxEITC Ages 0–18	390 (44)	457 (50)	1.53 (0.09)	-0.70 (0.06)	-0.55 (0.05)
N	1,997,000	1,997,000	1,997,000	1,997,000	1,997,000
Panel B: Men Ages 26–34					
MaxEITC Ages 0–18	2700 (191)	3241 (272)	1.63 (0.15)	-2.05 (0.17)	-2.28 (0.16)
N	684,000	684,000	684,000	684,000	684,000

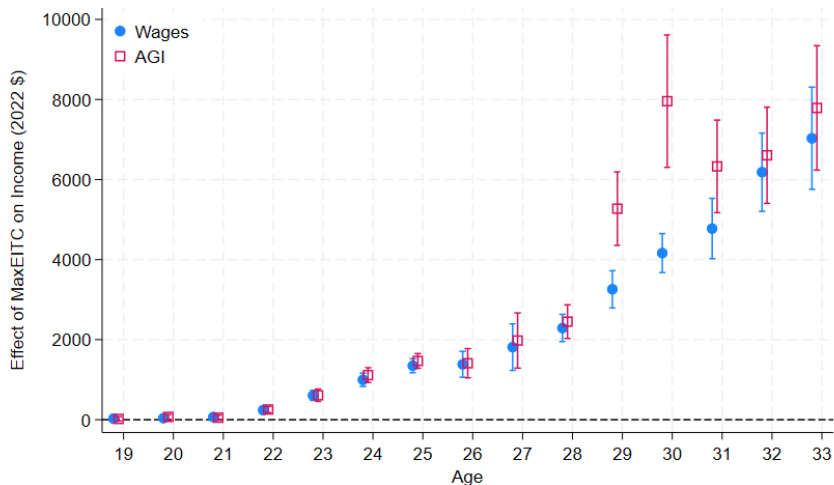
Childhood *MaxEITC* on Adult Female Outcomes

	Real Earnings	Real AGI	Employed	Poverty <100%	Poverty <150%
Panel C: Women Ages 19–25					
MaxEITC Ages 0–18	302 (43)	287 (53)	1.32 (0.07)	-0.81 (0.09)	-0.65 (0.07)
N	1,951,000	1,951,000	1,951,000	1,951,000	1,951,000
Panel D: Women Ages 26–34					
MaxEITC Ages 0–18	2596 (278)	2453 (383)	1.54 (0.10)	-2.53 (0.14)	-2.63 (0.14)
N	673,000	673,000	673,000	673,000	673,000

MaxEITC and Male Outcomes (Family FE)

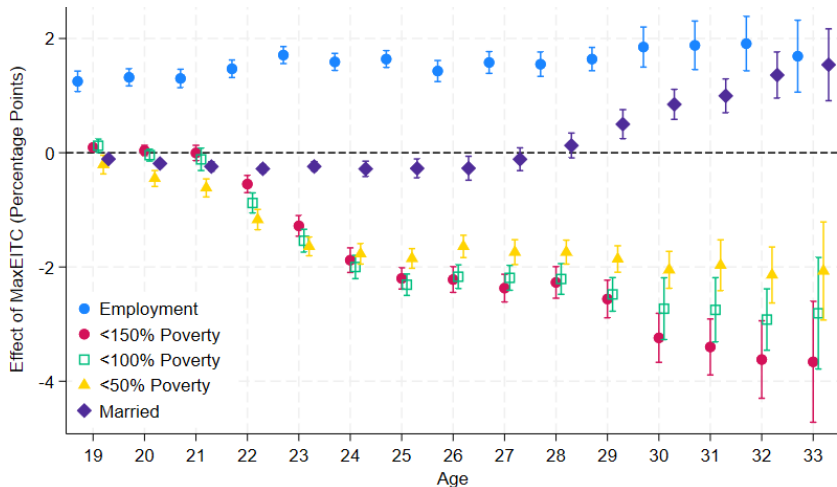
	Real Earnings	Real AGI	Employed	Poverty <100%	Poverty <50%
Panel B: Men Ages 25–29					
MaxEITC Ages 0–18	1932 (550)	2434 (843)	2.18 (0.40)	-2.37 (0.41)	-2.06 (0.37)
N = 709,000					
Panel B: Women Ages 25–29					
MaxEITC Ages 0–18	927 (406)	674 (451)	1.10 (0.44)	-2.16 (0.45)	-1.46 (0.40)
N = 698,000					

MaxEITC and Outcomes by Adult Age



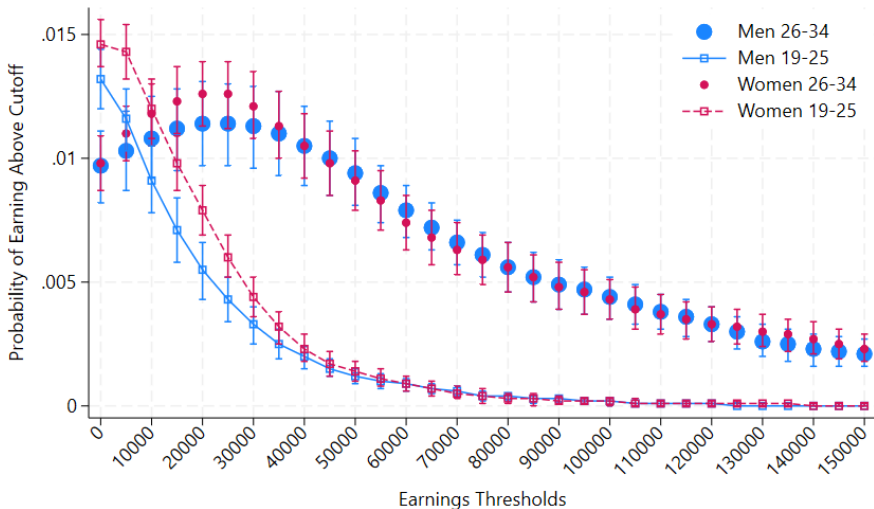
- Trend reflects increasing treatment effects and changing sample composition with age (disentangling these, in progress)

MaxEITC and More Outcomes by Adult Age



- Trend reflects increasing treatment effects and changing sample composition with age (disentangling these, in progress)

MaxEITC Impact on Earnings Distribution



- Binary outcomes = having earnings $>$ each threshold

Impact of *MaxEITC* by Average Childhood Family AGI

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Annual Earnings (2022 \$)	Annual AGI (2022 \$)	Employed	Poverty <50%	Poverty <100%	Poverty <150%
Panel A: Low Income (Avg. AGI \leq \$40,000 from Ages 0–18), N=976,000						
MaxEITC (Ages 0–18)	319 (27)	288 (30)	1.46 (0.075)	-1.26 (0.079)	-0.965 (0.060)	-0.547 (0.044)
Panel B: High Income (Avg. AGI $>$ \$40,000 from Ages 0–18), N=2,148,000						
MaxEITC (Ages 0–18)	-8 (34)	11 (38)	1.20 (0.072)	-0.200 (0.075)	0.169 (0.077)	0.099 (0.056)

- Sample = men and women combined, ages 19–24

MaxEITC by Child Age and Adult Outcomes

MaxEITC by Child Age and Adult Outcomes

	Real Wages	Real AGI	Employed	Poverty <50%	Poverty <100%	Poverty <150%
Panel A: Men 25–29, without Family FE						
MaxEITC Ages 0–5	633 (92)	647 (119)	0.65 (0.09)	-0.68 (0.10)	-0.78 (0.09)	-0.81 (0.08)
MaxEITC Ages 6–12	116 (157)	119 (189)	0.44 (0.12)	-0.43 (0.12)	-0.51 (0.14)	-0.44 (0.12)
MaxEITC Ages 13–18	1307 (156)	1461 (185)	0.72 (0.09)	-0.88 (0.10)	-0.96 (0.10)	-1.10 (0.10)

MaxEITC by Child Age and Adult Outcomes

	Real Wages	Real AGI	Employed	Poverty <50%	Poverty <100%	Poverty <150%
Panel A: Men 25–29, without Family FE						
MaxEITC Ages 0–5	633 (92)	647 (119)	0.65 (0.09)	-0.68 (0.10)	-0.78 (0.09)	-0.81 (0.08)
MaxEITC Ages 6–12	116 (157)	119 (189)	0.44 (0.12)	-0.43 (0.12)	-0.51 (0.14)	-0.44 (0.12)
MaxEITC Ages 13–18	1307 (156)	1461 (185)	0.72 (0.09)	-0.88 (0.10)	-0.96 (0.10)	-1.10 (0.10)
Panel B: Men 25–29, with Family FE						
MaxEITC Ages 0–5	398 (531)	643 (572)	0.55 (0.31)	-0.70 (0.30)	-0.99 (0.26)	-0.76 (0.23)
MaxEITC Ages 6–12	596 (278)	887 (508)	0.53 (0.29)	-0.37 (0.29)	-0.40 (0.31)	-0.46 (0.39)
MaxEITC Ages 13–18	773 (265)	746 (279)	1.04 (0.21)	-1.06 (0.22)	-1.00 (0.21)	-1.07 (0.24)

MaxEITC Effects by Race/Ethnicity

MaxEITC Effects by Race/Ethnicity

Outcome:	Annual Earnings (2022 \$)	Annual AGI (2022 \$)	Working	Poverty <50%	Poverty <100%
	(1)	(2)	(3)	(4)	(5)
Men Ages 19–25 (N = 1,997,000)					
MaxEITC (Ages 0–18) × White	413 (48)	538 (60)	1.39 (0.11)	-0.74 (0.11)	-0.29 (0.08)
MaxEITC (Ages 0–18) × Black	424 (55)	430 (58)	1.88 (0.11)	-1.49 (0.10)	-1.24 (0.10)
MaxEITC (Ages 0–18) × Asian	44 (142)	-9 (133)	0.10 (0.22)	0.52 (0.21)	0.47 (0.28)
MaxEITC (Ages 0–18) × Hispanic	345 (88)	328 (106)	1.65 (0.11)	-1.44 (0.13)	-1.07 (0.11)
MaxEITC (Ages 0–18) × Native	289 (525)	416 (519)	1.97 (1.21)	-1.75 (1.25)	-1.00 (1.00)
MaxEITC (Ages 0–18) × Other	303 (160)	495 (146)	1.35 (0.27)	-1.45 (0.26)	-1.28 (0.26)

MaxEITC and Tract Traits as Adults (in Percentiles)

MaxEITC and Tract Traits as Adults (in Percentiles)

	HH Income 2000 Rank	College 2000 Rank	College 2010 Rank	HH Income 1990 Rank	HH Income 2016 Rank	Math Score Rank
Panel A: Men Ages 19–25						
MaxEITC Ages 0–18	1.36 (0.066)	1.15 (0.077)	1.14 (0.071)	1.27 (0.078)	1.27 (0.055)	0.703 (0.071)
N	2,492,000	2,492,000	2,493,000	2,492,000	2,493,000	2,487,000
Panel B: Men Ages 26–34						
MaxEITC Ages 0–18	1.33 (0.091)	1.30 (0.115)	1.27 (0.114)	1.20 (0.094)	1.20 (0.079)	0.709 (0.073)
N	903,000	903,000	903,000	903,000	903,000	901,000

- Very similar with and without family FE

MaxEITC Effects on Parental and Child Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Parental Earnings (2022 \$)	Parental Working (Pct Pts)	Dead by 20 (Pct Pts)	Dead by 25 (Pct Pts)	Dead by 30 (Pct Pts)	Teen Birth (Pct Pts)
MaxEITC (Ages 0–18)	6778 (357)	4.60 (0.188)	-0.235 (0.0128)	-0.395 (0.0219)	-0.466 (0.0247)	-0.00765 (0.00229)
Observations = 1,026,000 (smaller for columns 4 & 5)						

MaxEITC Effects on Parental and Child Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Parental Earnings (2022 \$)	Parental Working (Pct Pts)	Dead by 20 (Pct Pts)	Dead by 25 (Pct Pts)	Dead by 30 (Pct Pts)	Teen Birth (Pct Pts)
MaxEITC (Ages 0–18)	6778 (357)	4.60 (0.188)	-0.235 (0.0128)	-0.395 (0.0219)	-0.466 (0.0247)	-0.00765 (0.00229)
Observations = 1,026,000 (smaller for columns 4 & 5)						

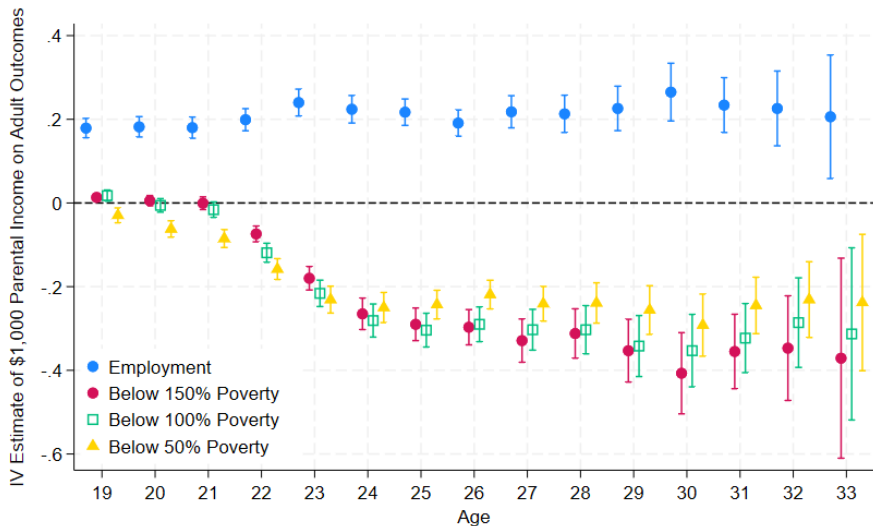
- The estimate on parental earnings is large but consistent with prior work when one accounts for (1) effects may grow throughout childhood; (2) we do not control for lagged family income, unlike Dahl and Lochner (2012; 2017); (3) our sample of children excludes women without children

MaxEITC Effects on Parental and Child Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Parental Earnings (2022 \$)	Parental Working (Pct Pts)	Dead by 20 (Pct Pts)	Dead by 25 (Pct Pts)	Dead by 30 (Pct Pts)	Teen Birth (Pct Pts)
MaxEITC (Ages 0–18)	6778 (357)	4.60 (0.188)	-0.235 (0.0128)	-0.395 (0.0219)	-0.466 (0.0247)	-0.00765 (0.00229)
Observations = 1,026,000 (smaller for columns 4 & 5)						

- The estimate on parental earnings is large but consistent with prior work when one accounts for (1) effects may grow throughout childhood; (2) we do not control for lagged family income, unlike Dahl and Lochner (2012; 2017); (3) our sample of children excludes women without children
- Column 1 is the first stage for the following IV regressions
- *MaxEITC* → parental earnings during childhood → children's long-run outcomes

IV Effects by Age: \$1,000 in Avg Annual Childhood Income



● First stage is strong (F-stats: 1,393–26,780)

IV Approach: Parent Income on Kids' Long-Run Outcomes

	Real AGI (2022 \$)	Real Earnings (2022 \$)	Working	Below 50% Pov.	Below 100% Pov.	Below 150% Pov.
	(1)	(2)	(3)	(4)	(5)	(6)
Parental AGI (\$1,000s) (Avg. Childhood AGI \leq \$40K)	210 (15)	233 (14)	1.070 (0.344)	-0.914 (0.035)	-0.704 (0.031)	-0.399 (0.025)
Parental AGI (\$1,000s) (Avg. Childhood AGI $>$ \$40K)	1 (3)	-1 (3)	0.109 (0.005)	-0.018 (0.004)	0.015 (0.004)	0.009 (0.003)

- *MaxEITC* as IV for average annual parental income during childhood, on children's long-run outcomes
- Large effects for lower-income families, near-zero effects for higher-income families
- Similarly, much larger effects for children of unmarried parents

Interpreting IV Estimates

- Goal: isolate the parental income channel, though the exclusion restriction is unlikely to hold literally since the EITC raises both income and employment simultaneously—so these IV estimates are best interpreted as suggestive

Interpreting IV Estimates

- Goal: isolate the parental income channel, though the exclusion restriction is unlikely to hold literally since the EITC raises both income and employment simultaneously—so these IV estimates are best interpreted as suggestive
- LATE: IV identifies effects for compliers—lower-income families whose earnings responds most to EITC

Interpreting IV Estimates

- Goal: isolate the parental income channel, though the exclusion restriction is unlikely to hold literally since the EITC raises both income and employment simultaneously—so these IV estimates are best interpreted as suggestive
- LATE: IV identifies effects for compliers—lower-income families whose earnings responds most to EITC
- IV captures only the earnings channel and misses EITC transfer income—explaining why IV effects are null for married parents, who respond little on the labor supply margin but still receive transfers; reduced-form *MaxEITC* captures the net effect across both channels

Interpreting IV Estimates

- Goal: isolate the parental income channel, though the exclusion restriction is unlikely to hold literally since the EITC raises both income and employment simultaneously—so these IV estimates are best interpreted as suggestive
- LATE: IV identifies effects for compliers—lower-income families whose earnings responds most to EITC
- IV captures only the earnings channel and misses EITC transfer income—explaining why IV effects are null for married parents, who respond little on the labor supply margin but still receive transfers; reduced-form *MaxEITC* captures the net effect across both channels
- Taken together, IV confirms the parental income channel is important and only affects EITC-eligible lower-income and unmarried families

Takeaways

- We find positive long-run effects of the EITC on children's outcomes
 - Results corroborate Bastian and Michelmore (2018) that found increased employment and earnings, especially during teenage years, using PSID data with $N=3,500$

Takeaways

- We find positive long-run effects of the EITC on children's outcomes
 - Results corroborate Bastian and Michelmore (2018) that found increased employment and earnings, especially during teenage years, using PSID data with N=3,500
- We find positive effects among all groups, including children of always-married parents
 - Married parents do not increase their labor supply in response to EITC \implies EITC transfer income itself—and not just increased earnings and parental employment—helps explain positive long run effects

Takeaways

- We find positive long-run effects of the EITC on children's outcomes
 - Results corroborate Bastian and Micheltore (2018) that found increased employment and earnings, especially during teenage years, using PSID data with N=3,500
- We find positive effects among all groups, including children of always-married parents
 - Married parents do not increase their labor supply in response to EITC \implies EITC transfer income itself—and not just increased earnings and parental employment—helps explain positive long run effects
- Next we consider EITC's short run effects on parental earnings and neighborhood quality

Empirical Strategy: Short-Run Outcomes

- We estimate effects on parental income, employment, moving census tracts, moving to a higher quality tract (compared to time t):

$$Y_{i,s,t+j} = \beta_1 \text{MaxEITC}_{i,s,t} + X'_{i,s,t} \gamma_1 + \epsilon_{i,s,t} \quad \text{for } j \in [1, 3]$$

- Treatment effect captured by β_1 reflects a \$1,000 increase in *MaxEITC* in year t (2022 \$)

Empirical Strategy: Short-Run Outcomes

- We estimate effects on parental income, employment, moving census tracts, moving to a higher quality tract (compared to time t):

$$Y_{i,s,t+j} = \beta_1 \text{MaxEITC}_{i,s,t} + X'_{i,s,t} \gamma_1 + \epsilon_{i,s,t} \quad \text{for } j \in [1, 3]$$

- Treatment effect captured by β_1 reflects a \$1,000 increase in *MaxEITC* in year t (2022 \$)
- X_{ist} includes same controls as before; no family FE

Empirical Strategy: Short-Run Outcomes

- We estimate effects on parental income, employment, moving census tracts, moving to a higher quality tract (compared to time t):

$$Y_{i,s,t+j} = \beta_1 \text{MaxEITC}_{i,s,t} + X'_{i,s,t} \gamma_1 + \epsilon_{i,s,t} \quad \text{for } j \in [1, 3]$$

- Treatment effect captured by β_1 reflects a \$1,000 increase in *MaxEITC* in year t (2022 \$)
- X_{ist} includes same controls as before; no family FE
- Standard errors robust to heteroskedasticity, clustered at state level
- No weights used (since it is a random sample of population data)

Empirical Strategy: Short-Run Outcomes

- We estimate effects on parental income, employment, moving census tracts, moving to a higher quality tract (compared to time t):

$$Y_{i,s,t+j} = \beta_1 \text{MaxEITC}_{i,s,t} + X'_{i,s,t} \gamma_1 + \epsilon_{i,s,t} \quad \text{for } j \in [1, 3]$$

- Treatment effect captured by β_1 reflects a \$1,000 increase in *MaxEITC* in year t (2022 \$)
- X_{ist} includes same controls as before; no family FE
- Standard errors robust to heteroskedasticity, clustered at state level
- No weights used (since it is a random sample of population data)
- We also estimate effects of *MaxEITC* by children's age:

$$Y_{i,s,t} = \sum_{a \in [0,18]} \beta_2^a \text{MaxEITC}_{i,s,t} + X'_{i,s,t} \gamma_2 + \epsilon_{i,s,t}$$

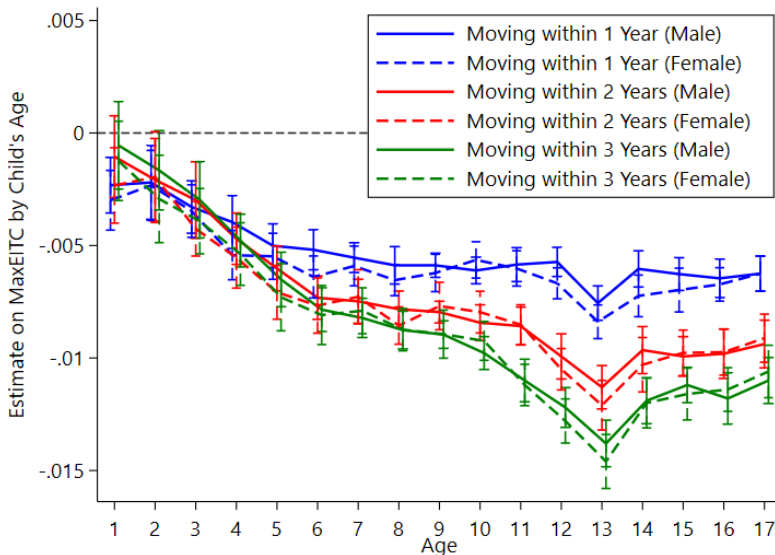
MaxEITC Effects on Parental Outcomes

Outcome in Year $t + 1$:	Parental Earnings (2022 \$)		Working Parent (Pct Pts)	
	(1)	(2)	(3)	(4)
MaxEITC in Year t	6430 (805)		0.496 (0.089)	
MaxEITC in Year $t \times$ (Ages 0–5)		5596 (905)		0.099 (0.095)
MaxEITC in Year $t \times$ (Ages 6–12)		6269 (841)		0.321 (0.087)
MaxEITC in Year $t \times$ (Ages 13–18)		6353 (800)		0.508 (0.084)
Observations	18,960,000		18,960,000	

- Previously showed estimate of average *MaxEITC* at ages 0–18 on average parental income at ages 0–18 (one obs per person)

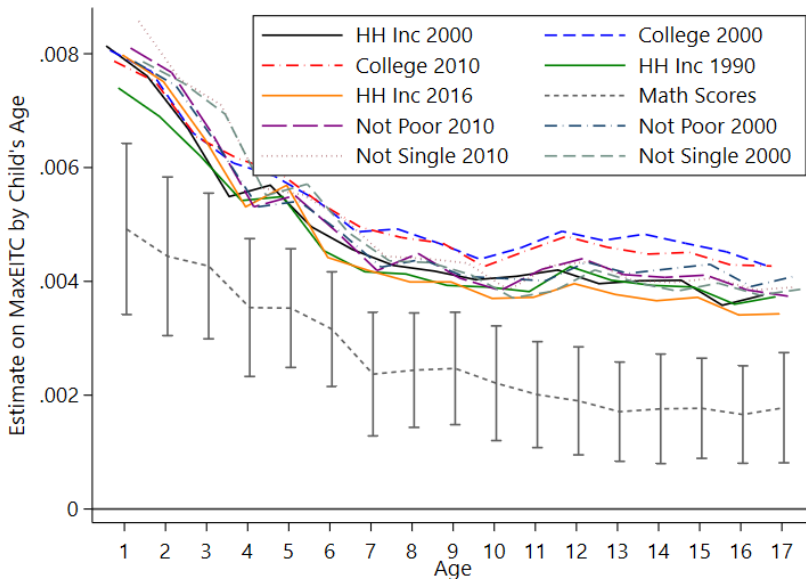
Results: *MaxEITC* Decreases Net Migration

Results: *MaxEITC* Decreases Net Migration

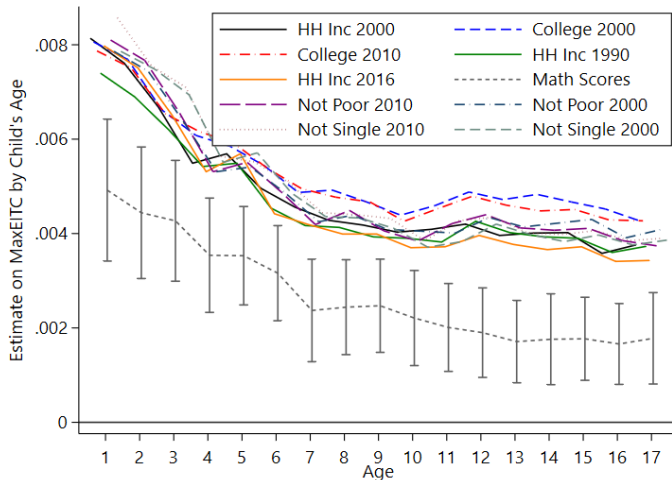


MaxEITC Increases Moves to Higher-Opportunity Tracts

MaxEITC Increases Moves to Higher-Opportunity Tracts

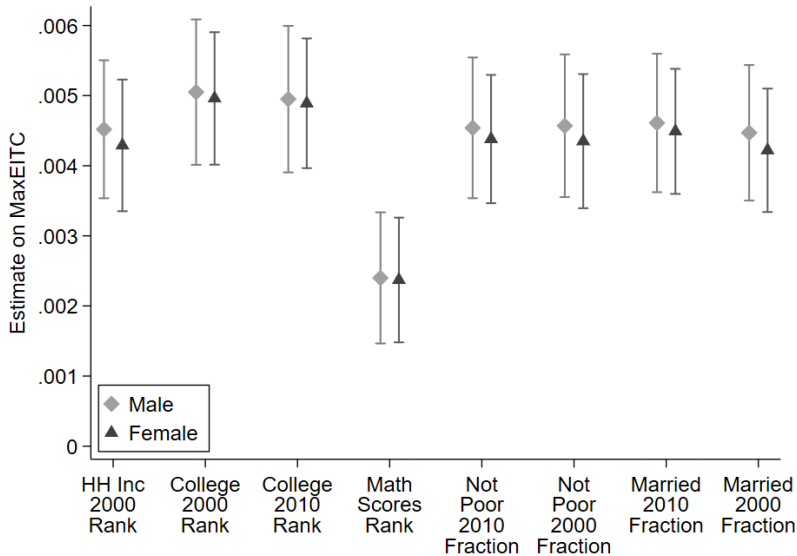


MaxEITC Increases Moves to Higher-Opportunity Tracts

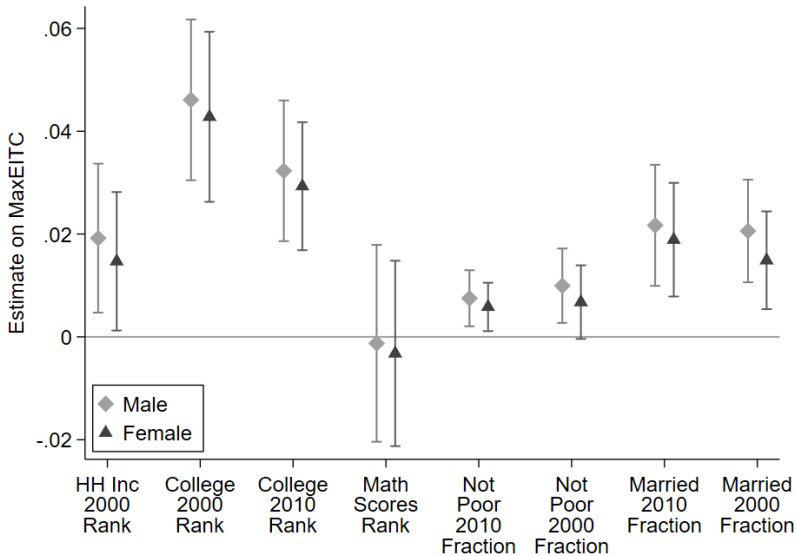


- About 70% of EITC-led moves to higher opportunity are within-county; zero impact on out-of-state moves

MaxEITC and Moving to Better Tracts in Childhood



MaxEITC and Tract-Traits in Levels in Childhood



Childhood EITC and Moving Outcomes (by Race)

Childhood EITC and Moving Outcomes (by Race)

	Moved Tracts	Moved to Higher-Income Census Tract
$MaxEITC_t \times \text{White}$	-1.16 (0.06)	0.27 (0.05)
$MaxEITC_t \times \text{Black}$	-0.29 (0.06)	0.68 (0.06)
$MaxEITC_t \times \text{Asian}$	-1.05 (0.19)	0.30 (0.06)
$MaxEITC_t \times \text{Hispanic}$	-0.84 (0.07)	0.47 (0.05)
$MaxEITC_t \times \text{Native}$	-0.72 (0.56)	0.71 (0.24)
$MaxEITC_t \times \text{Other}$	-0.68 (0.10)	0.48 (0.05)

- Female; similar for male

Childhood EITC & Moving Outcomes (by Parental Traits)

	Move	Moved to Higher-Quality Tract:	
	Tracts	Income (in 2000)	College (in 2000)
Panel A: Female, by Parental Marital Status			
$MaxEITC_t \times$ Married	-1.73 (0.05)	0.15 (0.05)	0.12 (0.05)
$MaxEITC_t \times$ Unmarried	-0.31 (0.06)	0.66 (0.05)	0.71 (0.05)

- More moves to opportunity for kids of unmarried
- More residential stability for kids of married

Mediation Analysis

- Childhood EITC exposure raises adult earnings by \$2,600–\$2,700 annually at ages 26–34, but *through what channels?*

Mediation Analysis

- Childhood EITC exposure raises adult earnings by \$2,600–\$2,700 annually at ages 26–34, but *through what channels?*
- Mediation analysis asks how much of a total effect can be attributed to specific intermediate pathways and mechanisms

Mediation Analysis

- Childhood EITC exposure raises adult earnings by \$2,600–\$2,700 annually at ages 26–34, but *through what channels?*
- Mediation analysis asks how much of a total effect can be attributed to specific intermediate pathways and mechanisms
- We estimate effects on neighborhood quality and parental earnings directly from this paper's data, and draw on causal estimates from other EITC research for health and human capital channels

Mediation Analysis

- Childhood EITC exposure raises adult earnings by \$2,600–\$2,700 annually at ages 26–34, but *through what channels?*
- Mediation analysis asks how much of a total effect can be attributed to specific intermediate pathways and mechanisms
- We estimate effects on neighborhood quality and parental earnings directly from this paper's data, and draw on causal estimates from other EITC research for health and human capital channels
- Estimated contributions per \$1,000 in childhood *MaxEITC*:
 - Parental earnings and EITC income: ~\$1,530–\$1,600 (57–62%)
 - Neighborhood quality: ~\$510 (19–20%)
 - Human capital (test scores, graduation): \$775–\$1,135 (29–44%)
 - Health (infant and adult): \$240–\$390 (9–15%)
- Note that channels overlap and should not be summed

Mediation Analysis

- Childhood EITC exposure raises adult earnings by \$2,600–\$2,700 annually at ages 26–34, but *through what channels?*
- Mediation analysis asks how much of a total effect can be attributed to specific intermediate pathways and mechanisms
- We estimate effects on neighborhood quality and parental earnings directly from this paper's data, and draw on causal estimates from other EITC research for health and human capital channels
- Estimated contributions per \$1,000 in childhood *MaxEITC*:
 - Parental earnings and EITC income: ~\$1,530–\$1,600 (57–62%)
 - Neighborhood quality: ~\$510 (19–20%)
 - Human capital (test scores, graduation): \$775–\$1,135 (29–44%)
 - Health (infant and adult): \$240–\$390 (9–15%)
- Note that channels overlap and should not be summed
- More details (and citations) in the paper

Conclusion

- Childhood *MaxEITC* improves children's long-run outcomes: higher earnings, higher employment, lower poverty, lower mortality

Conclusion

- Childhood *MaxEITC* improves children's long-run outcomes: higher earnings, higher employment, lower poverty, lower mortality
- Timing matters: exposure in the teen years (13–18) yields the largest effects; younger ages show smaller positive impacts
- Positive across groups; larger effects for Black, Hispanic, Native, and children of unmarried or younger parents
- Effects driven by children from lower-income families
- Gains for children of married parents imply transfer income itself (not only parental earnings) drives impacts

Conclusion

- Childhood *MaxEITC* improves children's long-run outcomes: higher earnings, higher employment, lower poverty, lower mortality
- Timing matters: exposure in the teen years (13–18) yields the largest effects; younger ages show smaller positive impacts
- Positive across groups; larger effects for Black, Hispanic, Native, and children of unmarried or younger parents
- Effects driven by children from lower-income families
- Gains for children of married parents imply transfer income itself (not only parental earnings) drives impacts
- **Thank you!**