The Effects of Exposure to Better Neighborhoods on Children's Long-Term Outcomes

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The opinions expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Internal Revenue Service or the U.S. Treasury Department. This work is a component of a larger project examining the effects of eliminating tax expenditures on the budget deficit and economic activity. Results reported here are contained in the SOI Working Paper "The Economic Impacts of Tax Expenditures: Evidence from Spatial Variation across the U.S.," approved under IRS contract TIRNO-12-P-00374.

Introduction

- Substantial disparities in economic outcomes across low vs. high poverty neighborhoods [e.g., Wilson 1987, Jencks and Mayer 1990, Cutler and Glaeser 1997]

- These disparities motivated the HUD Moving to Opportunity (MTO) experiment in the mid 1990's
    - Offered a randomly selected subset of families living in high-poverty housing projects housing vouchers to move to lower-poverty areas

- Large literature on MTO has found significant effects on adult health and subjective well-being

- But these studies have consistently found that the MTO treatments had no impact on earnings or employment rates of adults and older youth [e.g. Katz, Kling, and Liebman 2001, Oreopoulous 2003, Sanbonmatsu et al. 2011]

Revisiting MTO

- We revisit the MTO experiment and focus on its impacts on children who were young when their families moved to better neighborhoods

- Re-analysis motivated by a companion paper that presents quasi-experimental evidence on neighborhood effects [Chetty and Hendren 2015]

  - Key finding: **childhood exposure effects**

  - Every year in a better area during childhood → better outcomes in adulthood

  - Implies that gains from moving to a better area are larger for children who move when young

Revisiting MTO

- In light of this evidence on childhood exposure effects, we returned to MTO data to examine treatment effects on young children
- Link MTO data to tax data to analyze effects of MTO treatments on children's outcomes in adulthood
- Children we study were not old enough to observe outcomes in adulthood at the time of the MTO Final Impacts Evaluation (which used data up to 2008)

Outline

1. Background on MTO Experiment and Data

2. Estimates from MTO Experiment

3. Quasi-Experimental Estimates of Causal Effects by County [Chetty and Hendren 2015]

4. Conclusion: Policy Implications

Moving to Opportunity Experiment

- HUD Moving to Opportunity Experiment implemented from 1994-1998
- 4,600 families at 5 sites: Baltimore, Boston, Chicago, LA, New York
- Families randomly assigned to one of three groups:

1. Experimental: housing vouchers restricted to low-poverty (<10%) Census tracts
2. Section 8: conventional housing vouchers, no restrictions
3. Control: public housing in high-poverty (50% at baseline) areas

Most Common MTO Residential Locations in New York

Data

- MTO data obtained from HUD
  - 4,604 households and 15,892 individuals
  - Primary focus: 8,603 children born in or before 1991
- Link MTO data to federal income tax returns from 1996-2012
  - Approximately 85% of children matched
  - Match rates do not differ significantly across treatment groups
  - Baseline covariates balanced across treatment groups in matched data

Estimating MTO Treatment Effects

- In baseline analysis, estimate treatment effects for two groups:
  - Young children: below age 13 at random assignment (RA)
  - Older children: age 13-18 at random assignment
- Average age at move: 8.2 for young children vs. 15.1 for older children

  → Younger children had 7 more years of exposure to low-poverty nbhd.

- Estimates robust to varying age cutoffs and estimating models that interact age linearly with treatments

Estimating MTO Treatment Effects

- We replicate standard regression specifications used in prior work
  [Kling, Katz, Liebman 2007]

$$y_i = \alpha + \beta_E^{ITT} Exp_i + \beta_S^{ITT} S8_i + s_i\delta_s + \epsilon_i$$

Treatment Indicators **Site Indicators**

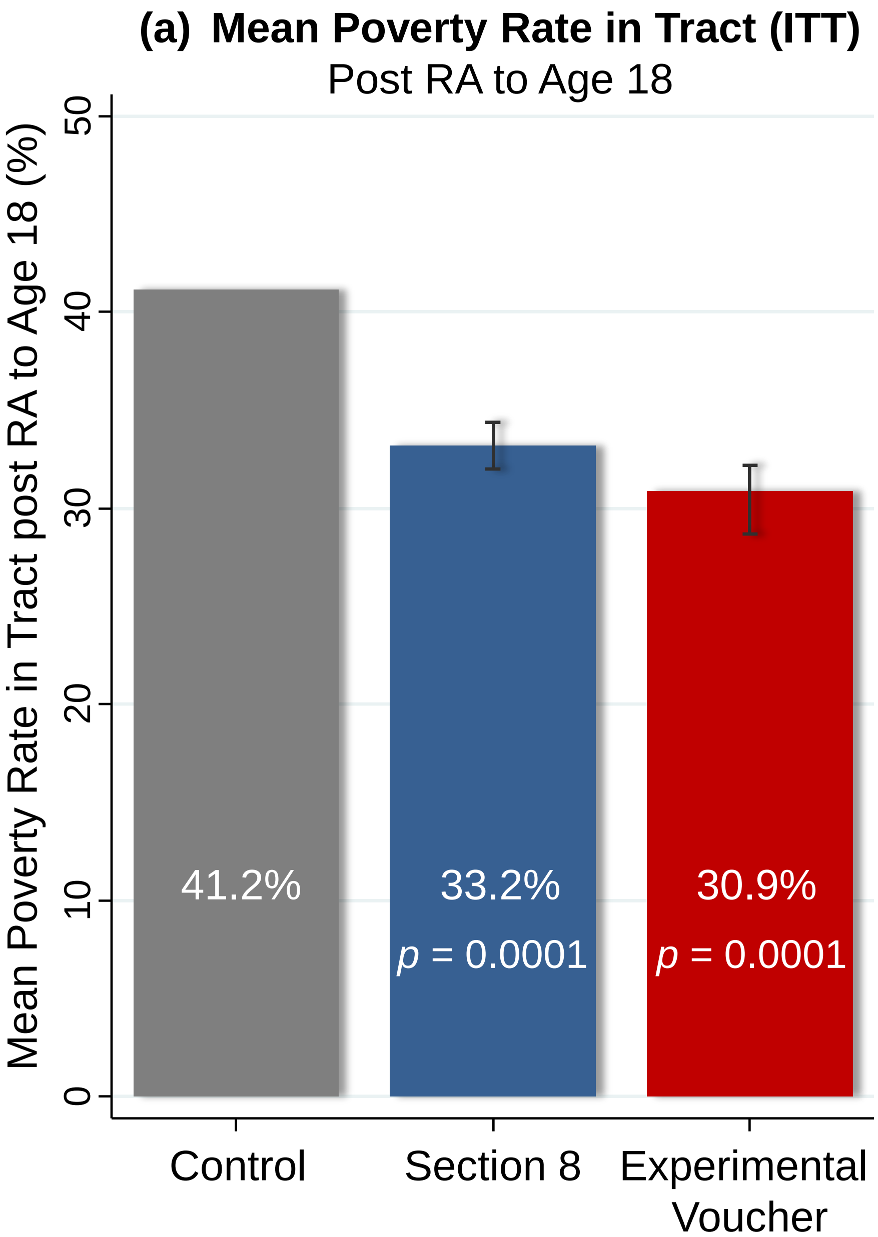
- These intent-to-treat (ITT) estimates identify effect of being *offered* a voucher to move through MTO

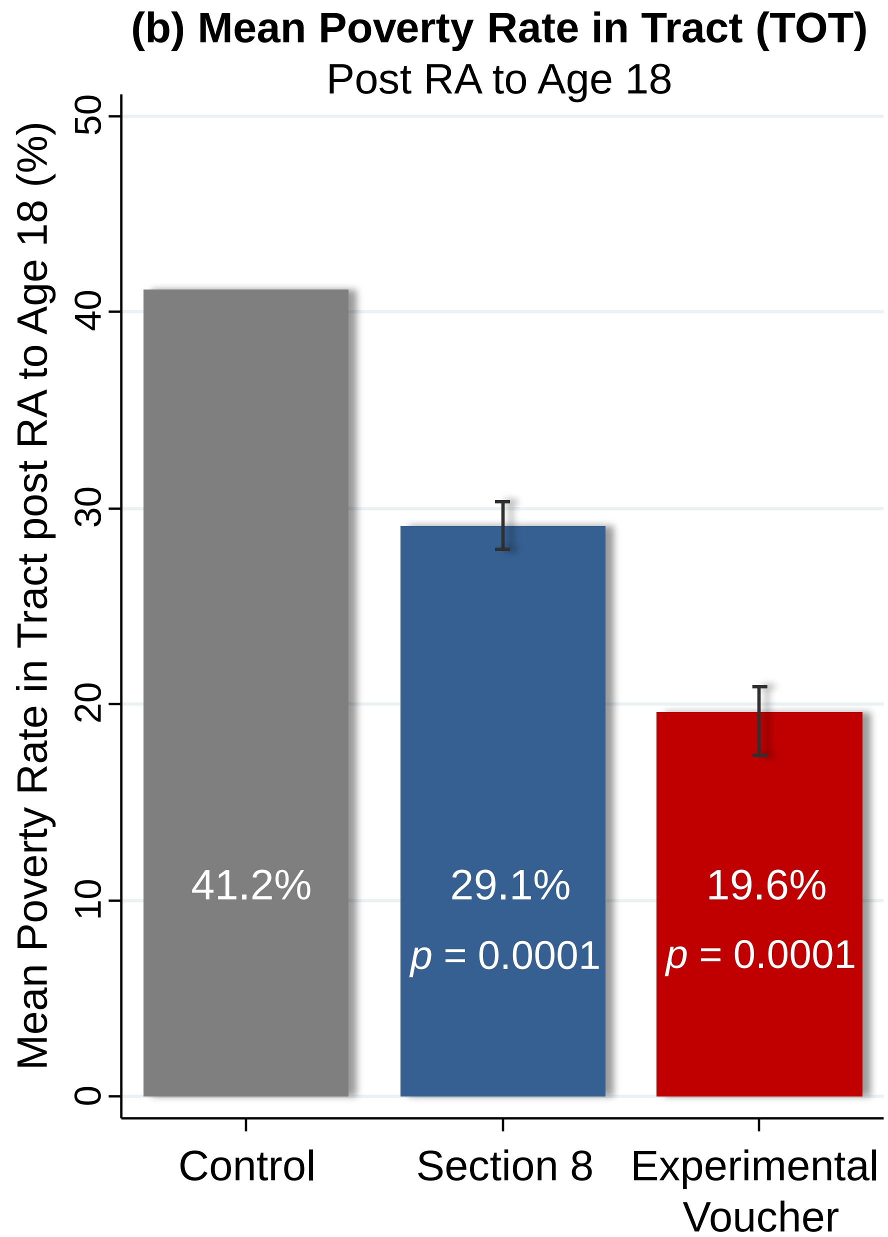
- Estimate treatment-on-treated (TOT) effects using 2SLS, instrumenting for voucher takeup with treatment indicators
  - Experimental take-up: 48% for young children, 40% for older children
  - Section 8 take-up: 65.8% for young children, 55% for older children

Treatment Effects on Neighborhood Poverty

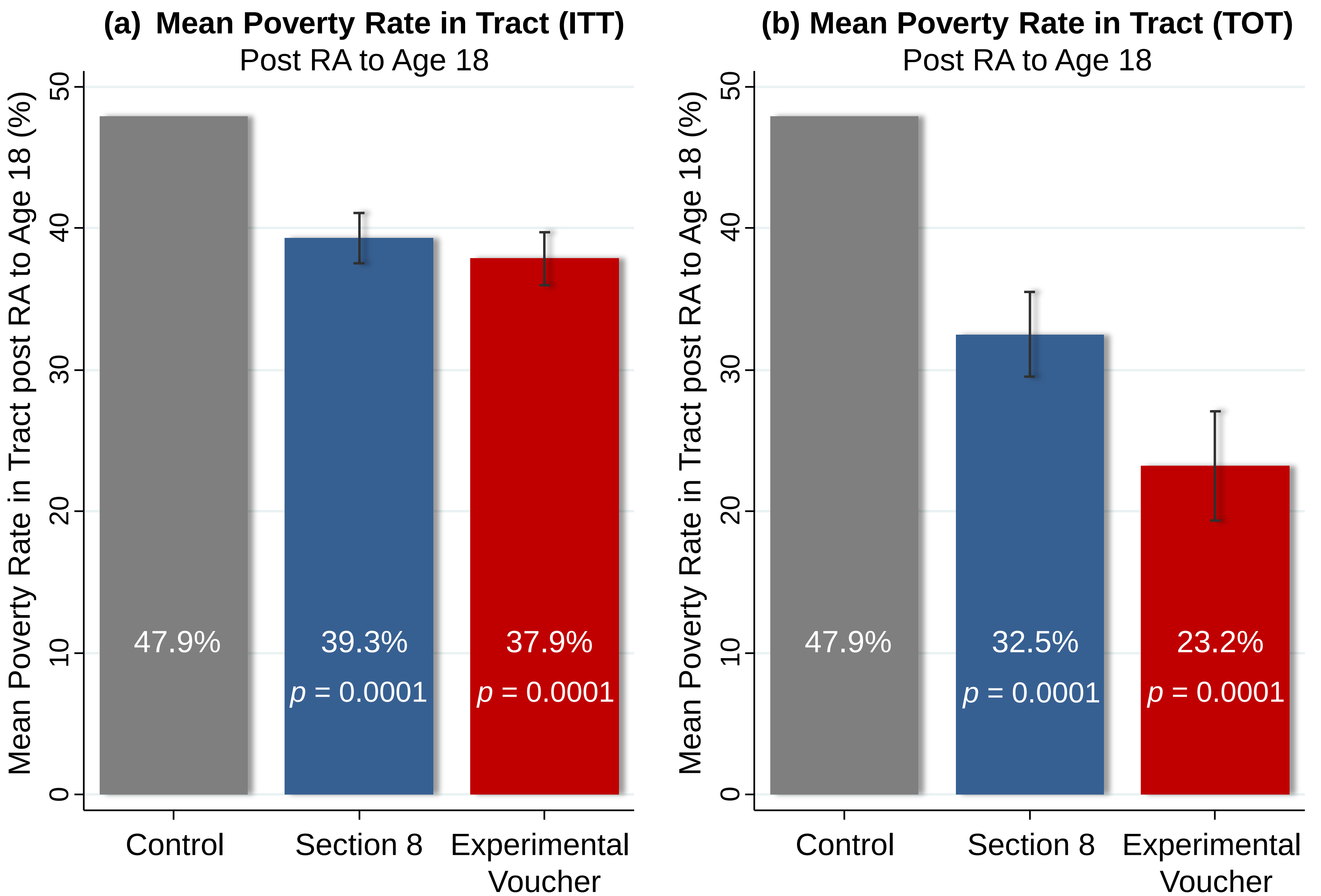
- Begin with “first stage” effects of MTO experiment on poverty rates
  - Measure mean poverty rates from random assignment to age 18 at tract level using Census data
- Use poverty rates as an index of nbhd. quality, but note that MTO treatments naturally changed many other features of neighborhoods too

Impacts of MTO on Children Below Age 13 at Random Assignment





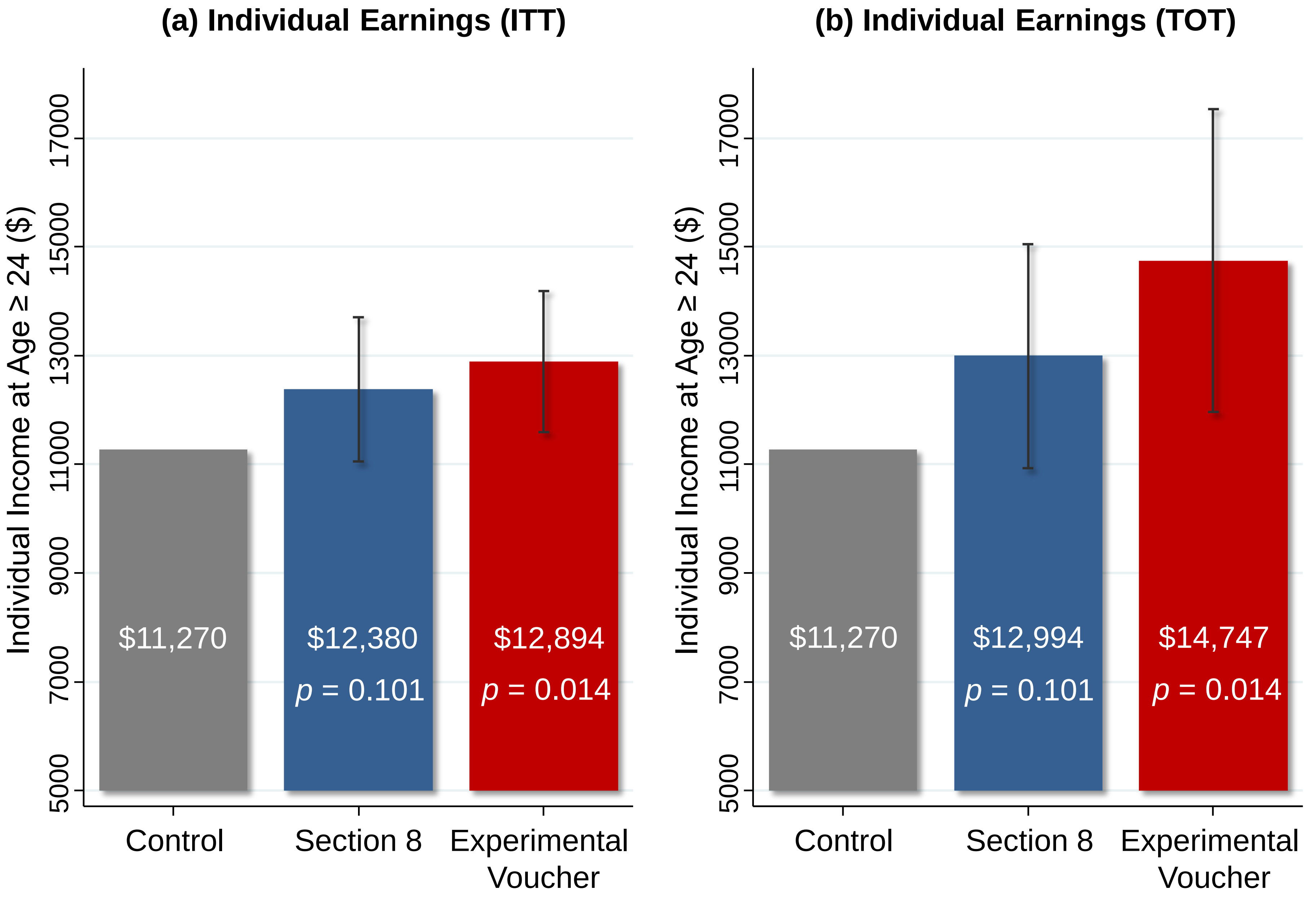
Impacts of MTO on Children Age 13-18 at Random Assignment

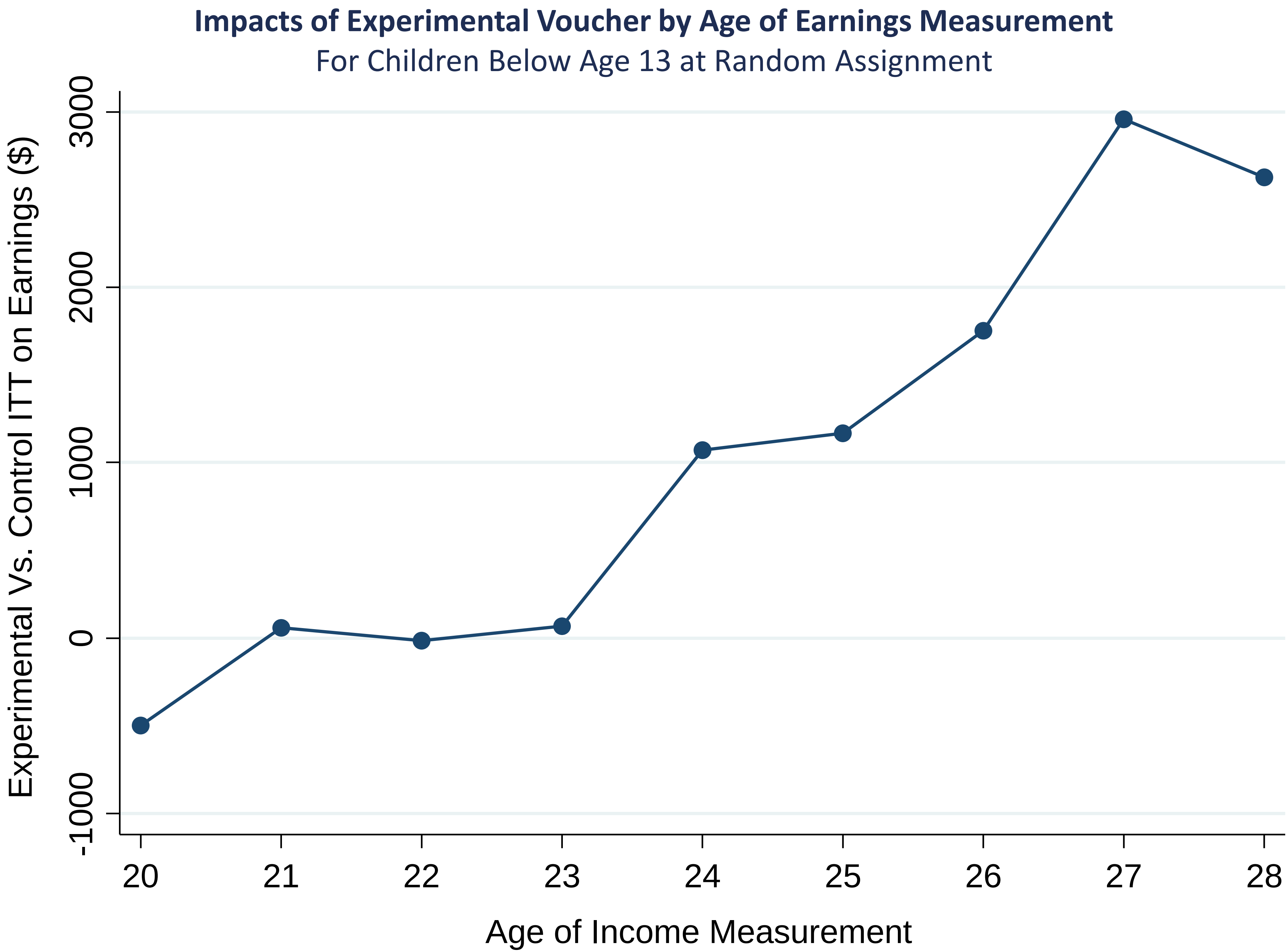


Treatment Effects on Outcomes in Adulthood

- Now turn to impacts on outcomes in adulthood
- Begin by analyzing effects on children below age 13 at RA
- Start with individual earnings (W-2 earnings + self-employment income)
  - Includes those who don’t file tax returns through W-2 forms
- Measured from 2008-12, restricting to years in which child is 24 or older
  - Evaluate impacts at different ages after showing baseline results

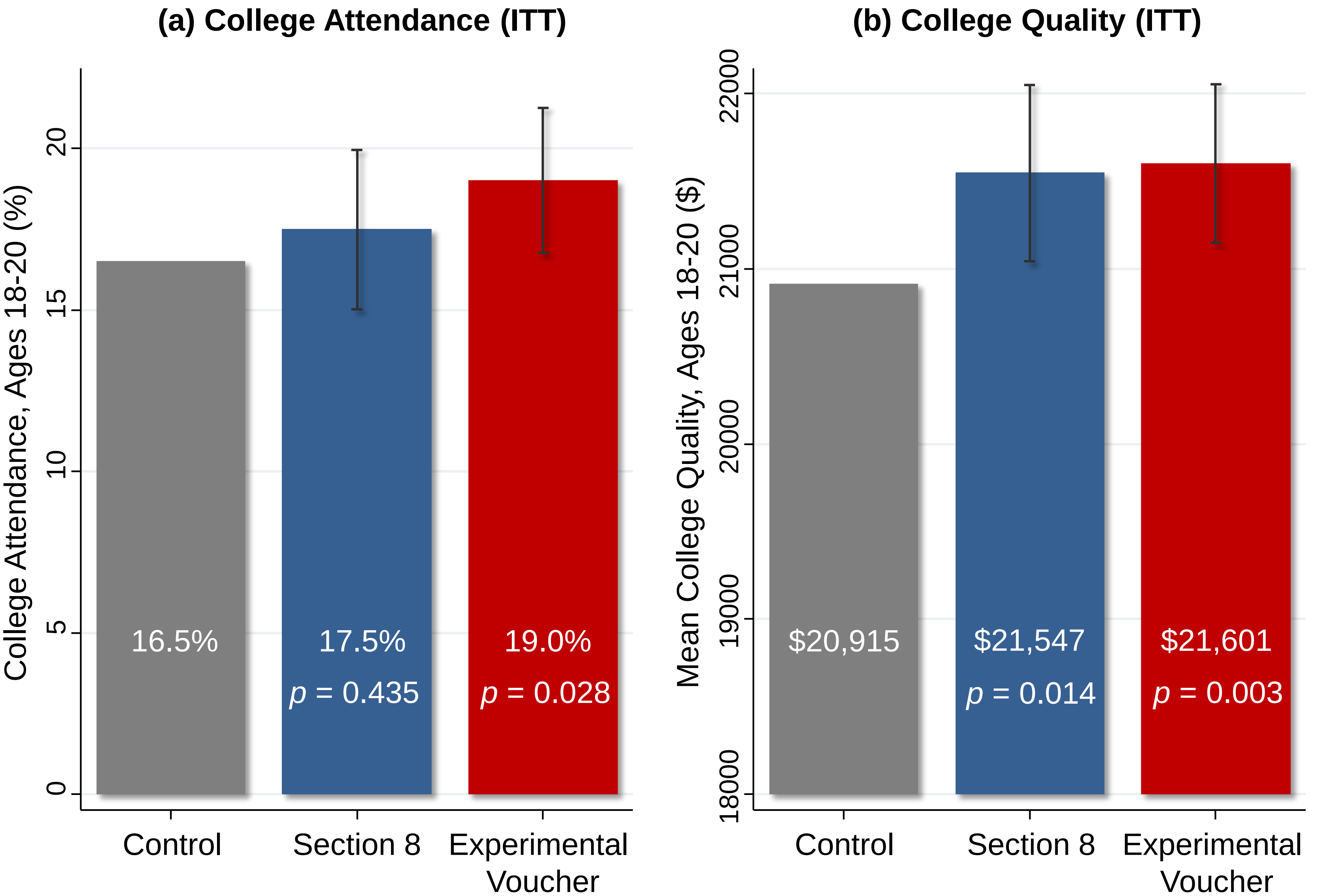
Impacts of MTO on Children Below Age 13 at Random Assignment



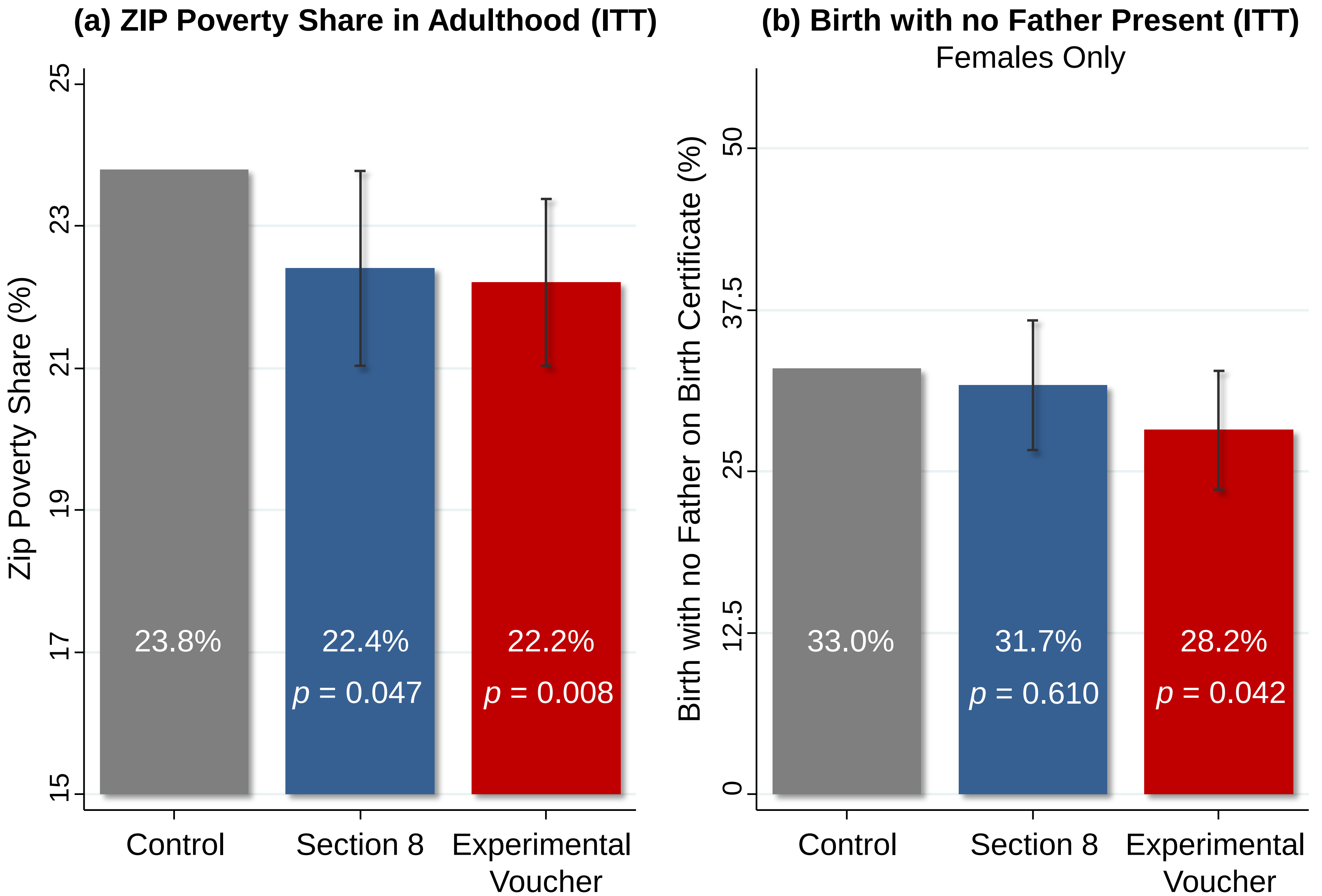


Impacts of Experimental Voucher by Age of Earnings Measurement
For Children Below Age 13 at Random Assignment
Experimental Vs. Control ITT on Earnings ($)
-1000
0
1000
2000
3000
20
21
22
23
24
25
26
27
28
Age of Income Measurement

Impacts of MTO on Children Below Age 13 at Random Assignment



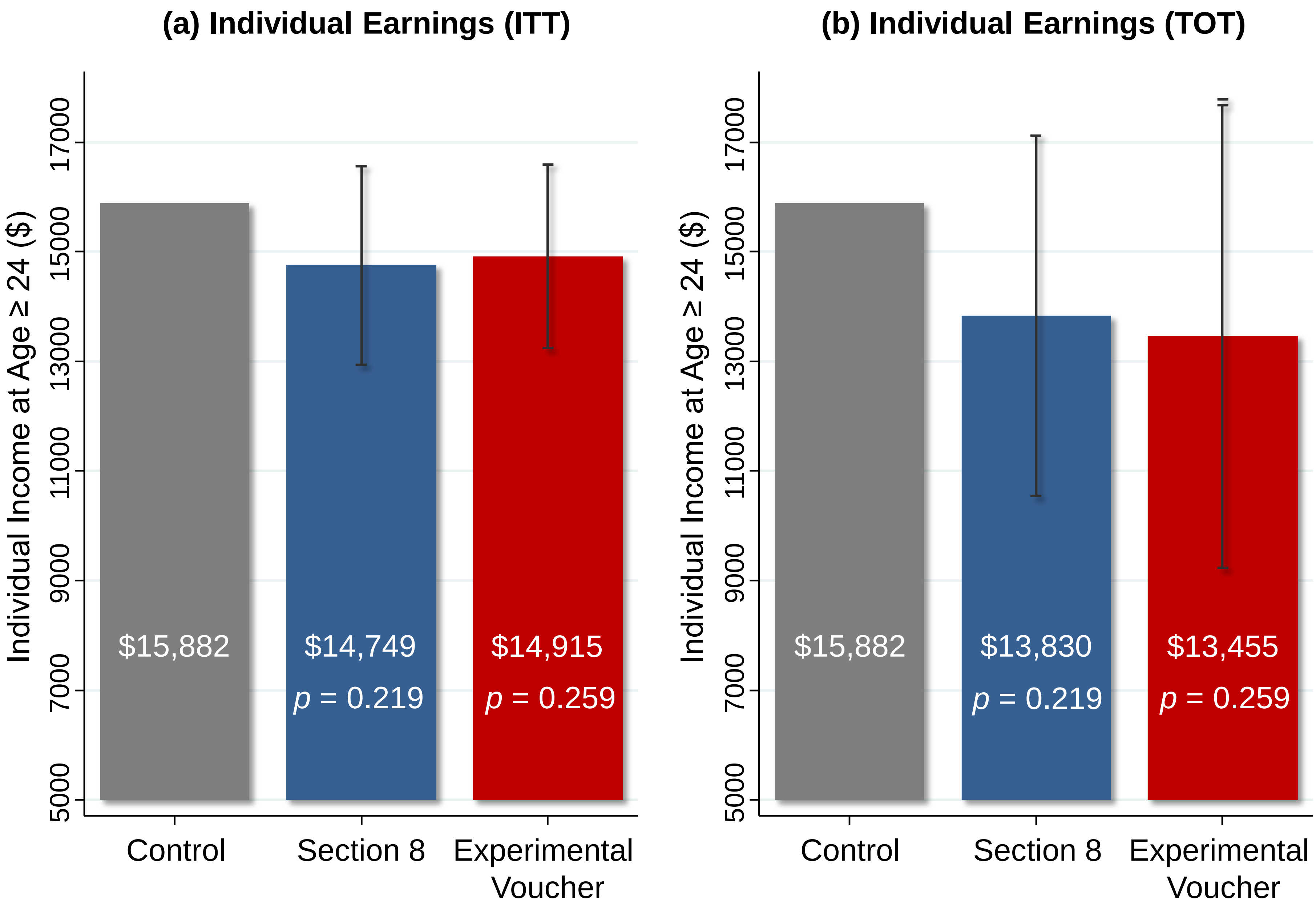
Impacts of MTO on Children Below Age 13 at Random Assignment



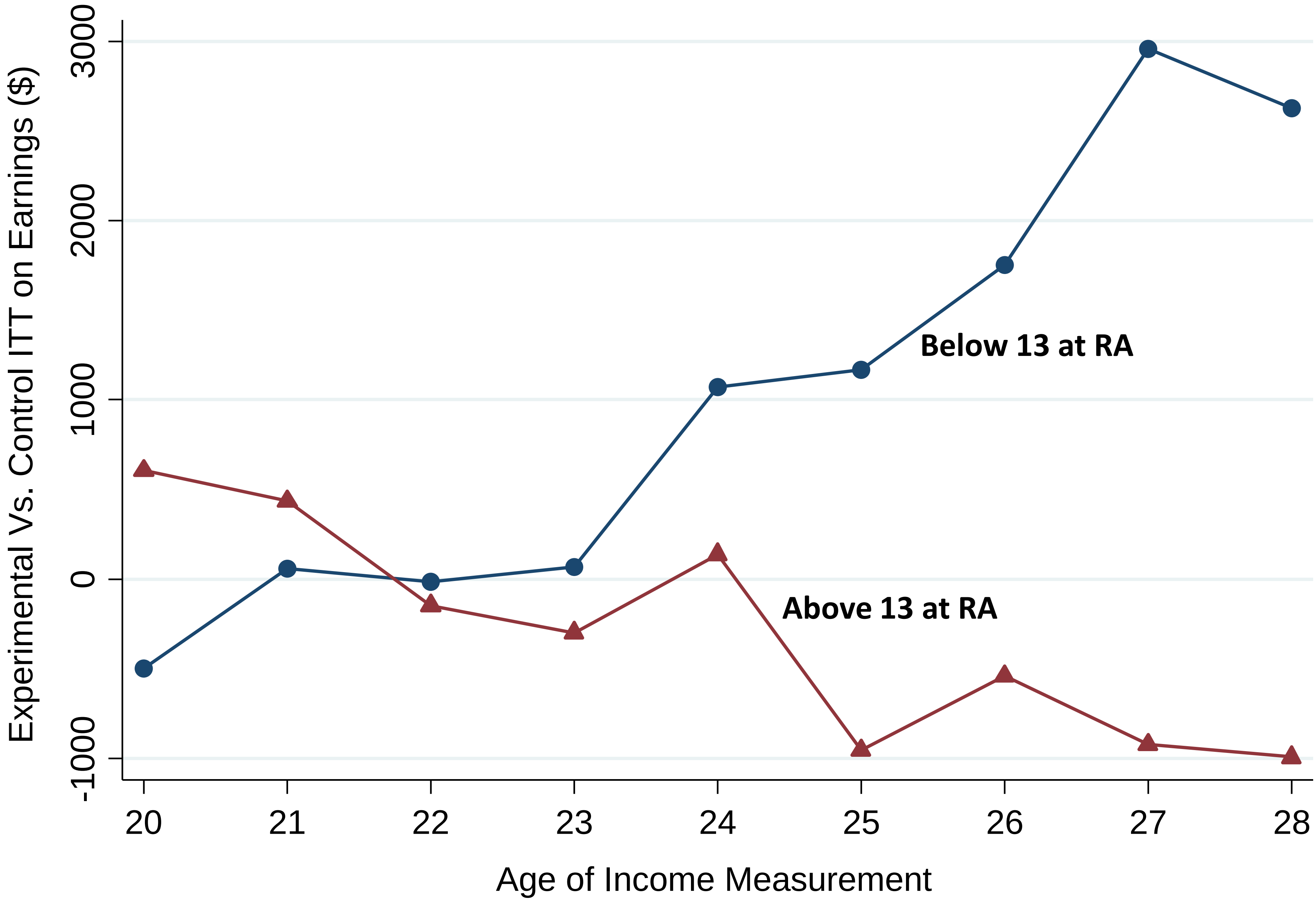
Treatment Effects on Older Children

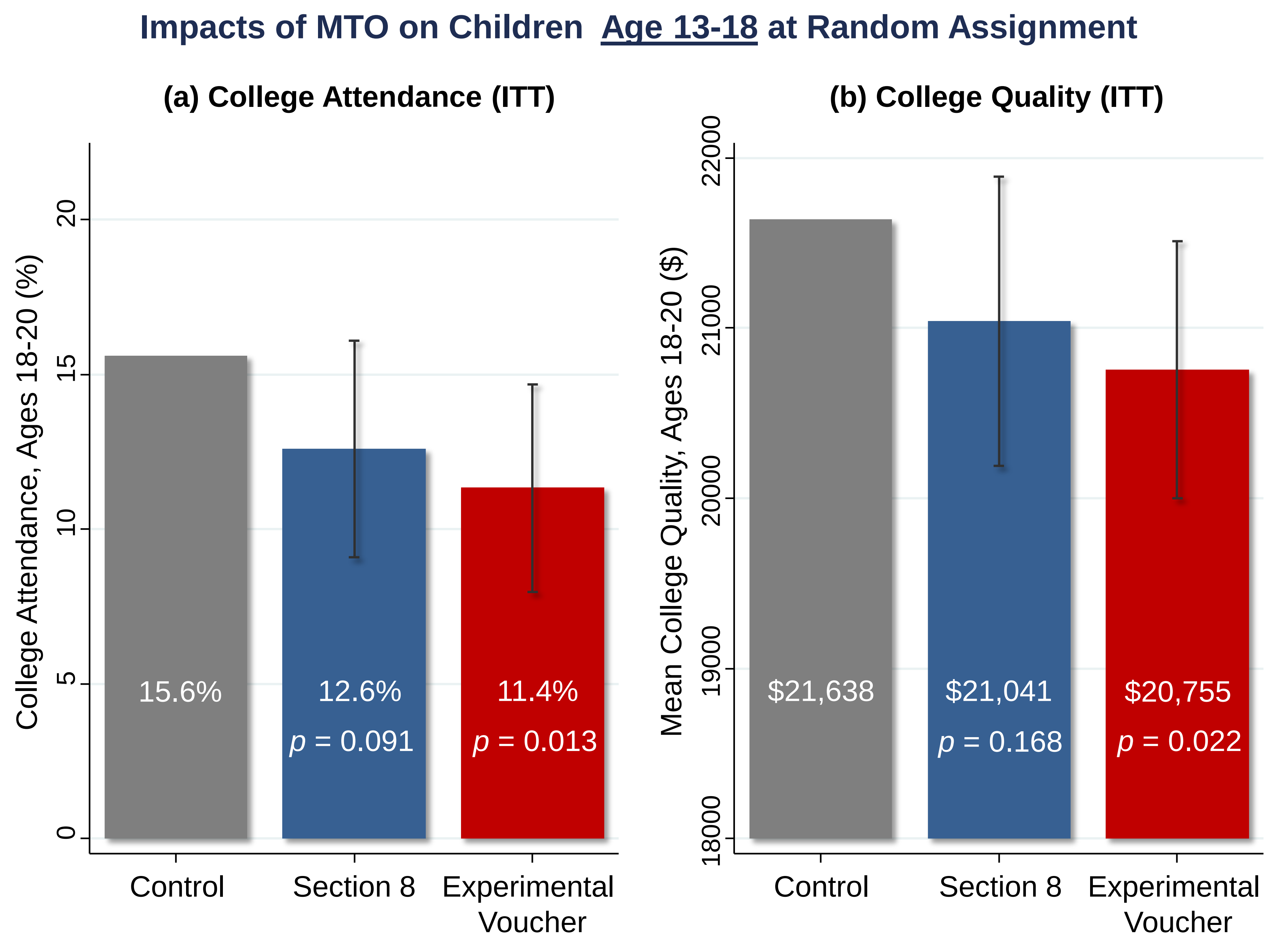
- Next, turn to children who were ages 13-18 at random assignment
  - Replicate same analysis as above

Impacts of MTO on Children Age 13-18 at Random Assignment

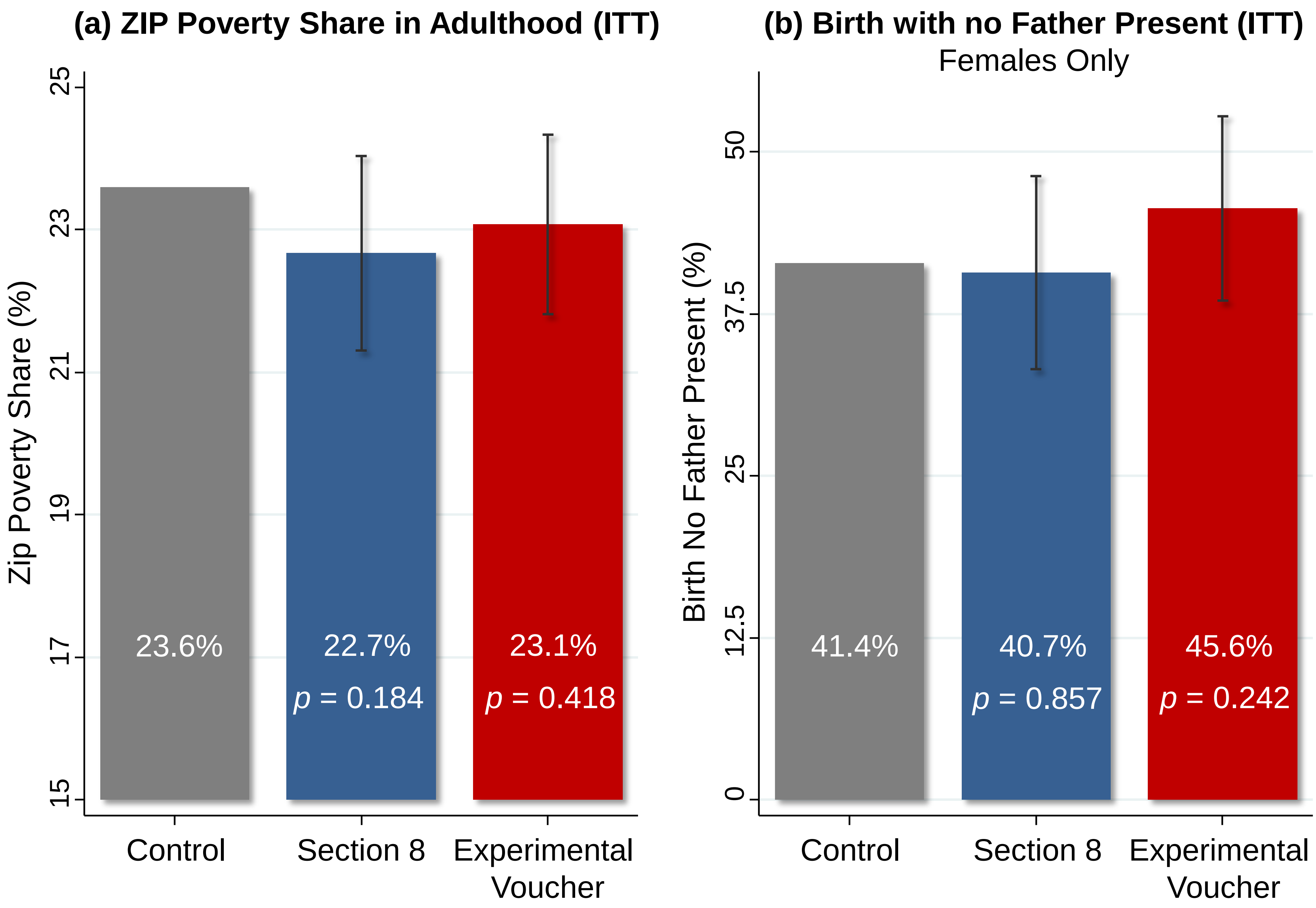


Impacts of Experimental Voucher by Age of Earnings Measurement




Impacts of MTO on Children Age 13-18 at Random Assignment
(a) College Attendance (ITT)
College Attendance, Ages 18-20 (%)
0
5
10
15
20
15.6%
12.6%
p = 0.091
11.4%
p = 0.013
Control
Section 8
Experimental Voucher
(b) College Quality (ITT)
Mean College Quality, Ages 18-20 ($)
18000
19000
20000
21000
22000
$21,638
$21,041
p = 0.168
$20,755
p = 0.022
Control
Section 8
Experimental Voucher

Impacts of MTO on Children Age 13-18 at Random Assignment



Robustness Checks: Varying Age Cutoffs

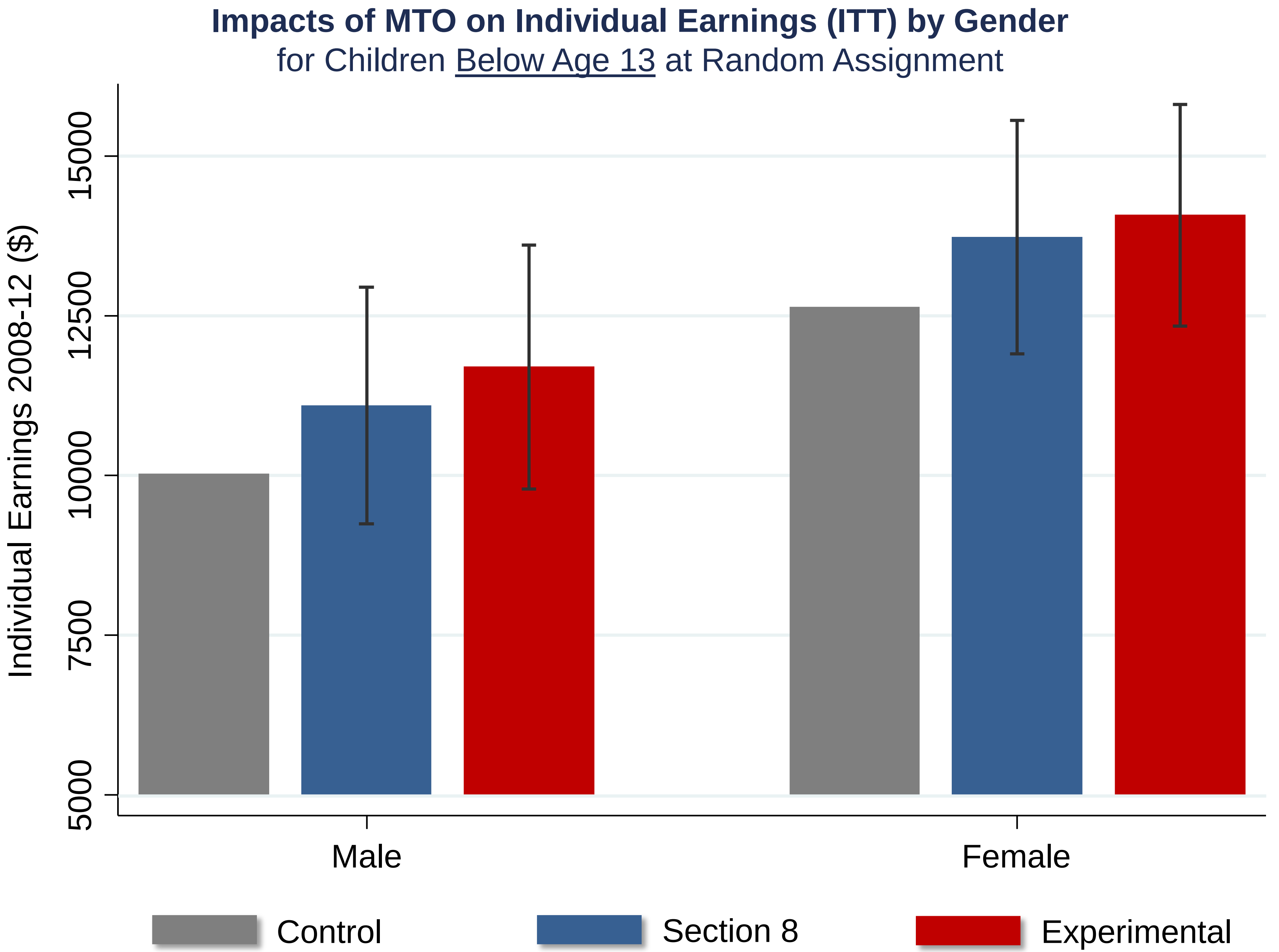
	< Age 12 at RA		< Age 13 at RA		< Age 14 at RA	
	Exp. vs. Control (1)	Sec. 8 vs. Control (2)	Exp. vs. Control (3)	Sec. 8 vs. Control (4)	Exp. vs. Control (5)	Sec. 8 vs. Control (6)
Individual Earnings ($)	1416.3⁺	1414.8⁺	1624.0*	1109.3	1034.4⁺	216.2
	(723.7)	(764.8)	(662.4)	(676.1)	(623.8)	(624.2)
College Quality 18-20 ($)	697.1**	587.9*	686.7**	632.7*	555.5*	524.5*
	(244.0)	(274.3)	(231.2)	(256.3)	(220.5)	(246.7)
Married (%)	2.217*	2.686*	1.934*	2.840**	1.804⁺	2.526*
	(0.911)	(1.087)	(0.892)	(1.055)	(0.936)	(1.043)
Poverty Share (%)	-1.481*	-1.029	-1.592**	-1.394*	-1.624**	-1.129⁺
	(0.650)	(0.764)	(0.602)	(0.699)	(0.569)	(0.661)
Income Taxes Paid ($)	159.4*	120.2⁺	183.9**	109.0*	151.7**	75.14
	(73.98)	(66.27)	(62.80)	(54.76)	(56.05)	(48.95)

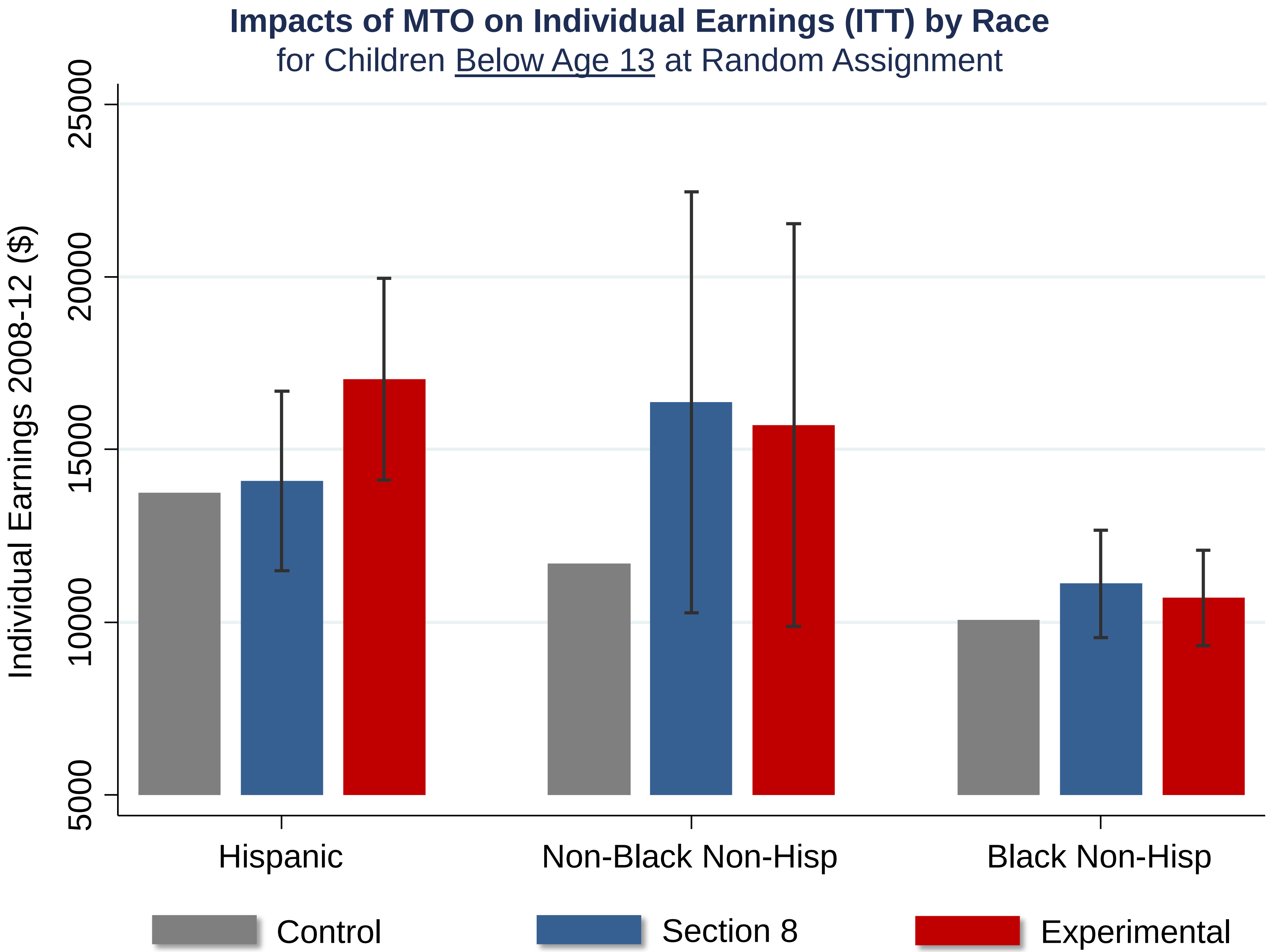
Linear Exposure Effect Estimates

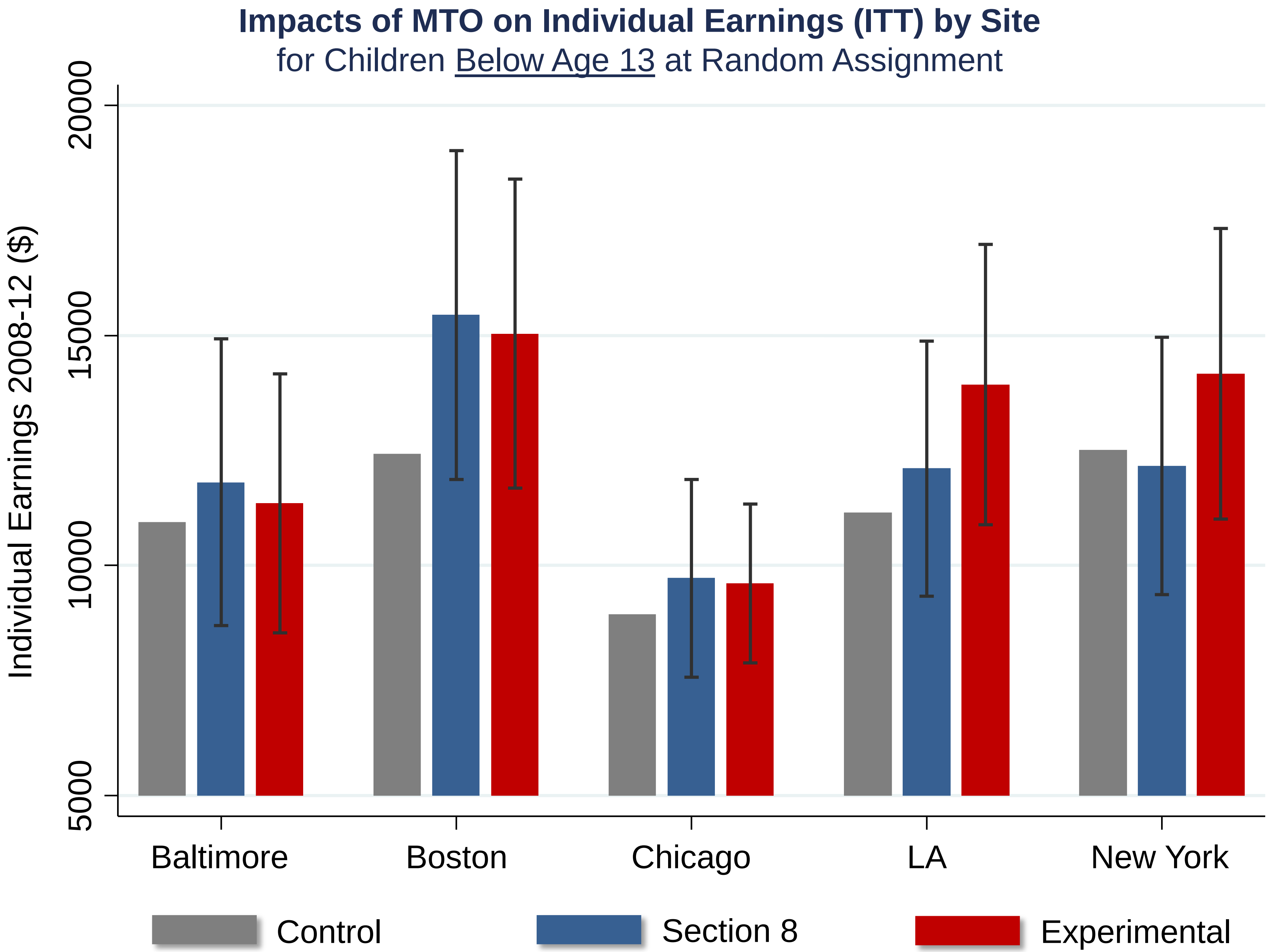
Dep. Var.:	Indiv. Earn. 2008-2012 ITT ($)	Household Income 2008-2012 ITT ($)	Coll. Qual. 18-20 ITT ($)	Married ITT (%)	ZIP Poverty Share ITT (%)
	(1)	(2)	(3)	(4)	(5)
Experimental × Age at RA	-364.1^{+}	-723.7**	-171.0**	-0.582*	0.261^{+}
	(199.5)	(255.5)	(55.16)	(0.290)	(0.139)
Section 8 × Age at RA	-229.5	-338.0	-117.1^{+}	-0.433	0.0109
	(208.9)	(266.4)	(63.95)	(0.316)	(0.156)
Experimental	4823.3*	9441.1**	1951.3**	8.309*	-4.371*
	(2404.3)	(3035.8)	(575.1)	(3.445)	(1.770)
Section 8	2759.9	4447.7	1461.1*	7.193^{+}	-1.237
	(2506.1)	(3111.3)	(673.6)	(3.779)	(2.021)
Number of Observations	20043	20043	20127	20043	15798
Control Group Mean	13807.1	16259.9	21085.1	6.6	23.7

Heterogeneity

- Prior work has analyzed variation in treatment effects across sites, racial groups, and gender
- Replicate analysis across these groups for children below age 13 at RA


Impacts of MTO on Individual Earnings (ITT) by Gender
for Children Below Age 13 at Random Assignment
Individual Earnings 2008-12 ($)
15000
12500
10000
7500
5000
Male
Female
Control
Section 8
Experimental


Impacts of MTO on Individual Earnings (ITT) by Race
for Children Below Age 13 at Random Assignment
Individual Earnings 2008-12 ($)
25000
20000
15000
10000
5000
Hispanic
Non-Black Non-Hisp
Black Non-Hisp
Control
Section 8
Experimental


Impacts of MTO on Individual Earnings (ITT) by Site
for Children Below Age 13 at Random Assignment
Individual Earnings 2008-12 ($)
20000
15000
10000
5000
Baltimore
Boston
Chicago
LA
New York
Control
Section 8
Experimental

Multiple Hypothesis Testing

- Given extent to which heterogeneity has been explored in MTO data, one should be concerned about multiple hypothesis testing
- Our study simply explores one more dimension of heterogeneity: age of child
- Any post-hoc analysis will detect "significant" effects ($p < 0.05$) even under the null of no effects if one examines a sufficiently large number of subgroups
- We account for multiple tests by testing omnibus null that treatment effect is zero in all subgroups studied to date (gender, race, site, and age)
  - Two approaches: parametric F test and non-parametric permutation test

Multiple Comparisons: F Tests for Subgroup Heterogeneity

Dep. Var.:	Indiv. Earnings 2008-12 ($) (1)	Hhold. Inc. 2008-12 ($) (2)	College Attendance 18-20 (%) (3)	College Quality 18-20 ($) (4)	Married (%) (5)	Poverty Share in ZIP 2008-12 (%) (6)
Panel A: p-values for Comparisons by Age Group						
Exp. vs. Control	0.0203	0.0034	0.0035	0.0006	0.0814	0.0265
Sec. 8 vs. Control	0.0864	0.0700	0.1517	0.0115	0.0197	0.0742
Exp & Sec. 8 vs. Control	0.0646	0.0161	0.0218	0.0020	0.0434	0.0627
Panel B: p-values for Comparisons by Age, Site, Gender, and Race Groups						
Exp. vs. Control	0.1121	0.0086	0.0167	0.0210	0.2788	0.0170
Sec. 8 vs. Control	0.0718	0.1891	0.1995	0.0223	0.1329	0.0136
Exp & Sec. 8 vs. Control	0.1802	0.0446	0.0328	0.0202	0.1987	0.0016

Multiple Comparisons: Permutation Tests for Subgroup Heterogeneity

	Age		Race			Gender		Site					
p-value	< 13	>= 13	Black	Hisp	Other	M	F	Balt	Bos	Chi	LA	NYC	Min
Truth	**0.014**	0.258	0.698	0.529	0.923	0.750	0.244	0.212	0.720	0.287	0.491	0.691	0.014

Multiple Comparisons: Permutation Tests for Subgroup Heterogeneity

	Age		Race			Gender		Site					
p-value	< 13	>= 13	Black	Hisp	Other	M	F	Balt	Bos	Chi	LA	NYC	Min
Truth	**0.014**	0.258	0.698	0.529	0.923	0.750	0.244	0.212	0.720	0.287	0.491	0.691	0.014
Placebos													
1	0.197	0.653	0.989	0.235	0.891	0.568	0.208	0.764	0.698	0.187	0.588	0.122	0.122
2	0.401	0.344	0.667	0.544	0.190	0.292	0.259	**0.005**	0.919	0.060	0.942	0.102	**0.005**
3	0.878	0.831	0.322	0.511	0.109	0.817	0.791	0.140	0.180	0.248	0.435	0.652	0.109
4	0.871	0.939	0.225	0.339	0.791	0.667	0.590	0.753	0.750	0.123	0.882	0.303	0.123
5	0.296	0.386	0.299	0.067	0.377	0.340	0.562	0.646	0.760	0.441	0.573	0.342	0.067
6	0.299	0.248	0.654	0.174	0.598	0.127	0.832	0.284	0.362	0.091	0.890	0.097	0.091
7	0.362	0.558	0.477	0.637	0.836	0.555	0.436	0.093	0.809	0.767	0.422	0.736	0.093
8	0.530	0.526	0.662	0.588	0.238	0.875	0.986	0.386	0.853	0.109	0.826	0.489	0.109
9	0.299	0.990	0.917	0.214	0.660	0.322	0.048	0.085	0.038	0.527	0.810	0.854	0.038
10	0.683	0.805	0.017	0.305	0.807	0.505	0.686	0.356	0.795	0.676	0.472	0.523	0.017

Adjusted p-value (example) 0.100

Multiple Hypothesis Testing

- Conduct permutation test for all five outcomes we analyzed above
- Calculate fraction of placebos in which p value for *all five* outcomes in any one of the 12 subgroups is below true p values for <13 group
  - Yields a p value for null hypothesis that there is no treatment effect on any of the five outcomes adjusted for multiple testing
  - Adjusted $p < 0.01$ based on 1000 replications
- Moreover, recall that we returned to MTO data to test a pre-specified hypothesis that treatment effects would be larger for young children

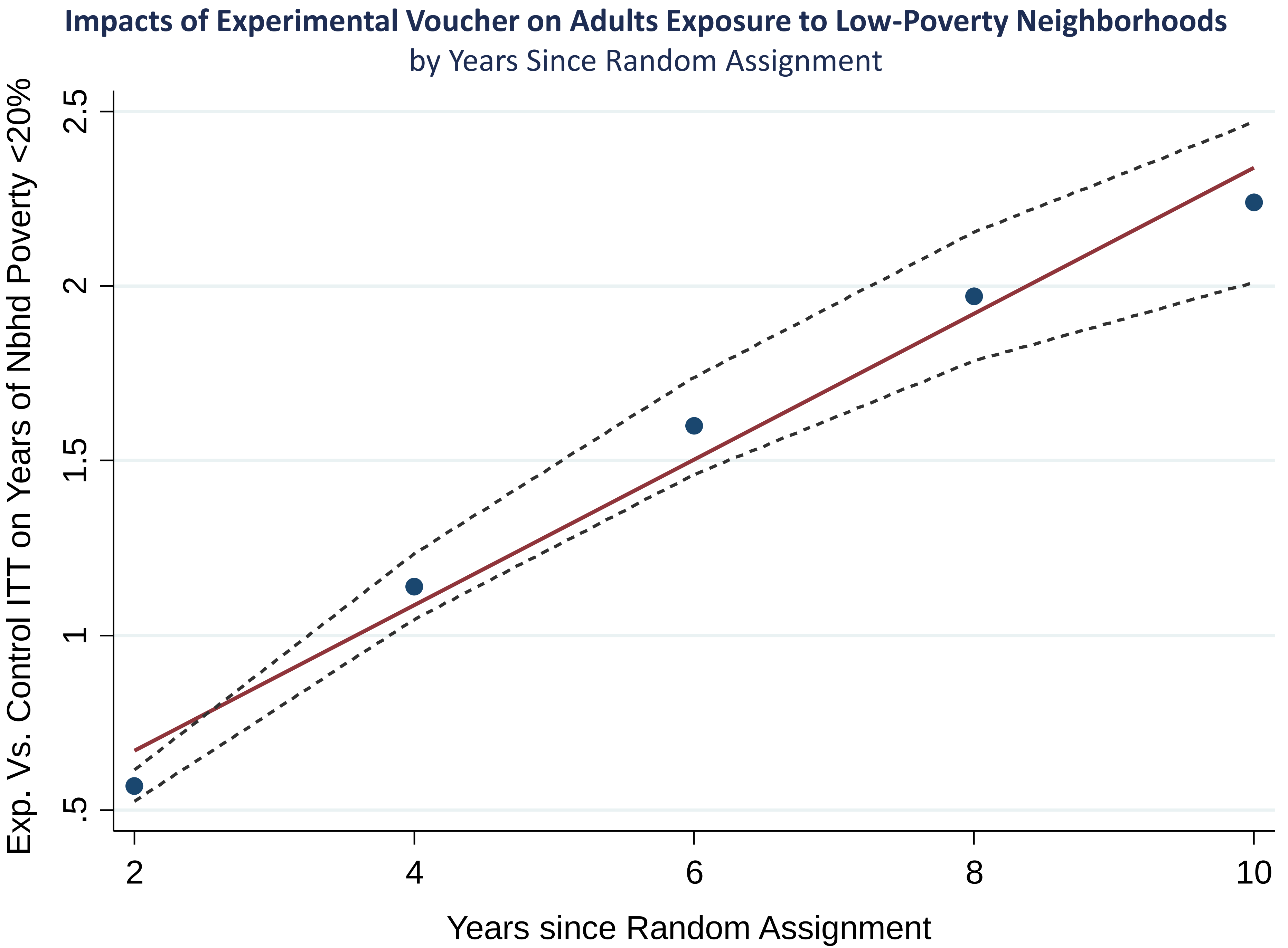
→ We believe results unlikely to be an artifact of multiple hypothesis testing

Treatment Effects on Adults

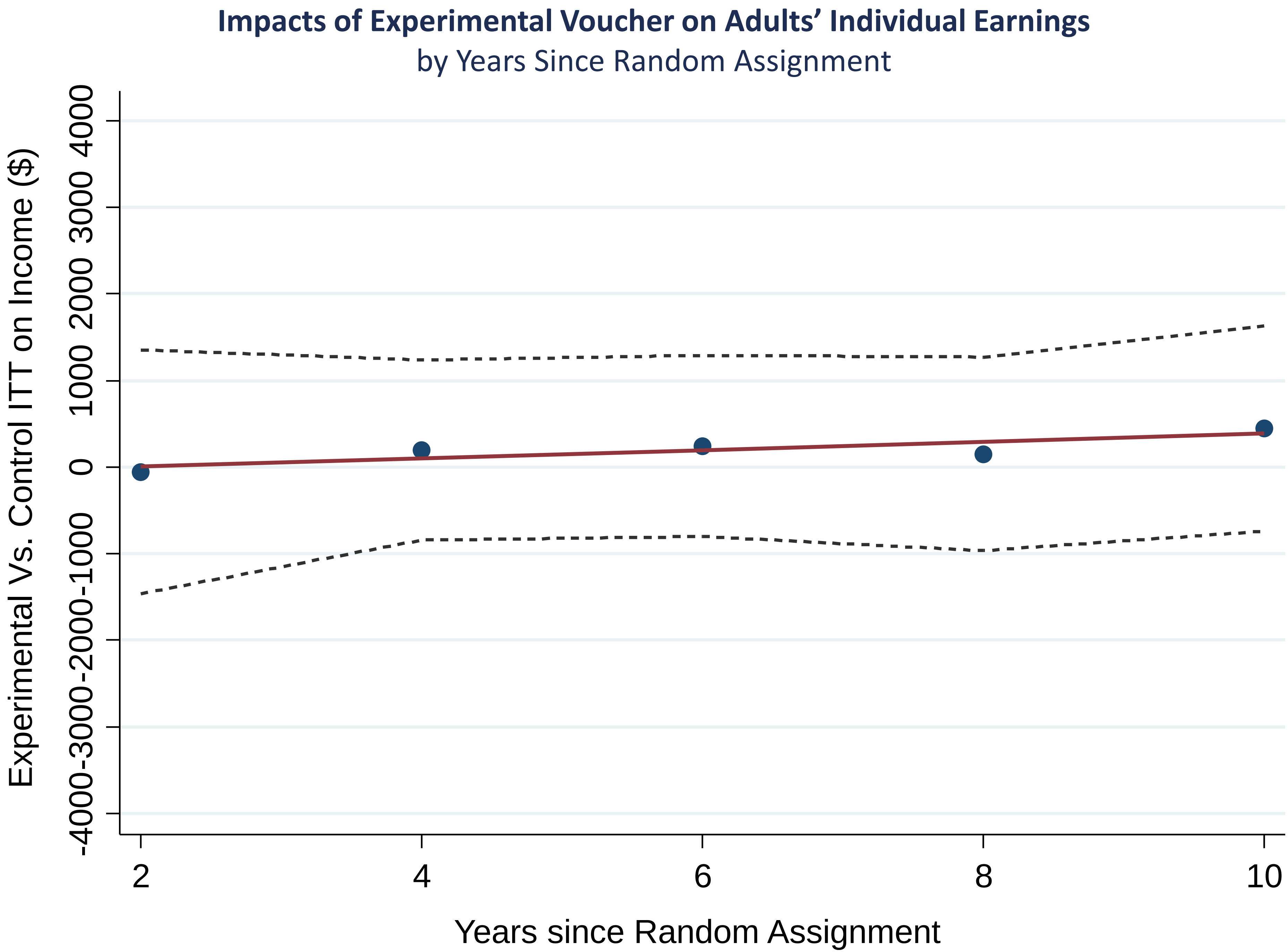
- Previous work finds no effects on adults' economic outcomes
  [Kling et al. 2007, Sanbonmatsu et al. 2011]

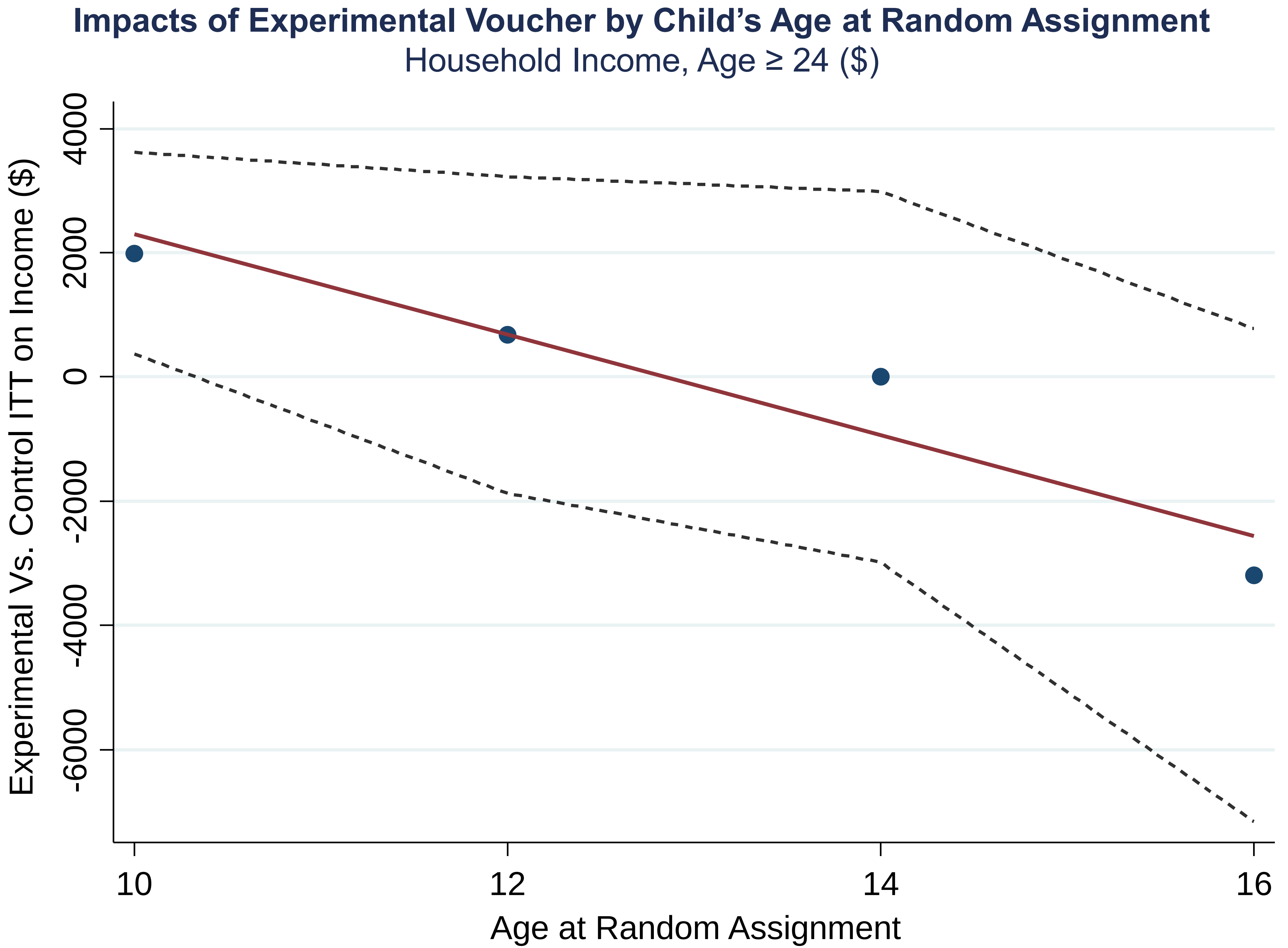
- Re-evaluate impacts on adults' outcomes using tax data

- Does exposure time matter for adults' outcomes as it does for children?
  [Clampet-Lundquist and Massey 2008]



Impacts of Experimental Voucher on Adults Exposure to Low-Poverty Neighborhoods
by Years Since Random Assignment
Exp. Vs. Control ITT on Years of Nbhd Poverty <20%
.5
1
1.5
2
2.5
2
4
6
8
10
Years since Random Assignment


Impacts of Experimental Voucher on Adults' Individual Earnings
by Years Since Random Assignment
Experimental Vs. Control ITT on Income ($)
-4000
-3000
-2000
-1000
0
1000
2000
3000
4000
2
4
6
8
10
Years since Random Assignment


Impacts of Experimental Voucher by Child's Age at Random Assignment
Household Income, Age ≥ 24 ($)
Experimental Vs. Control ITT on Income ($)
4000
2000
0
-2000
-4000
-6000
10
12
14
16
Age at Random Assignment

MTO: Limitations

- MTO experiment shows that neighborhoods matter, but has two limitations:

  1. Sample size insufficient to determine which ages of childhood matter most

  2. Does not directly identify which neighborhoods are good or bad

- Companion quasi-experimental study addresses these issues [Chetty and Hendren 2015]

Quasi-Experimental Estimates of Exposure Effects by County

Quasi-Experimental Analysis: Data

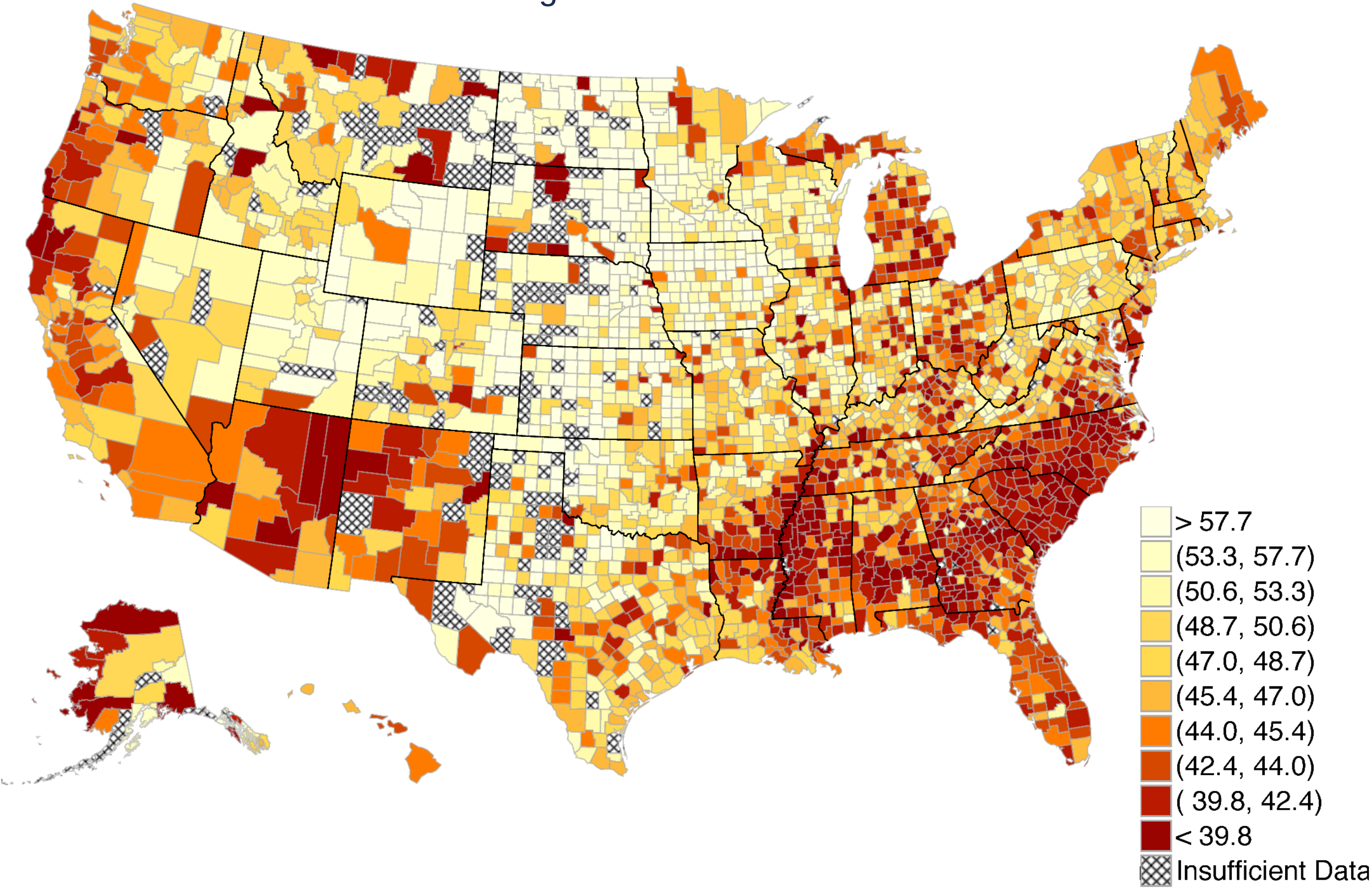
- Use full population of tax returns from 1996-2012

- Focus on children in 1980-1988 birth cohorts
  - Approximately 30 million children
  - Approximately 5 million families who move

- Begin with a descriptive characterization of children's outcomes across areas [Chetty, Hendren, Kline, Saez QJE 2014]
  - Measure mean percentile rank of a child who grows up in a family at 25th percentile of parent income distribution

The Geography of Intergenerational Mobility in the United States

Predicted Income Rank at Age 26 for Children with Parents at 25th Percentile



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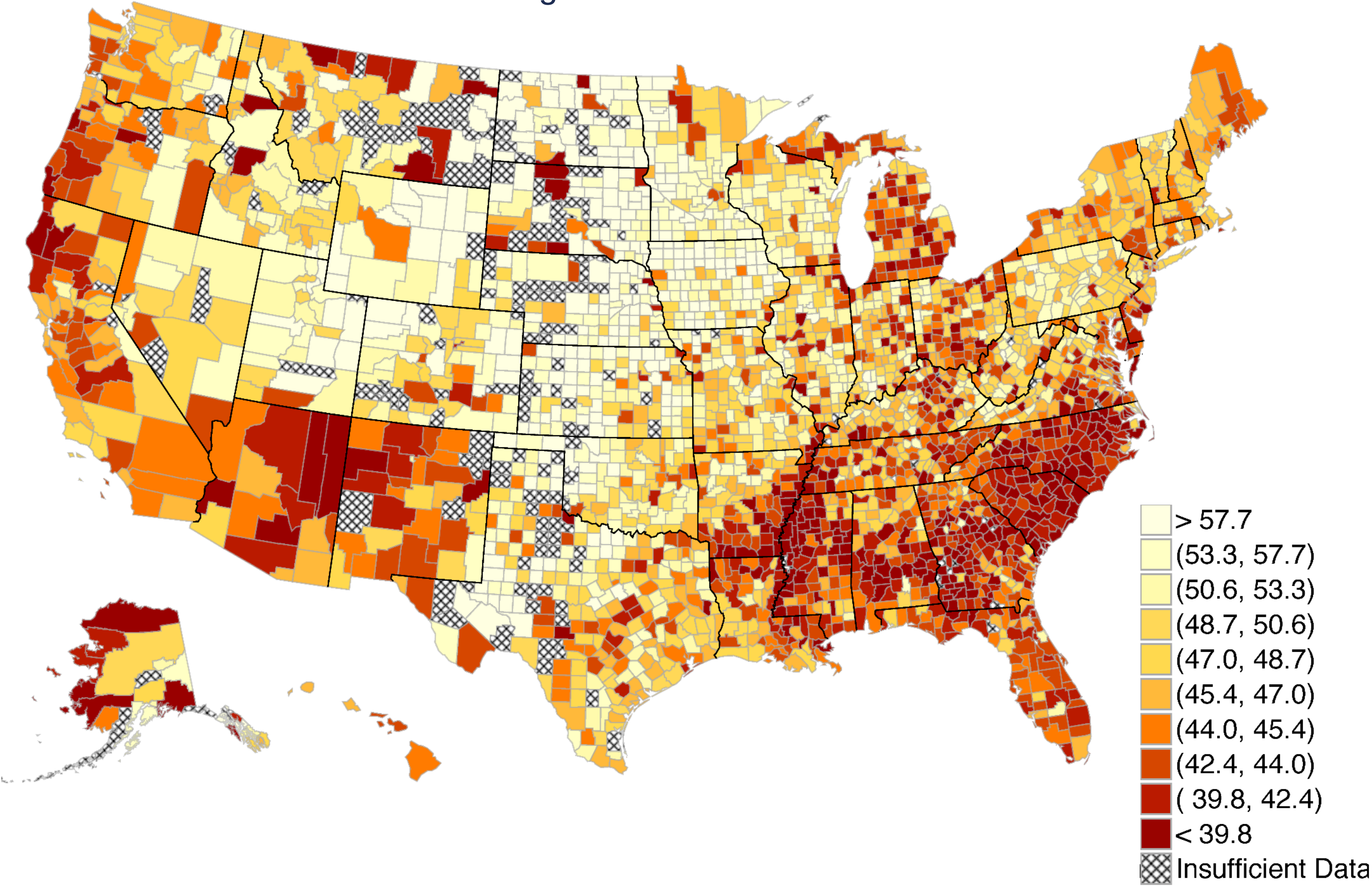


What Fraction of Variance in this Map is Due to Causal Place Effects?

Estimating Exposure Effects in Observational Data

- Identify exposure effects by studying families who move across neighborhoods in observational data

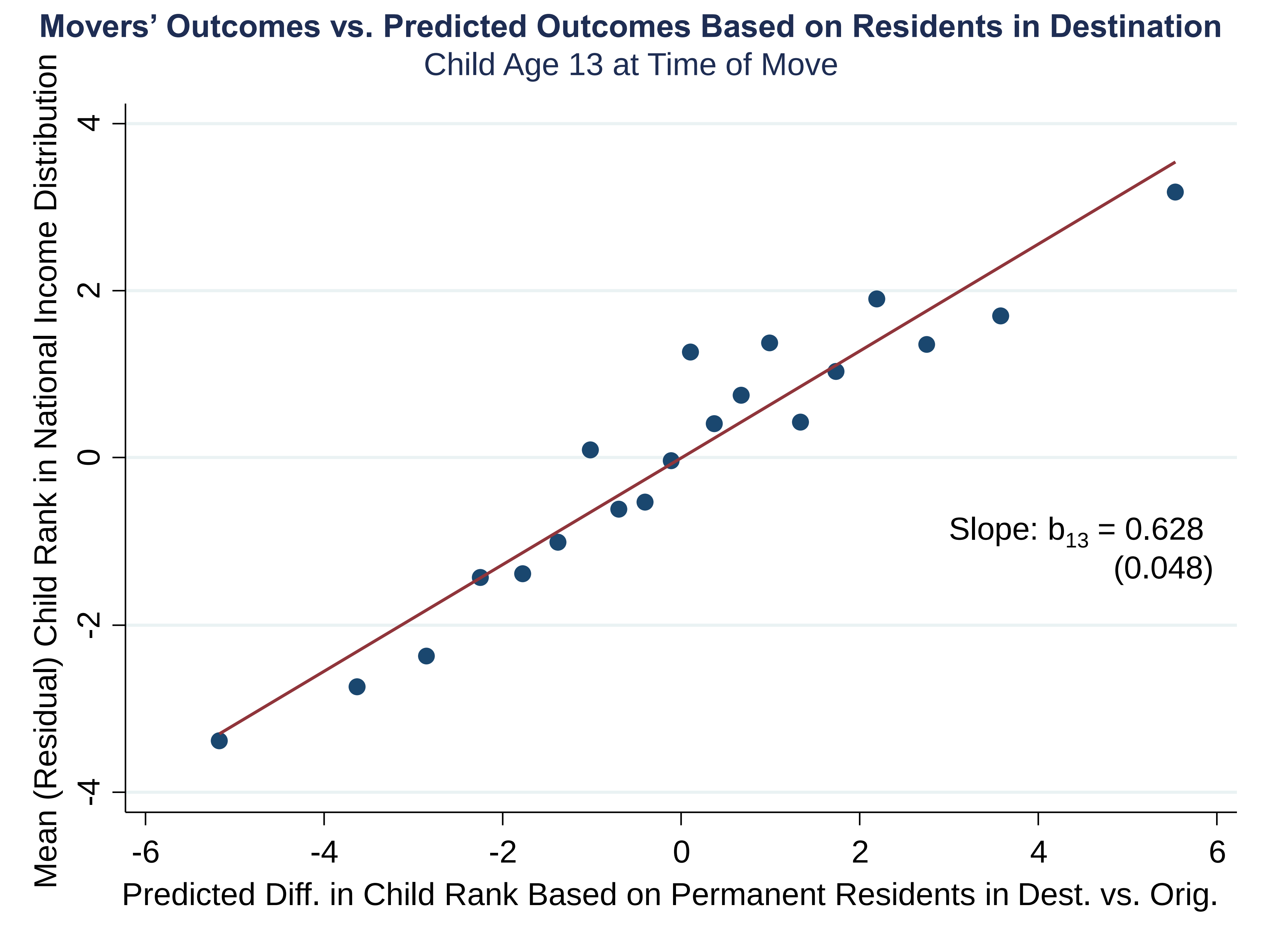
  - Key idea: identify from differences in *timing* of moves across families who make the same moves

- To begin, consider subset of families who move with a child who is exactly 13 years old

- Regress child's income rank at age 26 y_i on predicted outcome of permanent residents in destination:

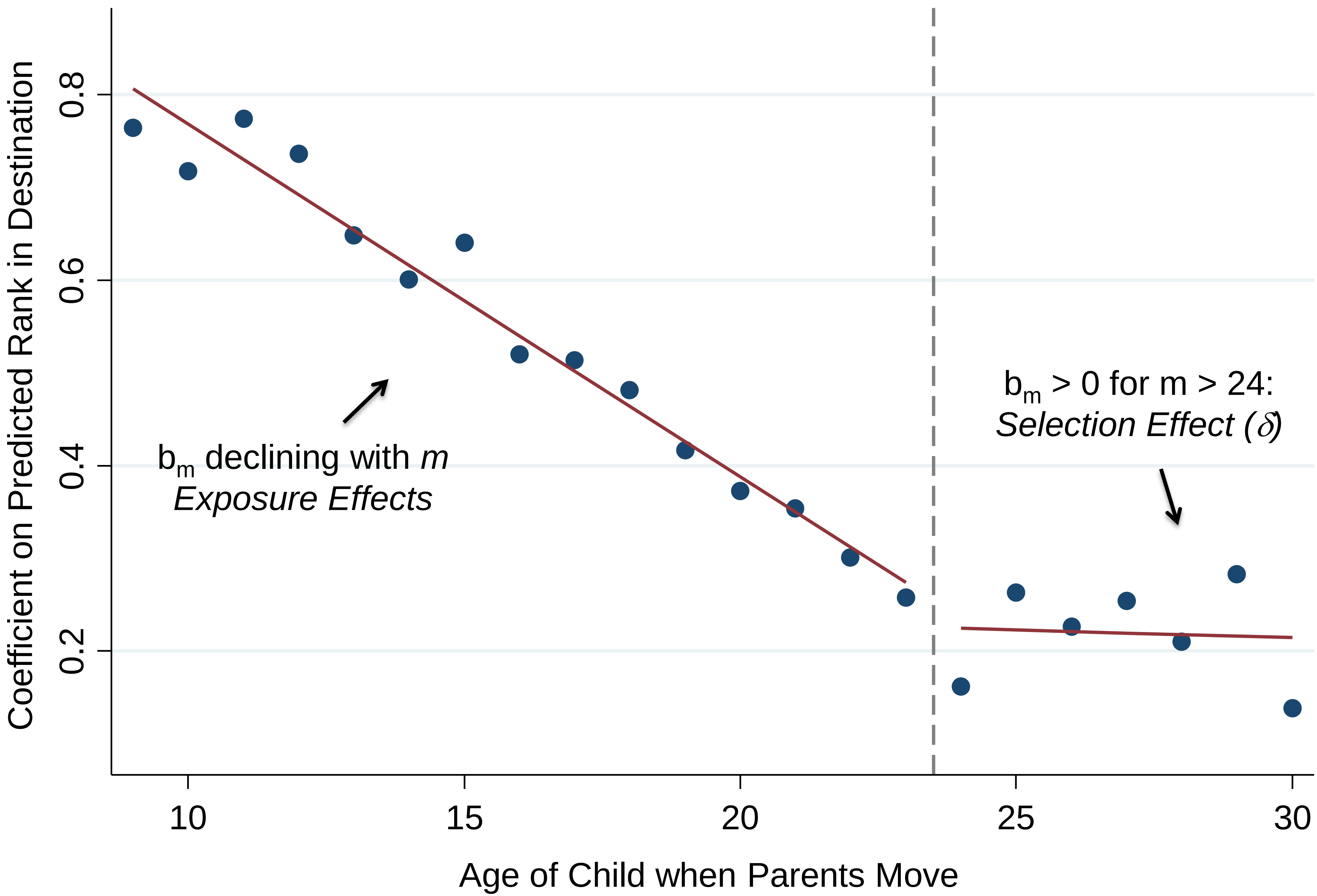
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

- Include parent decile (q) by origin (o) by birth cohort (s) fixed effects to identify b_m purely from differences in *destinations*


Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
Child Age 13 at Time of Move
Mean (Residual) Child Rank in National Income Distribution
4
2
0
-2
-4
-6
-4
-2
0
2
4
6
Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.
Slope: b_{13} = 0.628
(0.048)

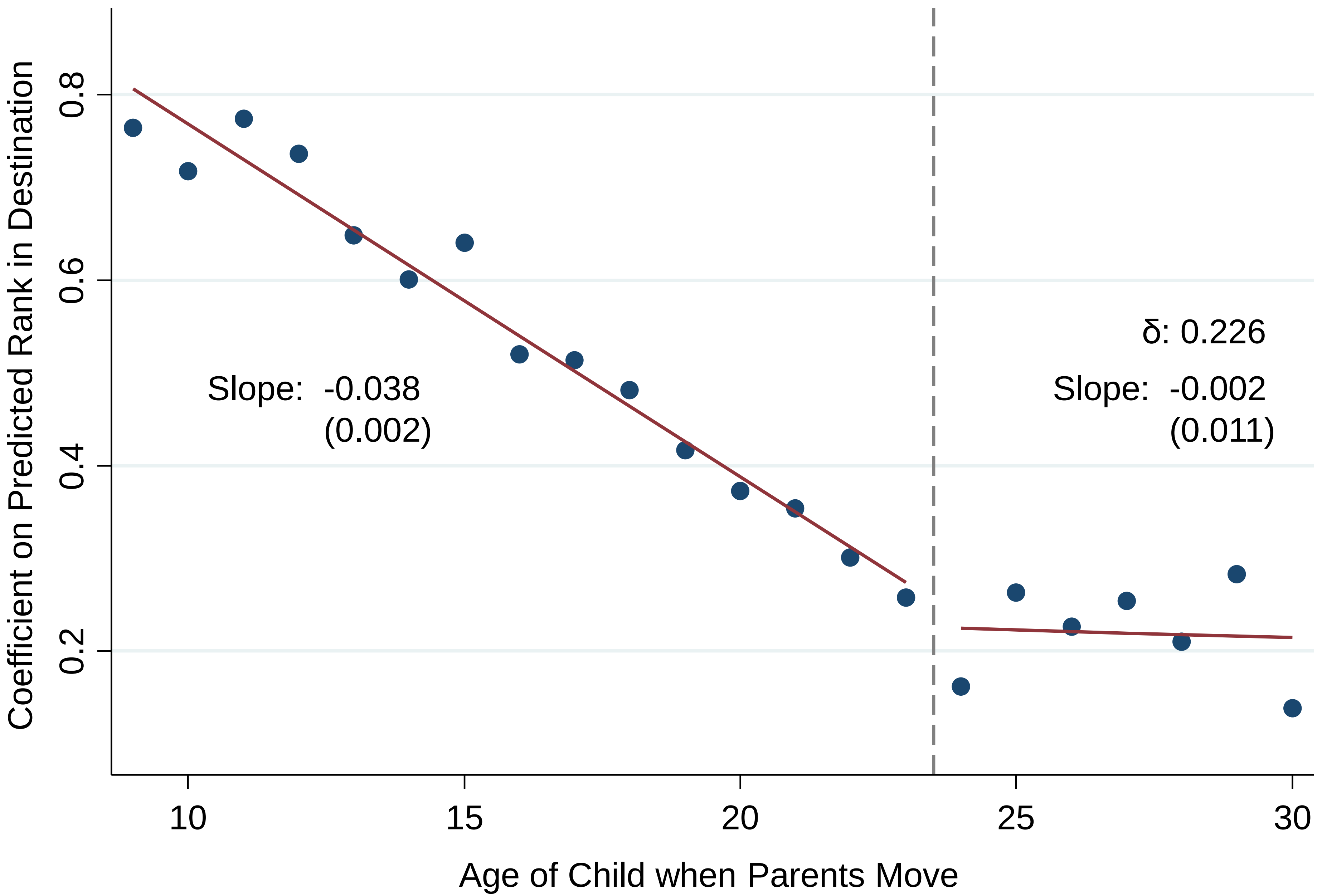
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination

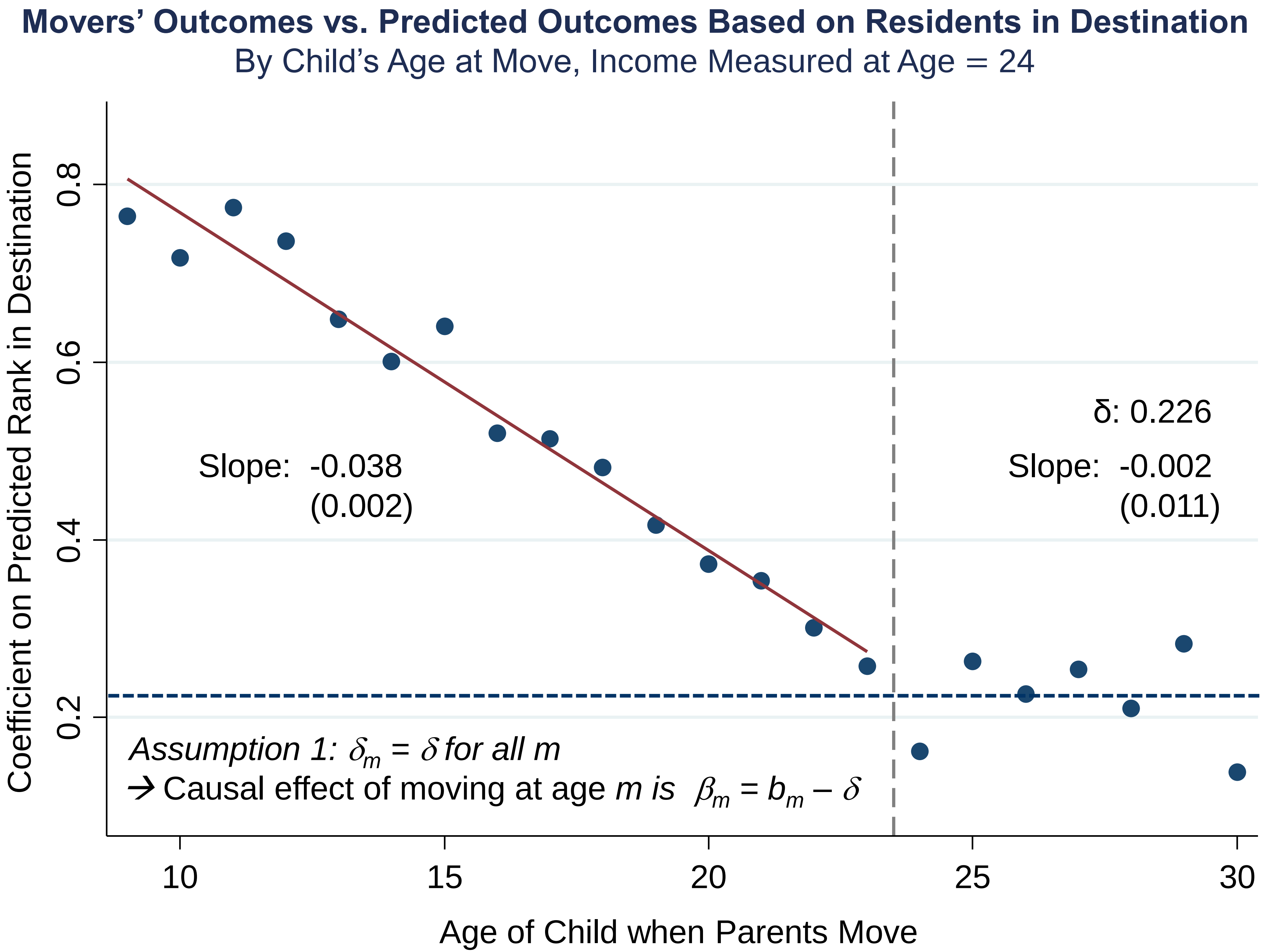
By Child's Age at Move, Income Measured at Age = 24

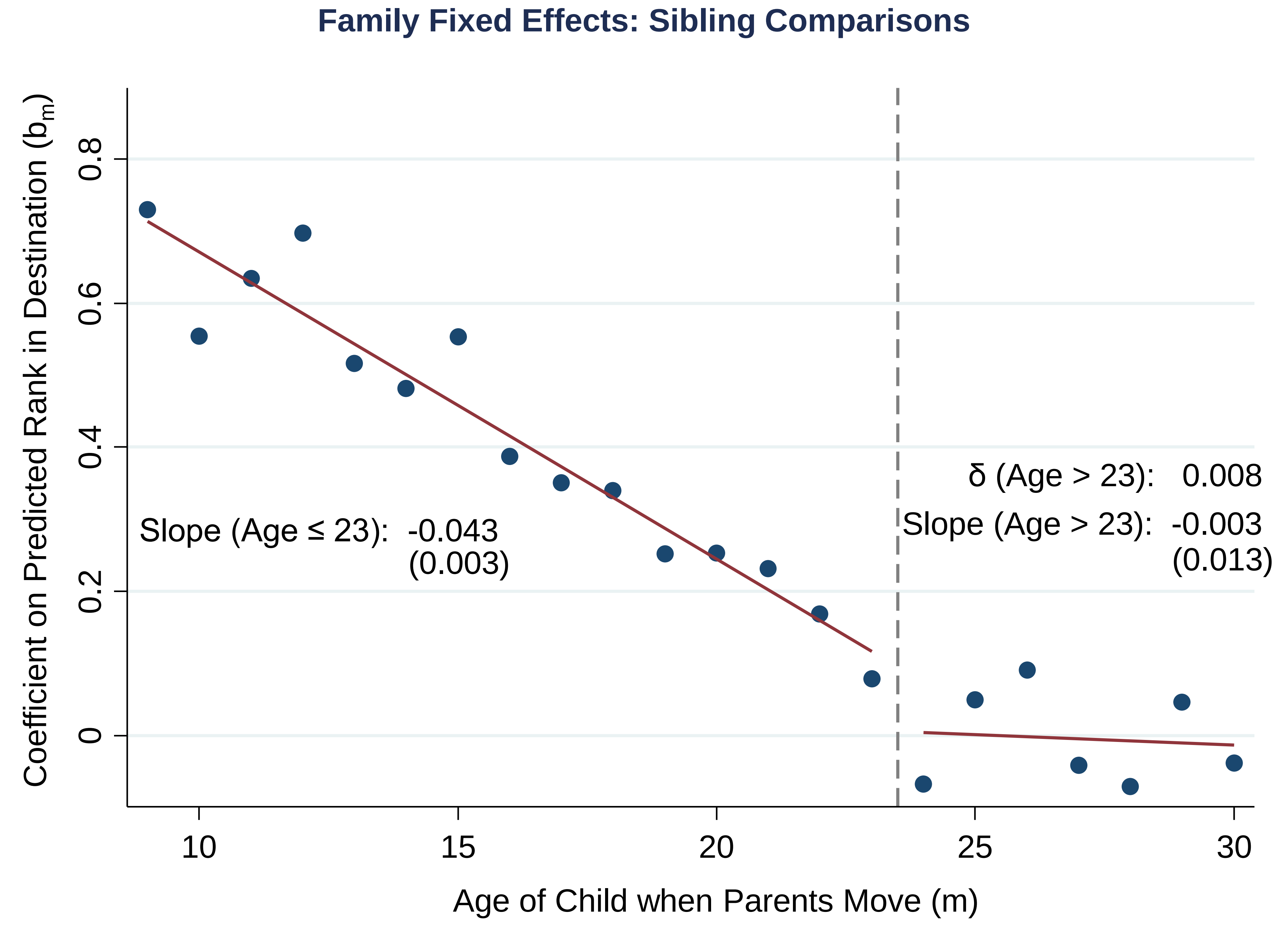


Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination

By Child's Age at Move, Income Measured at Age = 24




Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Age = 24
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Slope: -0.038
(0.002)
δ: 0.226
Slope: -0.002
(0.011)
Assumption 1: $\delta_m = \delta$ for all m
→ Causal effect of moving at age m is $\beta_m = b_m - \delta$



Family Fixed Effects: Sibling Comparisons
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)
Slope (Age ≤ 23): -0.043
(0.003)
δ (Age > 23): 0.008
Slope (Age > 23): -0.003
(0.013)

Additional Tests

- Family fixed effects do not rule out time-varying unobservables (e.g. wealth shocks) that affect children in proportion to exposure time

- Two approaches to evaluate such confounds:

  1. Outcome-based placebo (overidentification) tests

  2. Quasi-experimental variation from displacement shocks

- Focus on the first here in the interest of time

Outcome-based Placebo Tests

- General idea: exploit heterogeneity in place effects across subgroups to obtain overidentification tests of exposure effect model

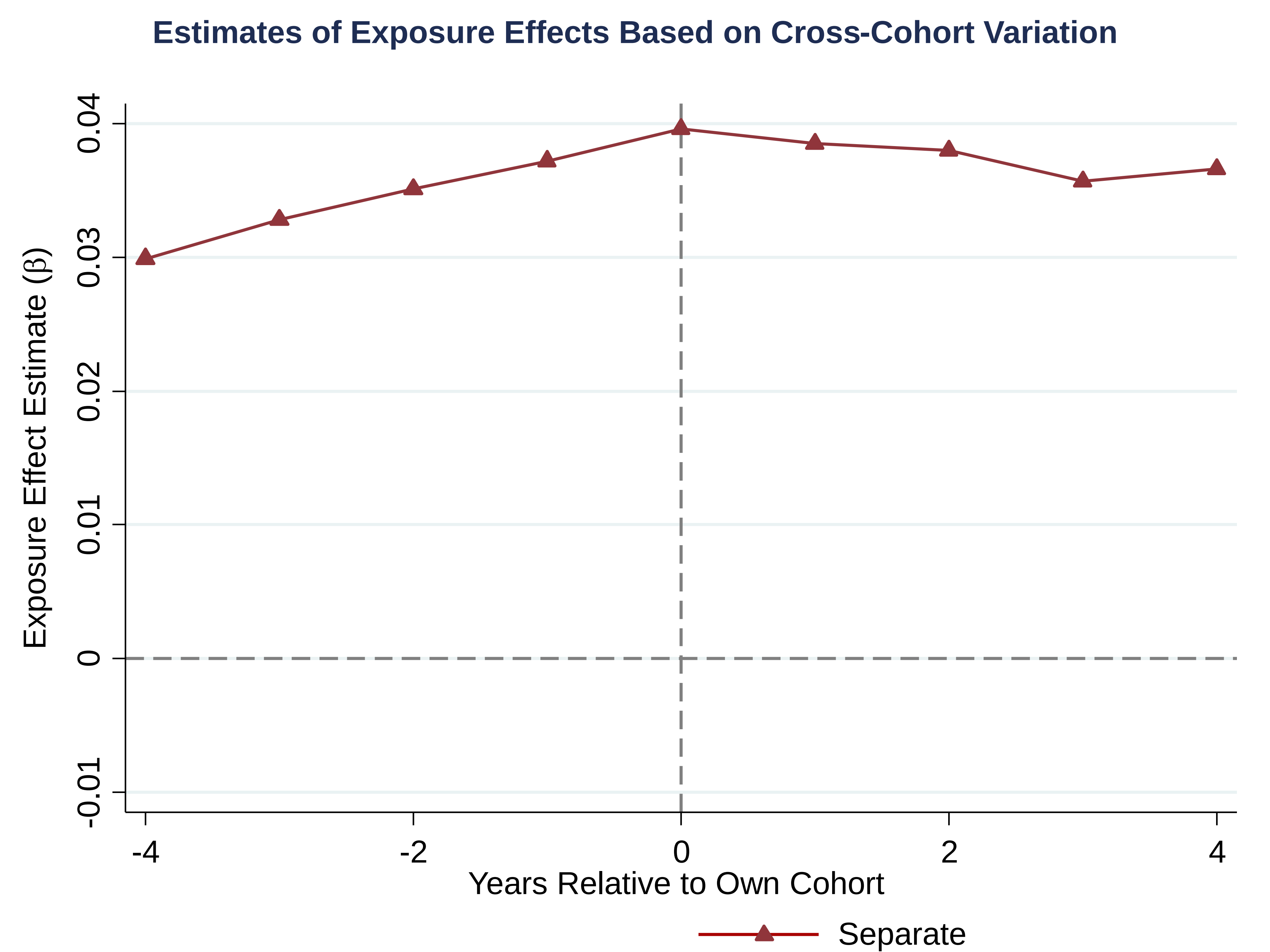
- Ability to implement such tests is a key advantage of defining neighborhood “quality” based on prior residents’ outcomes

  - Outcome-based measures yield sharp predictions on how movers’ outcomes should change when they move

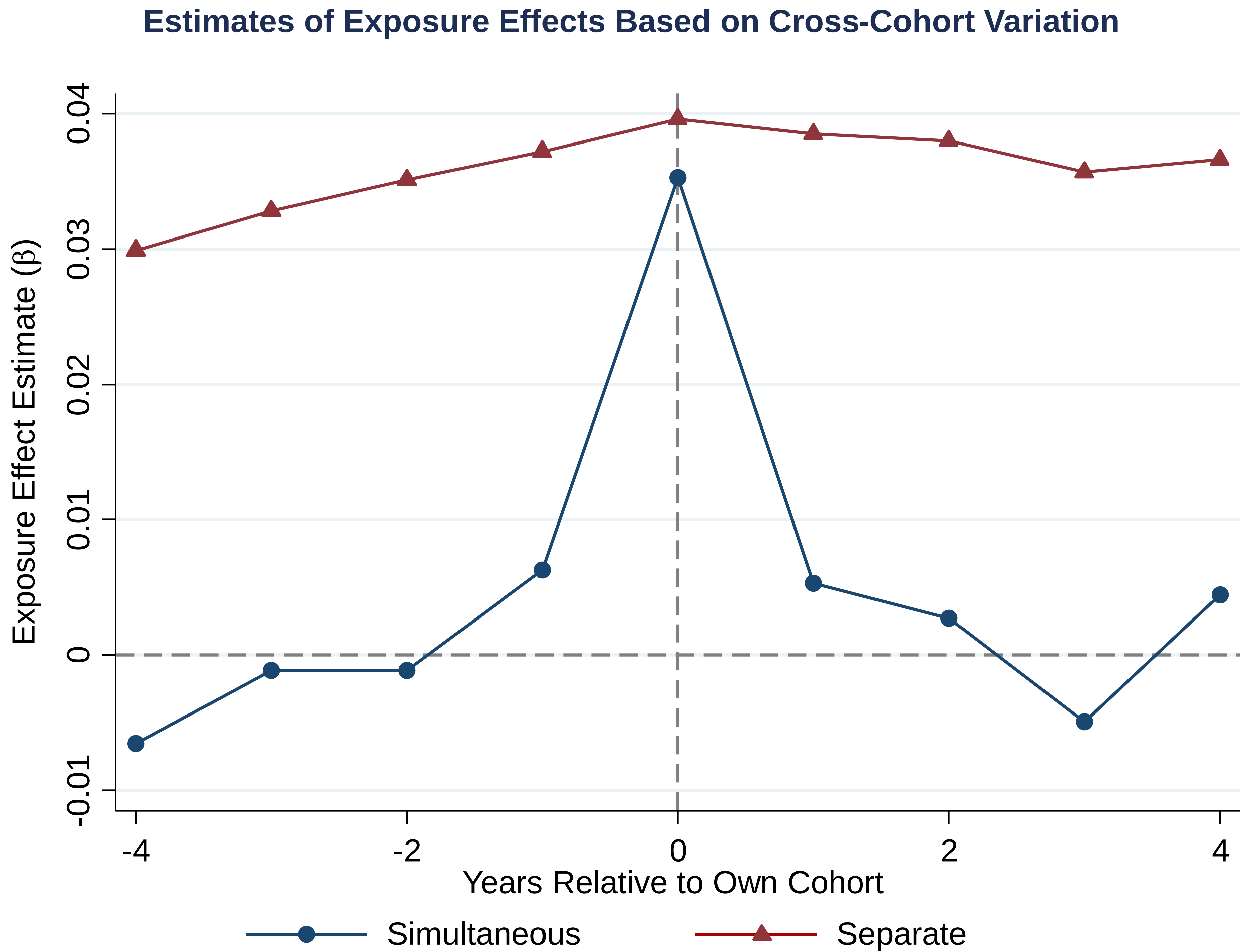
  - With traditional measures of nbhd. quality such as poverty rates, difficult to disentangle causal effect of nbhd. from contemporaneous shock

Outcome-based Placebo Tests

- Start with variation in place effects across birth cohorts
  - Some areas are getting better over time, others are getting worse
  - Causal effect of neighborhood on a child who moves in to an area should depend on properties of that area while he is growing up
- Parents choose neighborhoods based on their preferences and information set at time of move
  - Difficult to predict high-frequency differences that are realized 15 years later → hard to sort on this dimension



Estimates of Exposure Effects Based on Cross-Cohort Variation
Exposure Effect Estimate (β)
0.04
0.03
0.02
0.01
0
-0.01
-4
-2
0
2
4
Years Relative to Own Cohort
Separate



Estimates of Exposure Effects Based on Cross-Cohort Variation
Exposure Effect Estimate (β)
0.04
0.03
0.02
0.01
0
-0.01
-4
-2
0
2
4
Years Relative to Own Cohort
Simultaneous
Separate

Distributional Convergence

- Areas differ not just in mean child outcomes but also across distribution
- For example, compare outcomes in Boston and San Francisco for children with parents at 25th percentile
  - Mean expected rank is 46th percentile in both cities
  - Probability of reaching top 10%: 7.3% in SF vs. 5.9% in Boston
  - Probability of being in bottom 10%: 15.5% in SF vs. 11.7% in Boston
- Exposure model predicts convergence to permanent residents' outcomes not just on means but across *entire* distribution
  - Children who move to SF at younger ages should be more likely to end up in tails than those who move to Boston

Exposure Effects on Upper-Tail and Lower-Tail Outcomes

Comparisons of Impacts at P90 and Non-Employment

	Dependent Variable					
	Child Rank in top 10%			Child Employed		
	(1)	(2)	(3)	(4)	(5)	(6)
Distributional Prediction	0.043		0.040	0.046		0.045
	(0.002)		(0.003)	(0.003)		(0.004)
Mean Rank Prediction		0.022	0.004		0.021	0.000
(Placebo)		(0.002)	(0.003)		(0.002)	(0.003)

Gender Comparisons

- Finally, exploit heterogeneity across genders
- Construct separate predictions of expected income rank conditional on parent income for girls and boys in each CZ
  - Correlation of male and female predictions across CZ's is 0.90
- Low-income boys do worse than girls in areas with:
  1. Higher rates of crime
  2. More segregation and inequality
  3. Lower marriage rates (consistent with Autor and Wasserman 2013)

Exposure Effect Estimates: Gender-Specific Predictions

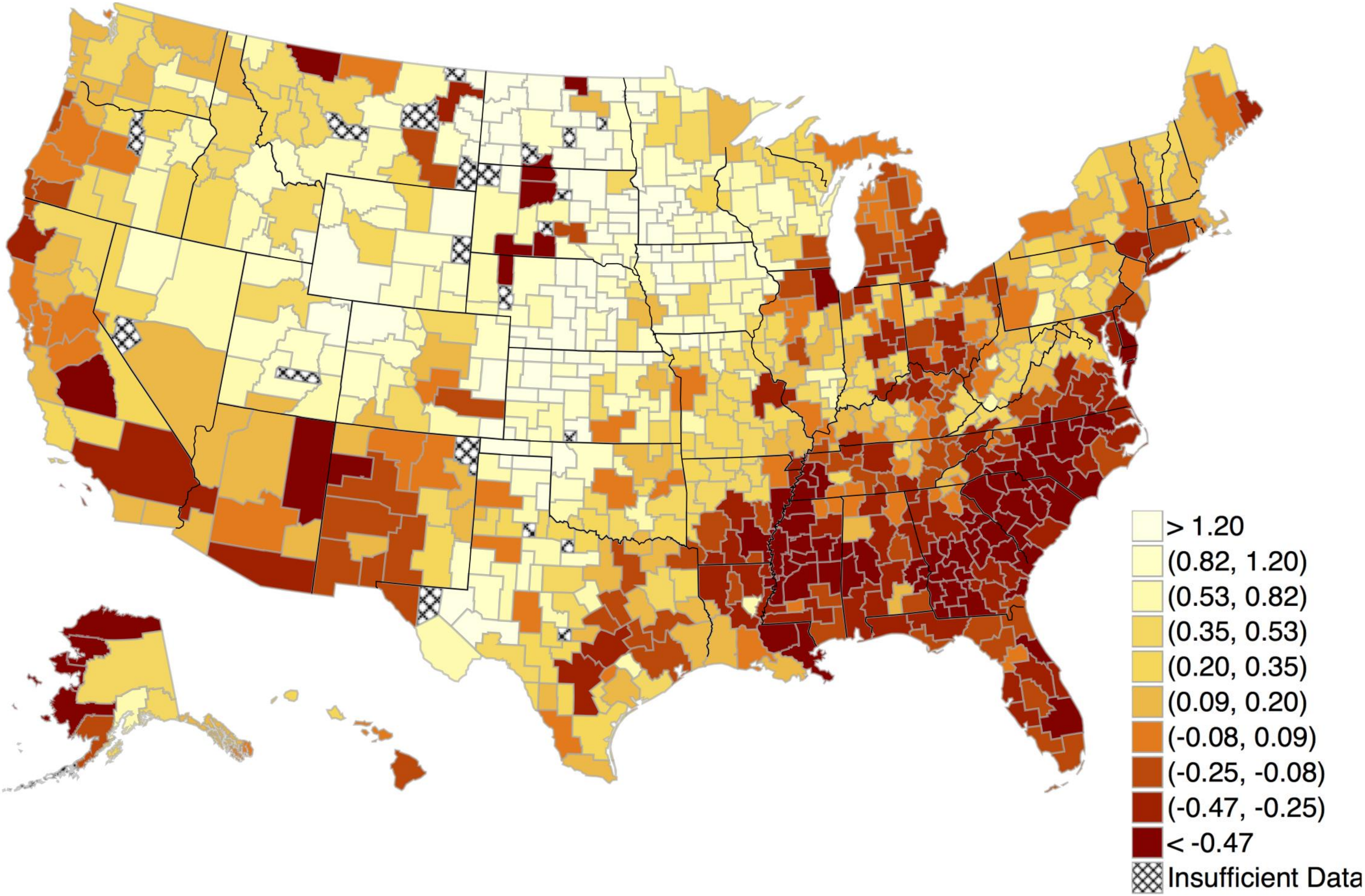
	No Family Fixed Effects			Family Fixed Effects
	(1)	(2)	(3)	(4)
Own Gender Prediction	0.038		0.031	**0.031**
	(0.002)		(0.003)	(0.007)
Other Gender Prediction (Placebo)		0.034	0.009	**0.012**
		(0.002)	(0.003)	(0.007)
Sample	Full Sample			2-Gender HH

Estimating Fixed Effects by County

- Apply exposure-time design to estimate causal effects of each area in the U.S. using a fixed effects model
  - Focus exclusively on movers, without using data on permanent residents
- Intuition: suppose children who move from Manhattan to Queens at younger ages earn more as adults
  - Can infer that Queens has positive exposure effects relative to Manhattan
- Build on this logic to estimate fixed effects of all counties using five million movers, identifying purely from differences in *timing* of moves across areas
- Use these fixed effects to form unbiased forecasts of each county and CZ’s causal effect

Predicted Exposure Effects on Child's Income Level at Age 26 by CZ

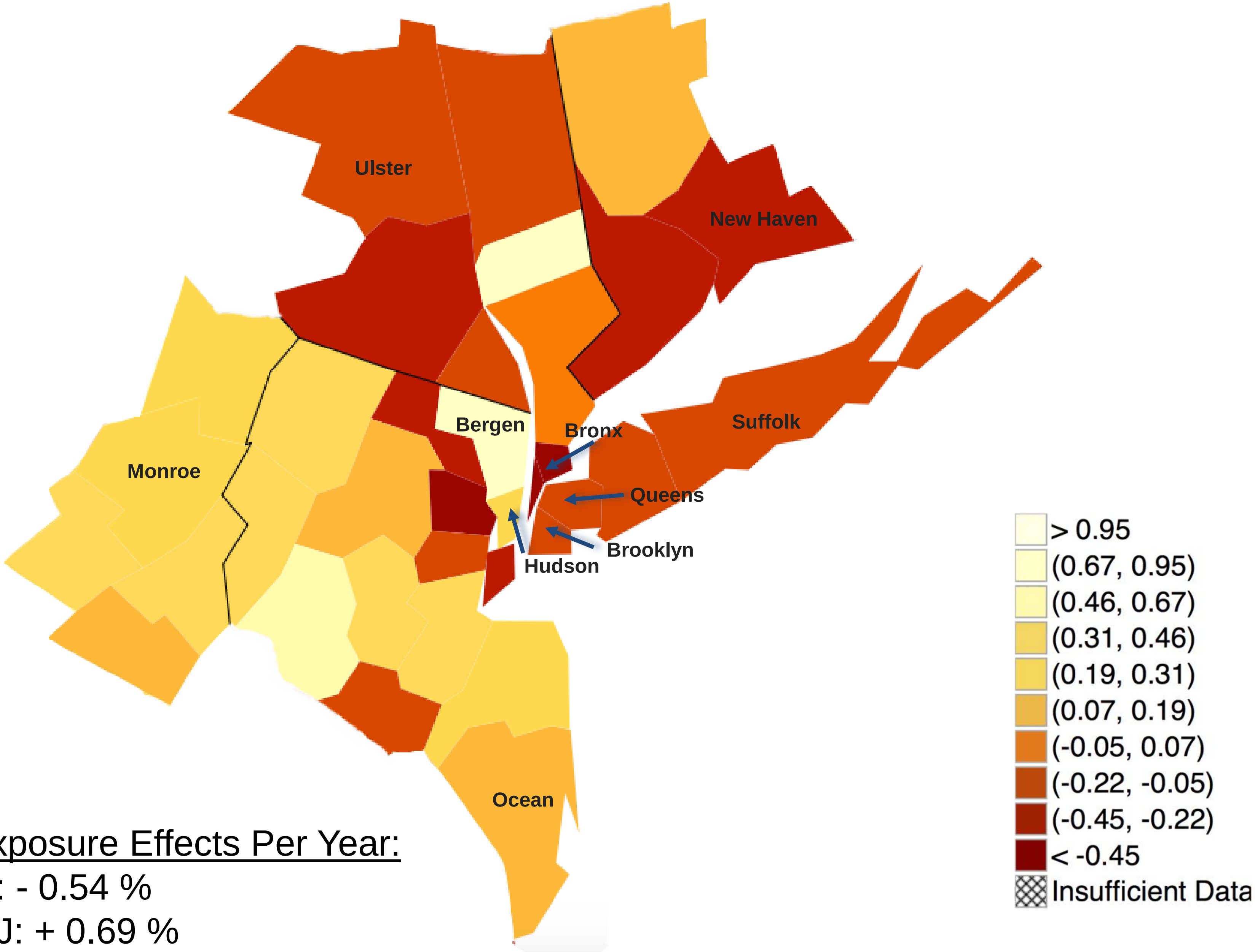
For Children with Parents at 25th Percentile of Income Distribution



Note: Estimates represent % change in earnings from spending one more year of childhood in CZ

Exposure Effects on Income in the New York CSA

For Children with Parents at 25th Percentile of Income Distribution



<u>Causal Exposure Effects Per Year:</u>

Bronx NY: - 0.54 %

Bergen NJ: + 0.69 %

Causal Effect Forecasts on Earnings Per Year of Childhood Exposure (p25)

Top 10 and Bottom 10 Among the 100 Largest Counties in the U.S.

Top 10 Counties			Bottom 10 Counties		
Rank	County	Annual Exposure Effect (%)	Rank	County	Annual Exposure Effect (%)
1	Dupage, IL	0.80	91	Wayne, MI	-0.57
2	Fairfax, VA	0.75	92	Orange, FL	-0.61
3	Snohomish, WA	0.70	93	Cook, IL	-0.64
4	Bergen, NJ	0.69	94	Palm Beach, FL	-0.65
5	Bucks, PA	0.62	95	Marion, IN	-0.65
6	Norfolk, MA	0.57	96	Shelby, TN	-0.66
7	Montgomery, PA	0.49	97	Fresno, CA	-0.67
8	Montgomery, MD	0.47	98	Hillsborough, FL	-0.69
9	King, WA	0.47	99	Baltimore City, MD	-0.70
10	Middlesex, NJ	0.46	100	Mecklenburg, NC	-0.72

Exposure effects represent % change in adult earnings per year of childhood spent in county

Causal Effect Forecasts on Earnings Per Year of Childhood Exposure (p25)

Male Children

Top 10 Counties			Bottom 10 Counties		
Rank	County	Annual Exposure Effect (%)	Rank	County	Annual Exposure Effect (%)
1	Bucks, PA	0.84	91	Milwaukee, WI	-0.74
2	Bergen, NJ	0.83	92	New Haven, CT	-0.75
3	Contra Costa, CA	0.72	93	Bronx, NY	-0.76
4	Snohomish, WA	0.70	94	Hillsborough, FL	-0.81
5	Norfolk, MA	0.62	95	Palm Beach, FL	-0.82
6	Dupage, IL	0.61	96	Fresno, CA	-0.84
7	King, WA	0.56	97	Riverside, CA	-0.85
8	Ventura, CA	0.55	98	Wayne, MI	-0.87
9	Hudson, NJ	0.52	99	Pima, AZ	-1.15
10	Fairfax, VA	0.46	100	Baltimore City, MD	-1.39

Exposure effects represent % change in adult earnings per year of childhood spent in county

Causal Effect Forecasts on Earnings Per Year of Childhood Exposure (p25)

Female Children

Top 10 Counties			Bottom 10 Counties		
Rank	County	Annual Exposure Effect (%)	Rank	County	Annual Exposure Effect (%)
1	Dupage, IL	0.91	91	Hillsborough, FL	-0.51
2	Fairfax, VA	0.76	92	Fulton, GA	-0.58
3	Snohomish, WA	0.73	93	Suffolk, MA	-0.58
4	Montgomery, MD	0.68	94	Orange, FL	-0.60
5	Montgomery, PA	0.58	95	Essex, NJ	-0.64
6	King, WA	0.57	96	Cook, IL	-0.64
7	Bergen, NJ	0.56	97	Franklin, OH	-0.64
8	Salt Lake, UT	0.51	98	Mecklenburg, NC	-0.74
9	Contra Costa, CA	0.47	99	New York, NY	-0.75
10	Middlesex, NJ	0.47	100	Marion, IN	-0.77

Exposure effects represent % change in adult earnings per year of childhood spent in county

Characteristics of Good Areas

- What types of areas produce better outcomes for low-income children?

- Strong correlations with five factors:

    1. Segregation
    2. Inequality
    3. School Quality
    4. Social Capital
    5. Family Structure

- Not correlated with poverty rates at CZ level, but strong correlation at county level, consistent with MTO evidence

- Better areas not generally more expensive in terms of housing costs

    - But significantly more expensive in highly segregated large cities

Conclusion: Policy Lessons

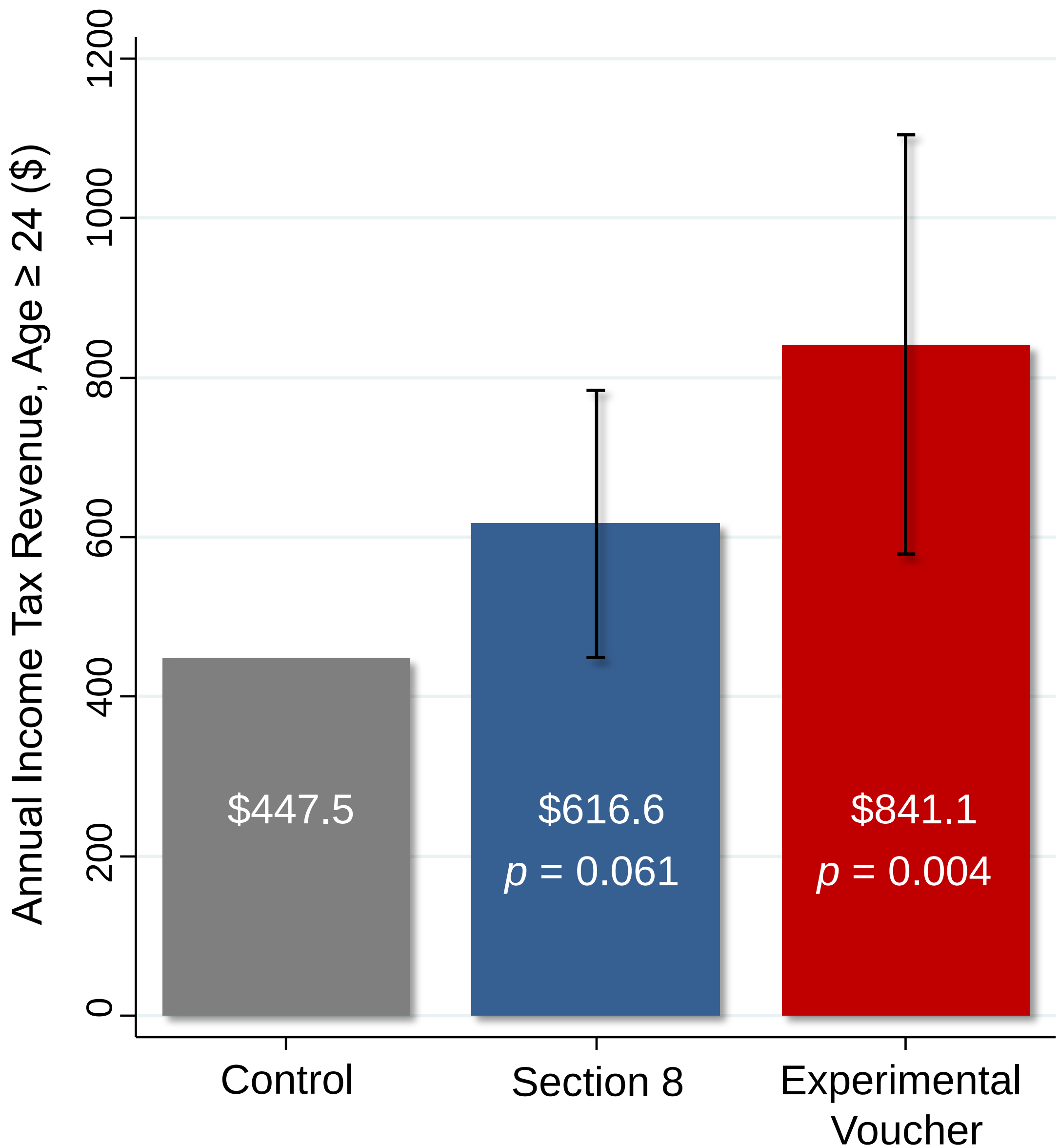
- How can we improve neighborhood environments for disadvantaged youth?

  1. Short-term solution: Provide targeted housing vouchers at birth conditional on moving to better (e.g. mixed-income) areas

     - Benefit: MTO experimental vouchers increased PDV of earnings by $100K for children who moved at young ages

     - Cost: MTO experimental vouchers increased tax revenue substantially → taxpayers may ultimately gain from this investment

Impacts of MTO on Annual Income Tax Revenue in Adulthood for Children Below Age 13 at Random Assignment (TOT Estimates)



Conclusion: Policy Lessons

- How can we improve neighborhood environments for disadvantaged youth?

1. Short-term solution: Provide targeted housing vouchers at birth conditional on moving to better (e.g. mixed-income) areas

   - Taxpayers may ultimately gain from this investment

2. Long-term solution: improve neighborhoods with poor outcomes, concentrating on factors that affect children

   - Estimates here tell us which areas need improvement, but further work needed to determine which policies can make a difference