The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects

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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

- How much do neighborhood environments affect children's outcomes?

  - Observational studies document substantial variation in outcomes across areas [Wilson 1987, Massey and Denton 1993, Cutler and Glaeser 1997, Wodtke et al. 1999, Altonji and Mansfield 2014]

  - But experimental studies find no significant effects of moving to better areas on economic outcomes [e.g. Katz, Kling, and Liebman 2001, Oreopoulous 2003, Sanbonmatsu et al. 2011]

This Talk

- We use data from de-identified tax records on 7 million families who move across counties to present two sets of results:

    1. Quasi-experimental evidence that neighborhoods have significant causal effects in proportion to *childhood exposure*

    2. Estimates of causal effects of each county in the U.S. on children's earnings

- Results presented in two companion papers:

    - **First paper:** "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects"

    - **Second Paper:** "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates"

Data

- Data source: de-identified data from 1996-2012 tax returns
- Children linked to parents based on dependent claiming
- Focus on children in 1980-1993 birth cohorts
  - Approximately 50 million children

Variable Definitions

- Parent income: mean pre-tax household income between 1996-2000
    - For non-filers, use W-2 wage earnings + SSDI + UI income
- Child income: pre-tax household income at various ages
- Results robust to varying definitions of income and age at which child's income is measured
- Focus on percentile ranks in **national** income distribution
    - Rank children relative to others in the same birth cohort
    - Rank parents relative to other parents

Defining “Neighborhoods”

- We conceptualize neighborhood effects as the sum of effects at different geographies (hierarchical model)

$$\mu_{nbhd} = \mu_{CZ} + \mu_{County} + \mu_{Zip} + \mu_{Block}$$

- Our primary estimates are at the commuting zone (CZ) and county level
  - CZ’s are aggregations of counties analogous to MSAs [Tolbert and Sizer 1996; Autor and Dorn 2013]

- Variance of place effects at broad geographies is a lower bound for total variance of neighborhood effects

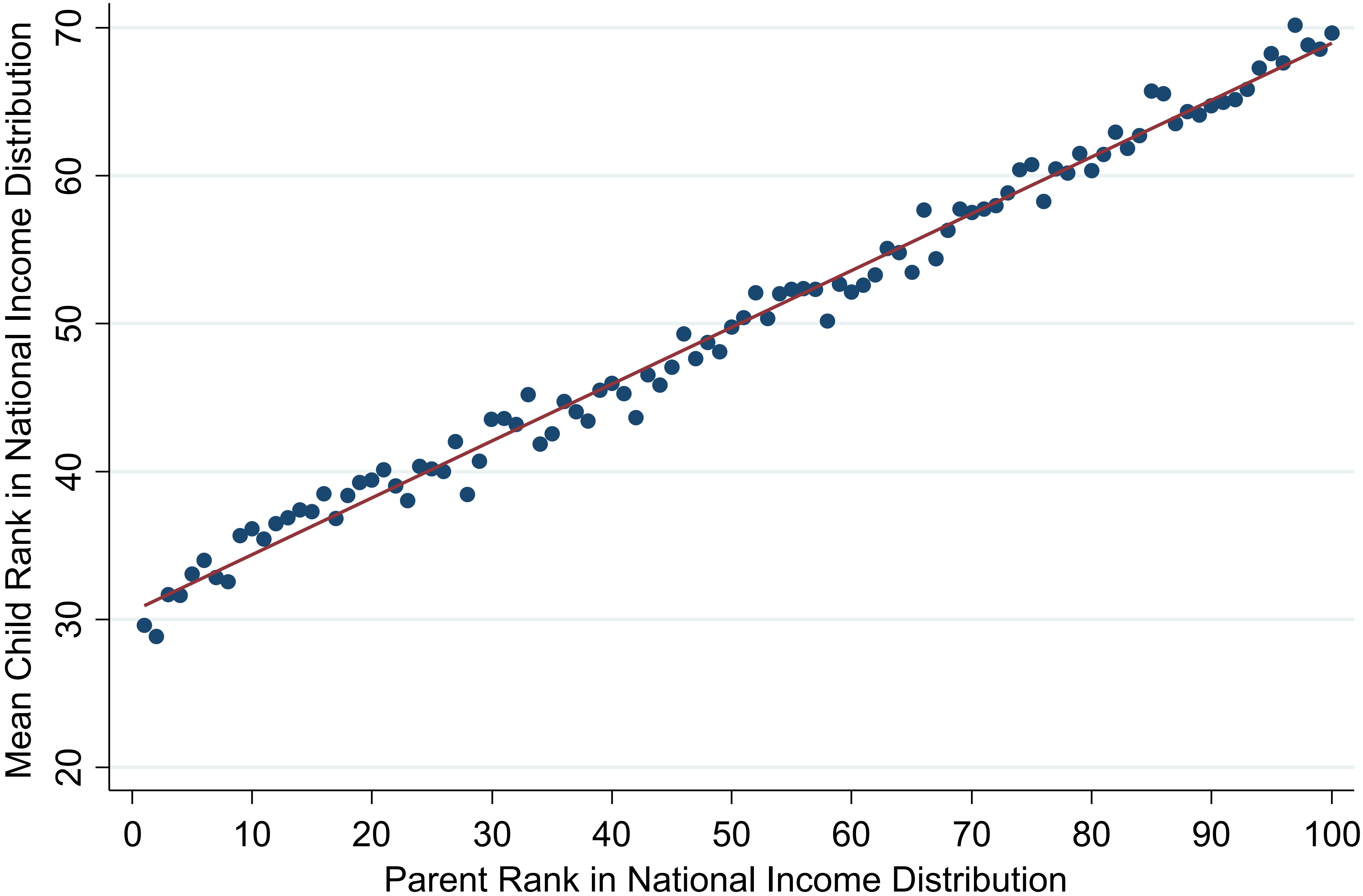
Intergenerational Mobility by CZ

- Begin with a descriptive characterization of children's outcomes in each CZ

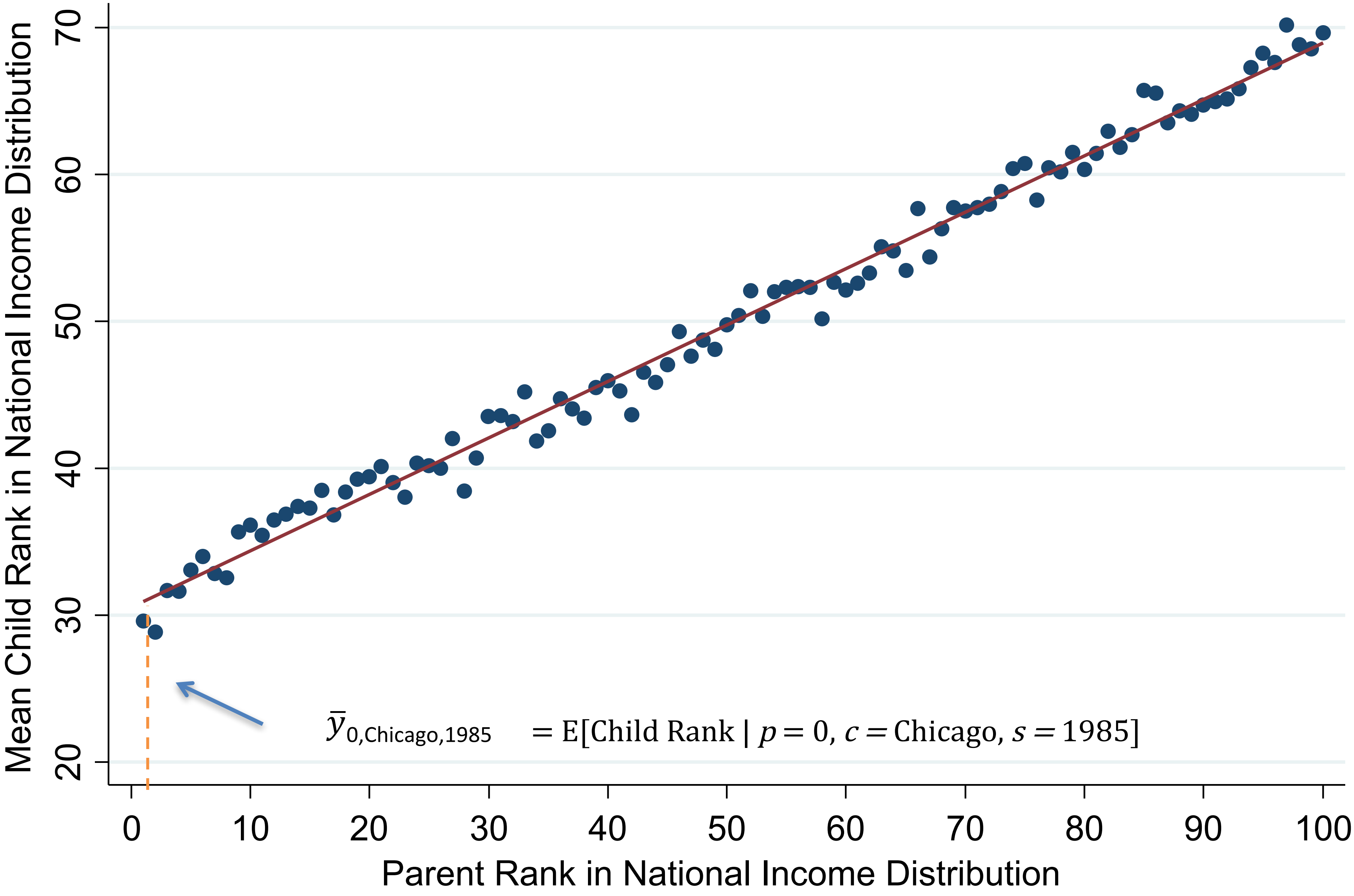
- Focus on "permanent residents" of CZs
  - Permanent residents = parents who stay in CZ c between 1996-2012
  - Note that children who grow up in CZ c may move out as adults

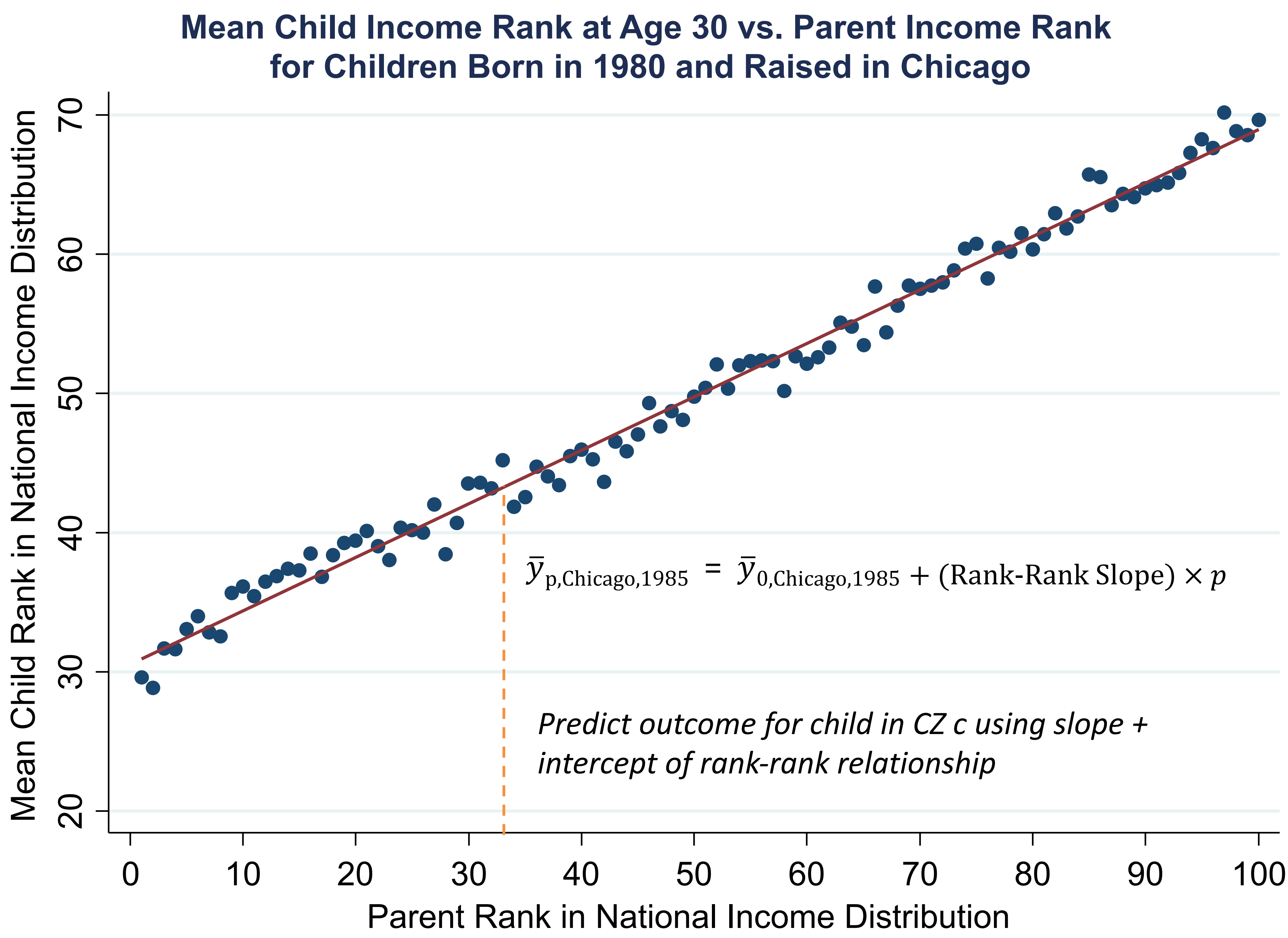
- Characterize relationship between child's income rank and parent's income rank p for each CZ c and birth cohort s

Mean Child Income Rank at Age 30 vs. Parent Income Rank
for Children Born in 1980 and Raised in Chicago



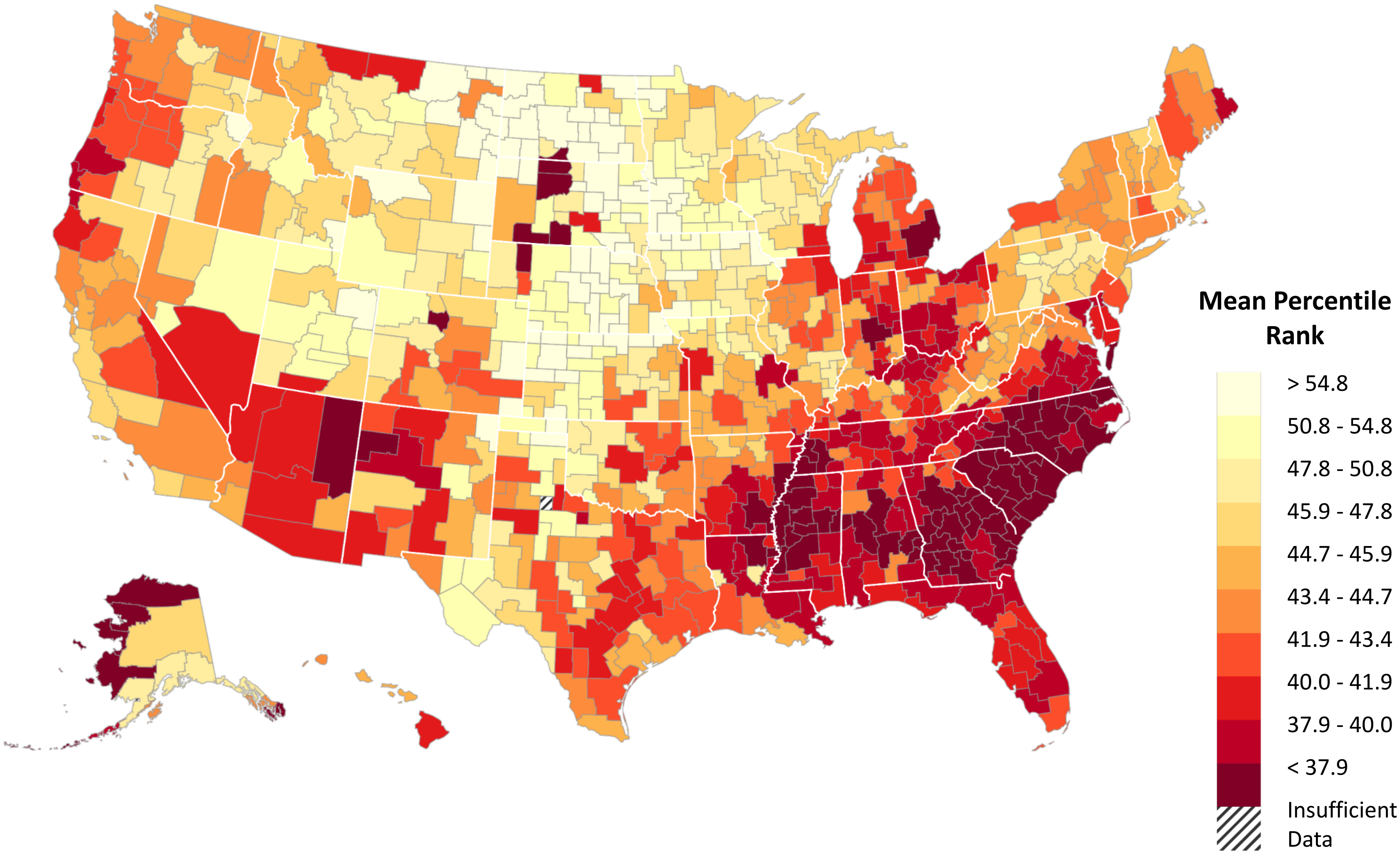
Mean Child Income Rank at Age 30 vs. Parent Income Rank for Children Born in 1980 and Raised in Chicago




Mean Child Income Rank at Age 30 vs. Parent Income Rank
for Children Born in 1980 and Raised in Chicago
Mean Child Rank in National Income Distribution
Parent Rank in National Income Distribution
$\bar{y}_{p,\text{Chicago},1985} = \bar{y}_{0,\text{Chicago},1985} + (\text{Rank-Rank Slope}) \times p$
Predict outcome for child in CZ c using slope +
intercept of rank-rank relationship

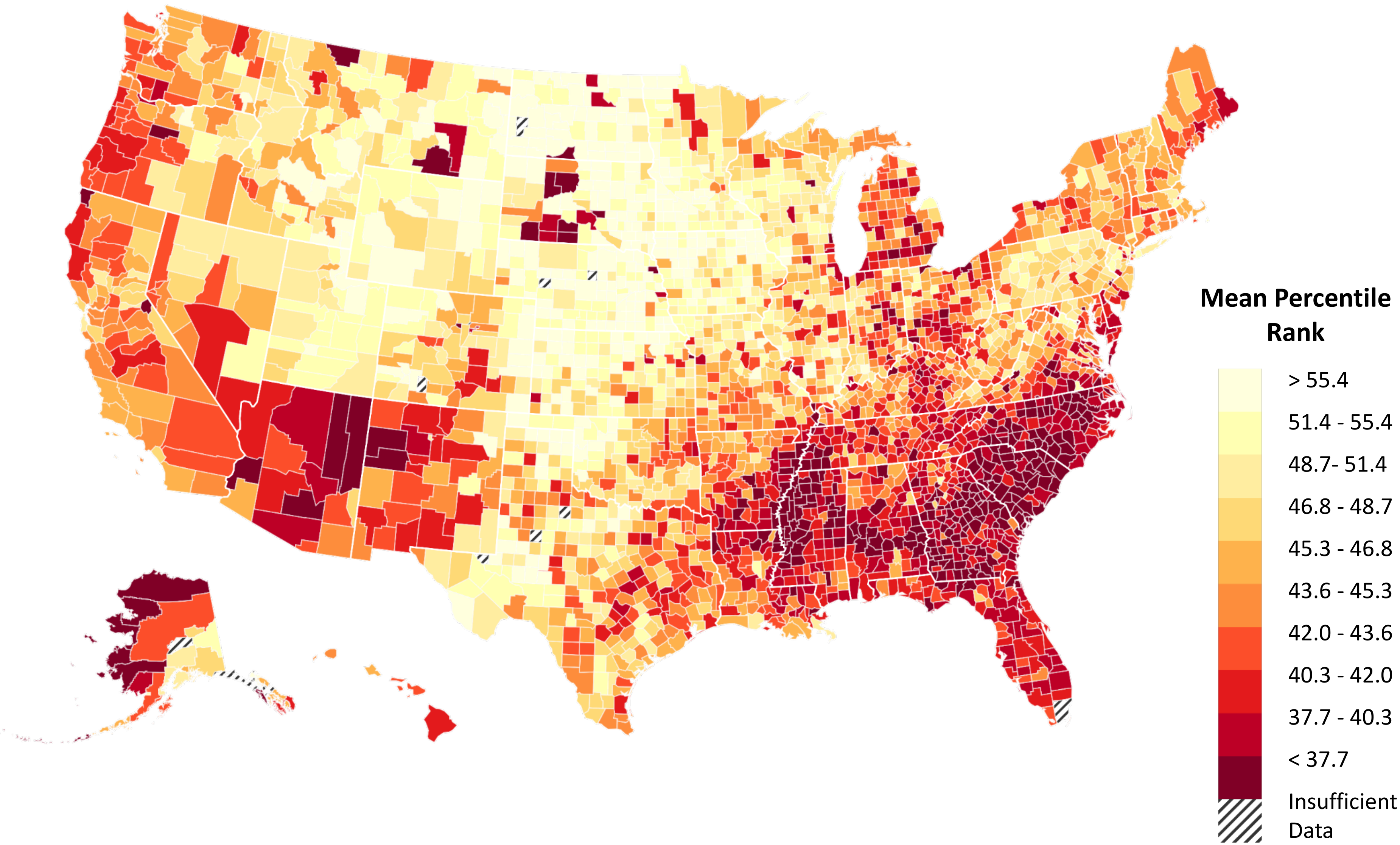
The Geography of Intergenerational Mobility in the United States

Predicted Income Rank at Age 30 for Children with Parents at 25th Percentile



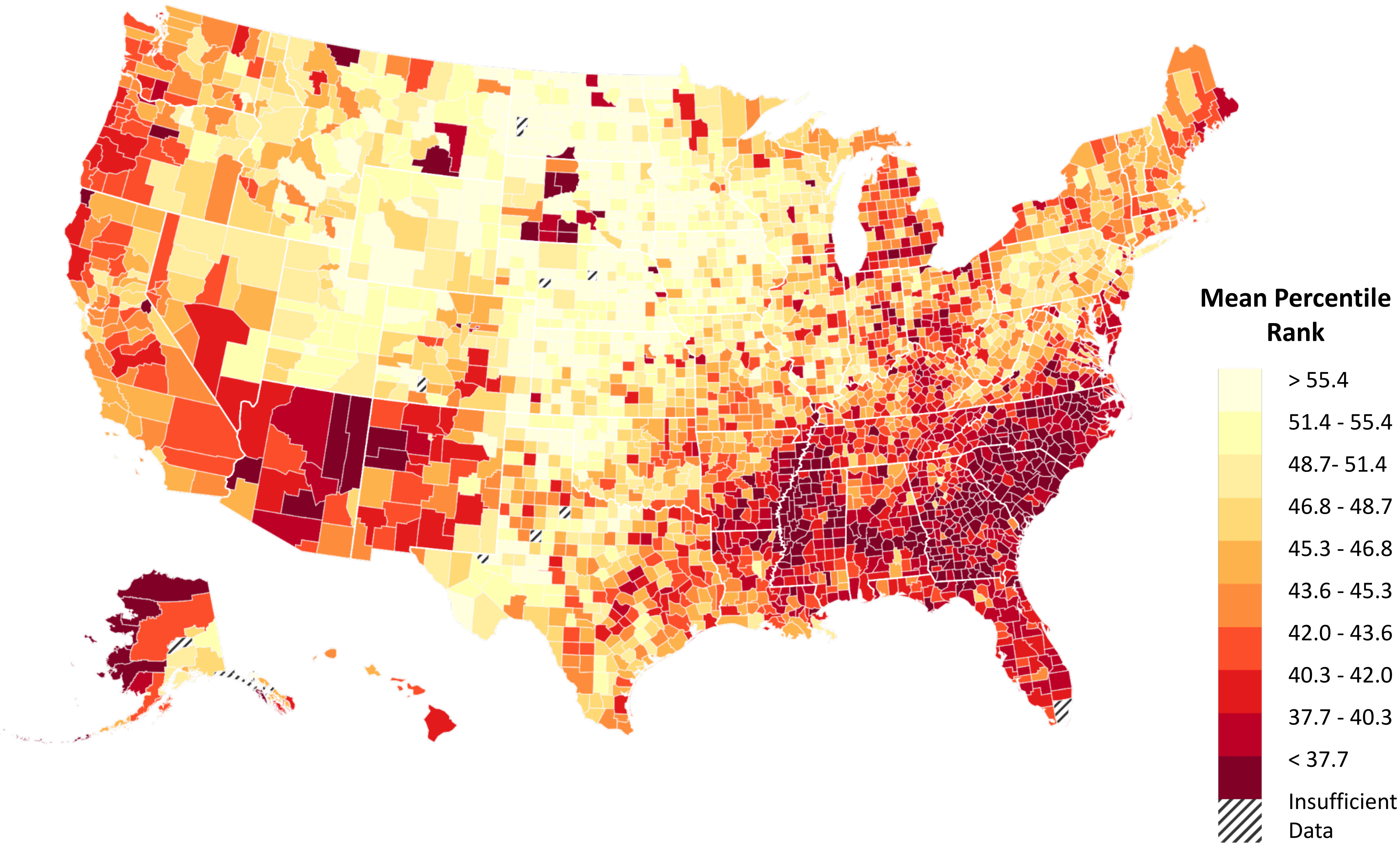
The Geography of Intergenerational Mobility in the United States

Predicted Income Rank at Age 30 for Children with Parents at 25th Percentile



The Geography of Intergenerational Mobility in the United States

Predicted Income Rank at Age 30 for Children with Parents at 25th Percentile



What is the Average Causal Impact of Growing Up in place with Better Outcomes?

Neighborhood Exposure Effects

- We identify causal effects of neighborhoods by analyzing childhood **exposure effects**
    - Exposure effect at age *m*: impact of spending year *m* of childhood in an area where permanent residents' outcomes are 1 percentile higher
- Ideal experiment: randomly assign children to new neighborhoods *d* starting at age *m* for the rest of childhood
    - Regress income in adulthood (y_i) on mean outcomes of prior residents:

$$y_i = \alpha + \beta_m \bar{y}_{pds} + \epsilon_i \qquad (1)$$

    - Exposure effect at age *m* is $\beta_{m-1} - \beta_m$

Estimating Exposure Effects in Observational Data

- We estimate exposure effects by studying families that move across CZ's with children at different ages in observational data

- Of course, choice of neighborhood is likely to be correlated with children's potential outcomes

  - Ex: parents who move to a good area may have latent ability or wealth (θ_i) that produces better child outcomes

- Estimating (1) in observational data yields a coefficient

$$b_m = \beta_m + \delta_m$$

where $\delta_m = \frac{Cov\left(\theta_i, \bar{y}_{pds}\right)}{var\left(\bar{y}_{pds}\right)}$ is a standard selection effect

Estimating Exposure Effects in Observational Data

- But identification of exposure effects does not require that *where* people move is orthogonal to child's potential outcomes

- Instead, requires that *timing* of move to better area is orthogonal to child's potential outcomes

Assumption 1. Selection effects do not vary with child's age at move:

$$\delta_m = \delta \text{ for all } m$$

- Certainly plausible that this assumption could be violated

  - Ex: parents who move to better areas when kids are young may have better unobservables

  - First present baseline estimates and then evaluate this assumption in detail

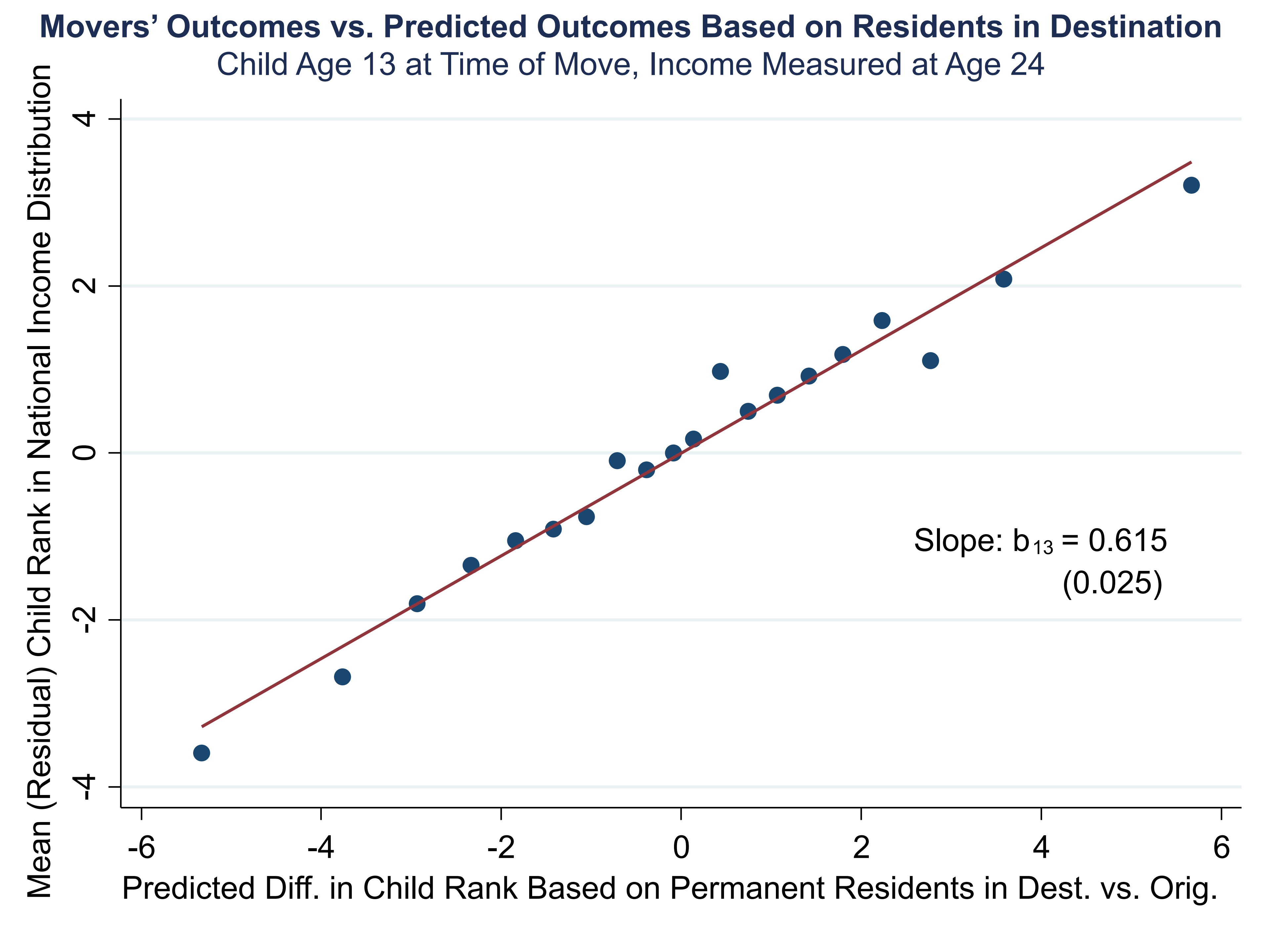
Estimating Exposure Effects in Observational Data

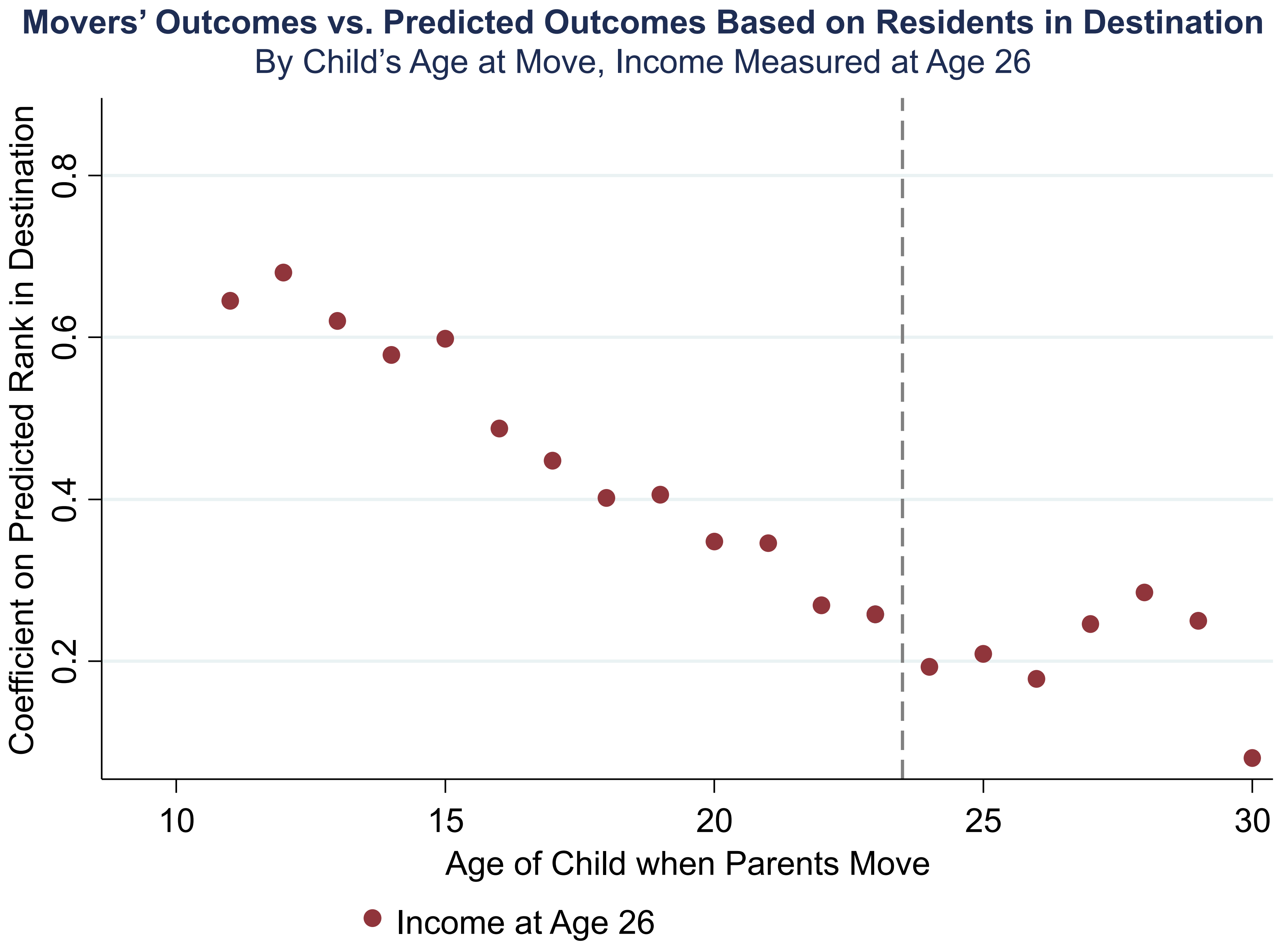
- To begin, consider subset of families who move with a child who is exactly 13 years old

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

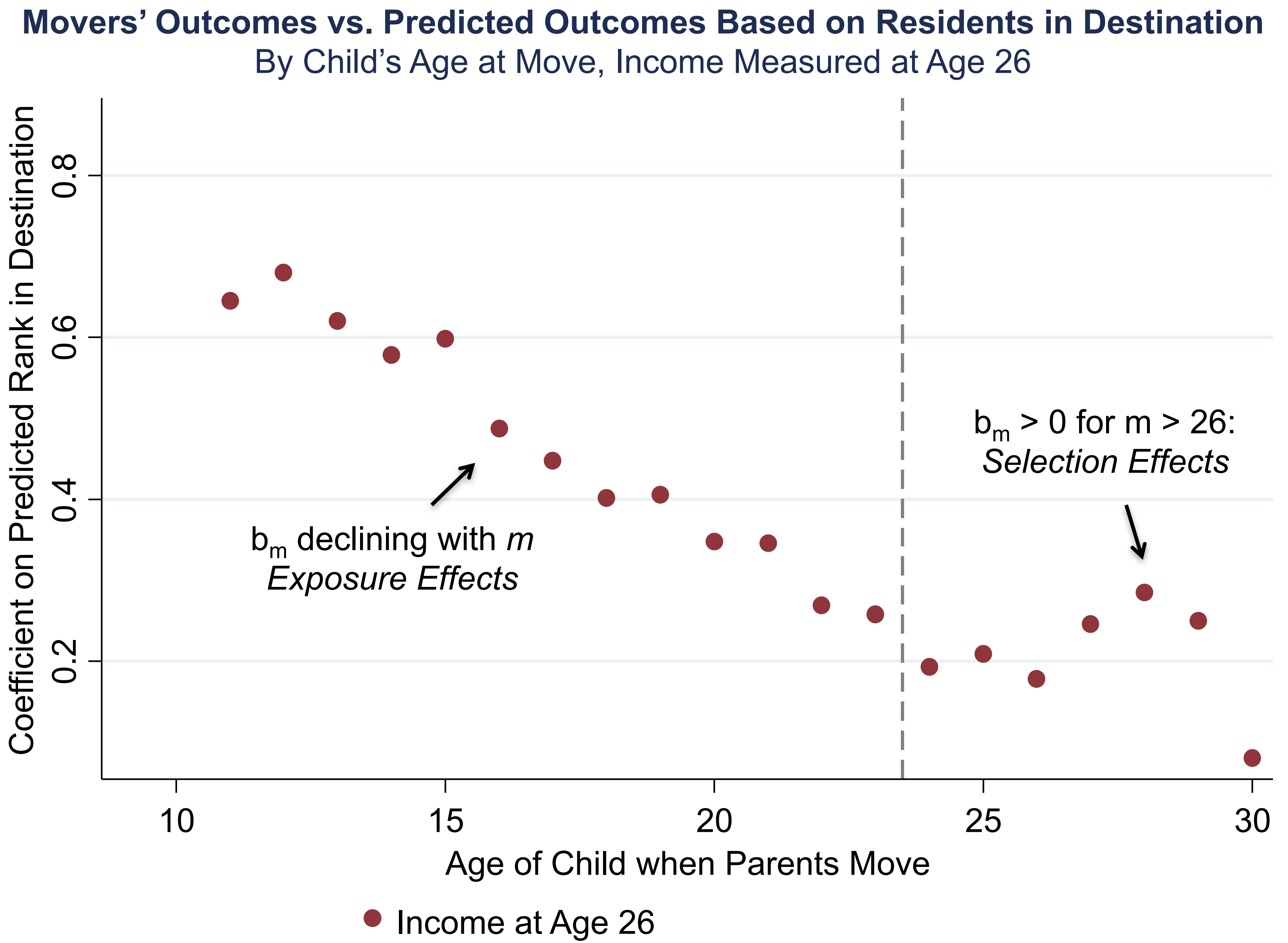
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

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

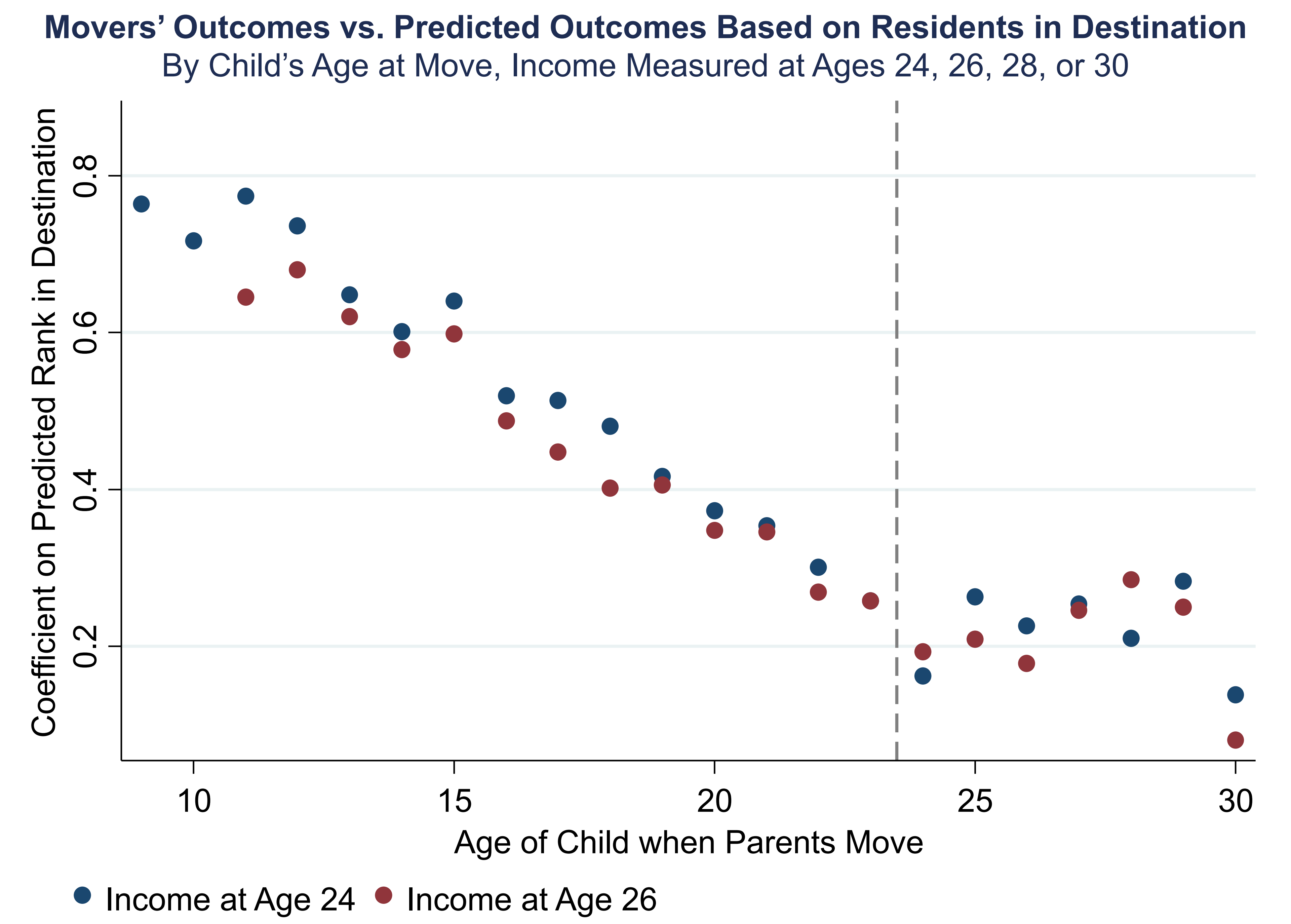

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
Child Age 13 at Time of Move, Income Measured at Age 24
Mean (Residual) Child Rank in National Income Distribution
-4
-2
0
2
4
Slope: b_{13} = 0.615
(0.025)
-6
-4
-2
0
2
4
6
Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.



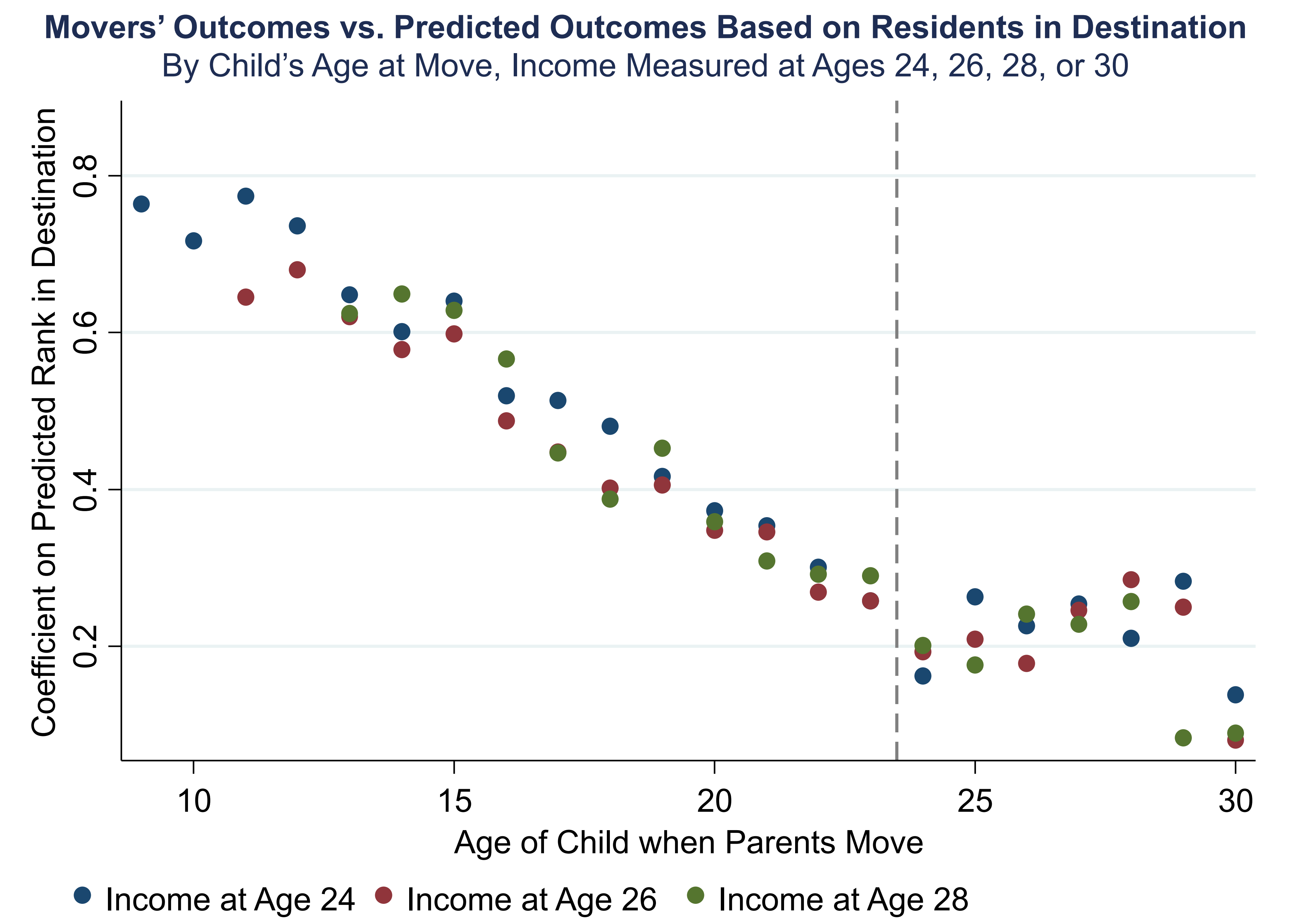
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Age 26
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Income at Age 26



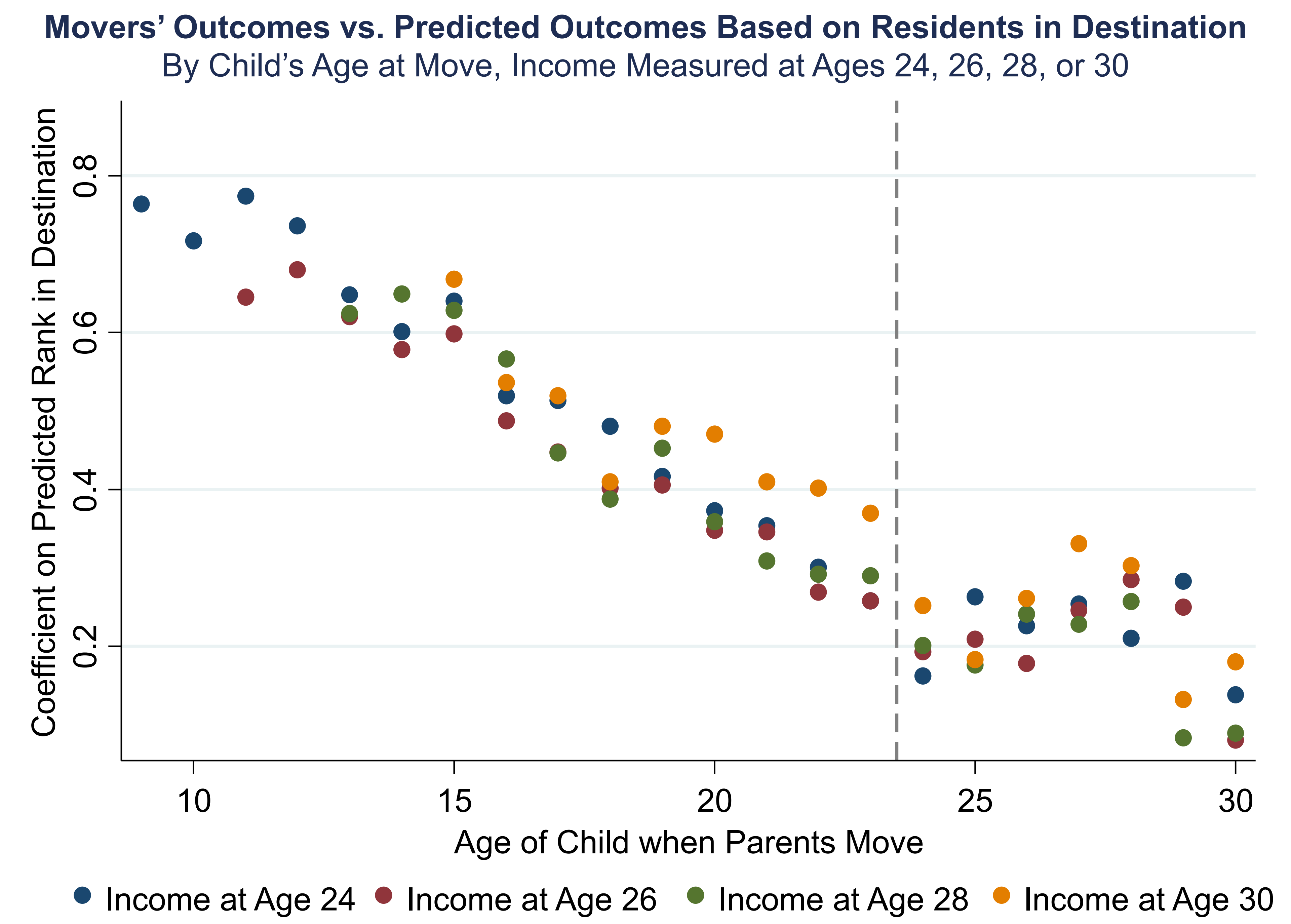
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Age 26
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
b_m declining with m
Exposure Effects
$b_m > 0$ for $m > 26$:
Selection Effects
Income at Age 26

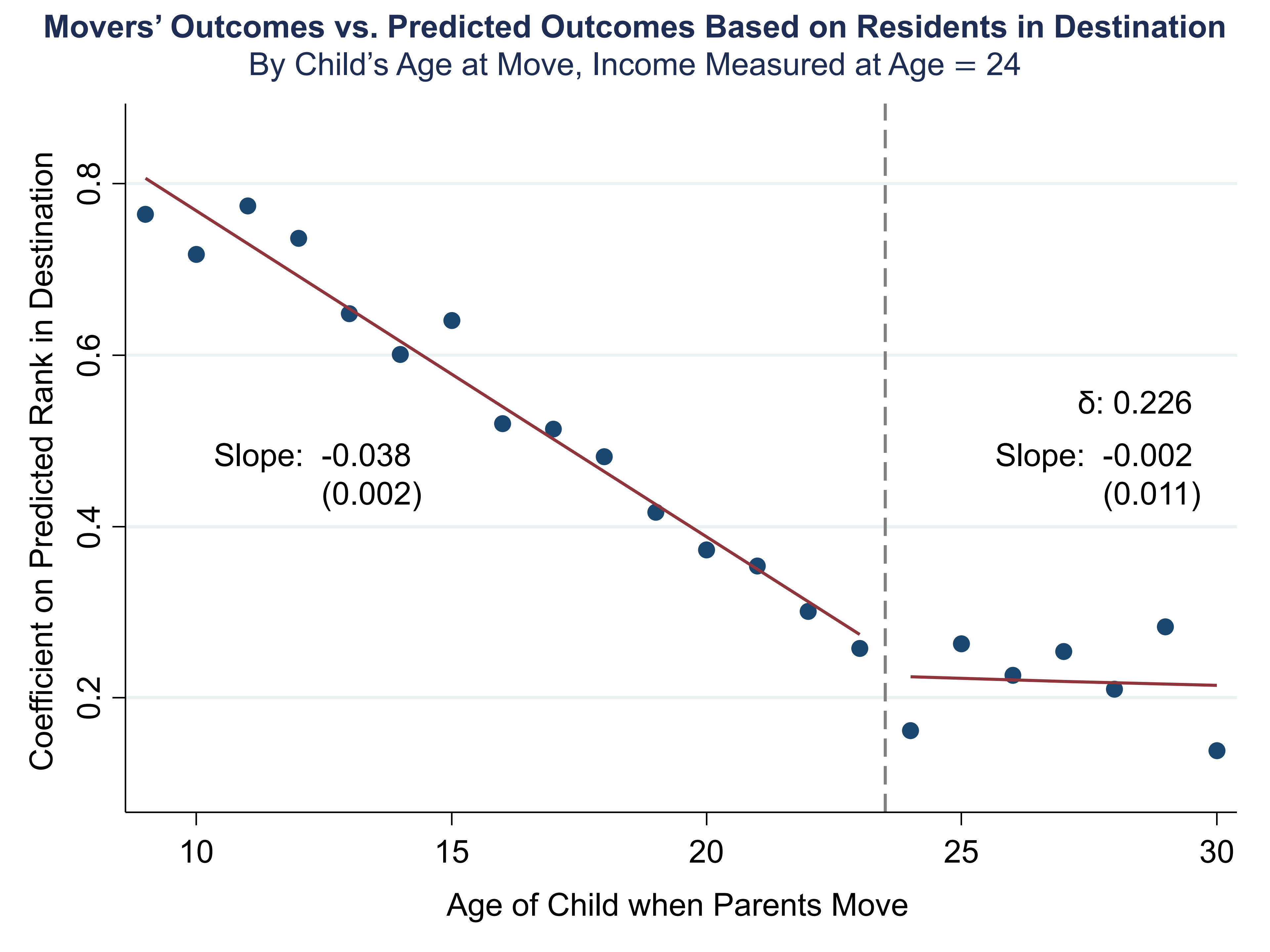


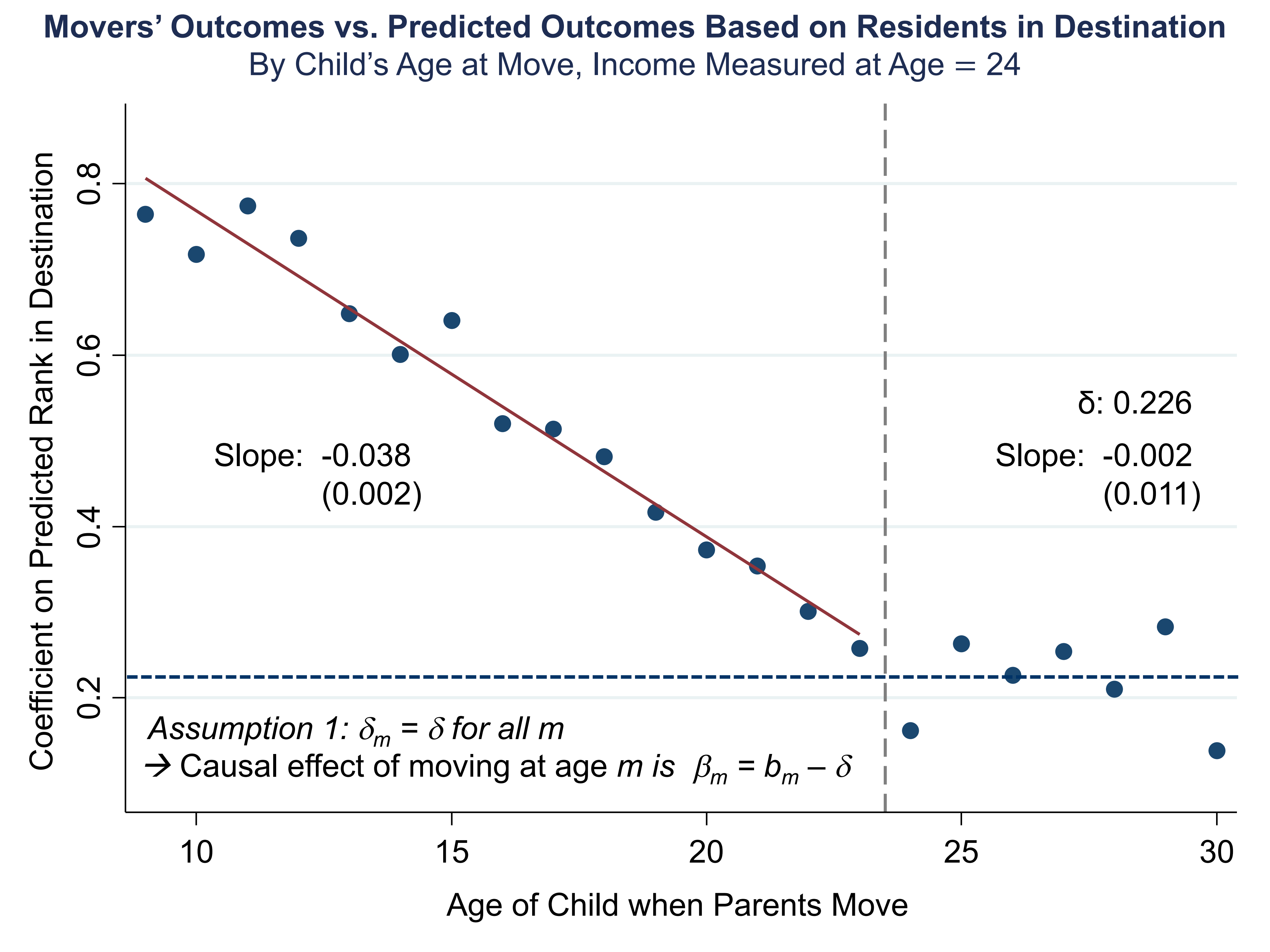
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 24, 26, 28, or 30
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Income at Age 24
Income at Age 26



Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 24, 26, 28, or 30
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
Income at Age 24
Income at Age 26
Income at Age 28

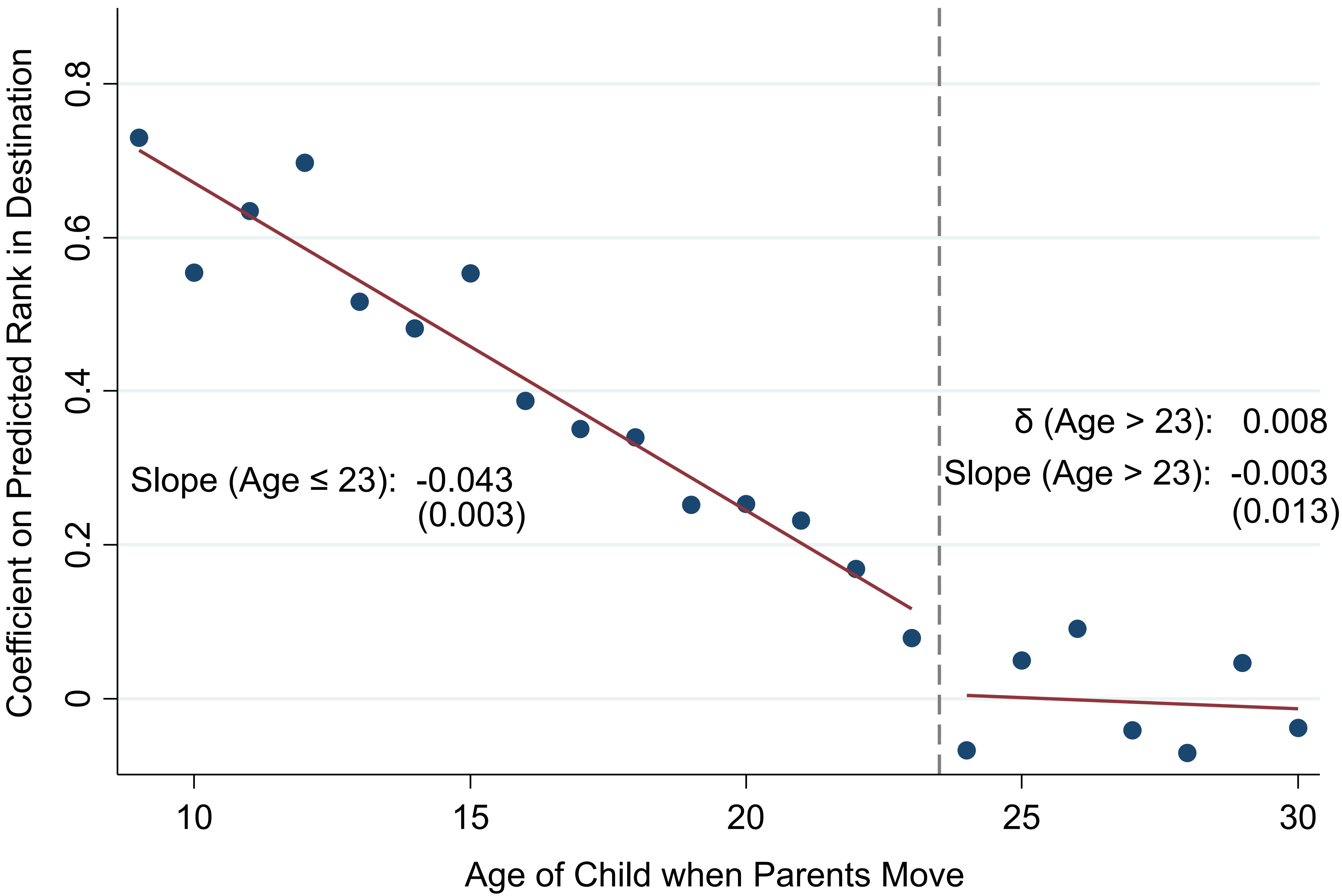

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 24, 26, 28, or 30
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Income at Age 24
Income at Age 26
Income at Age 28
Income at Age 30

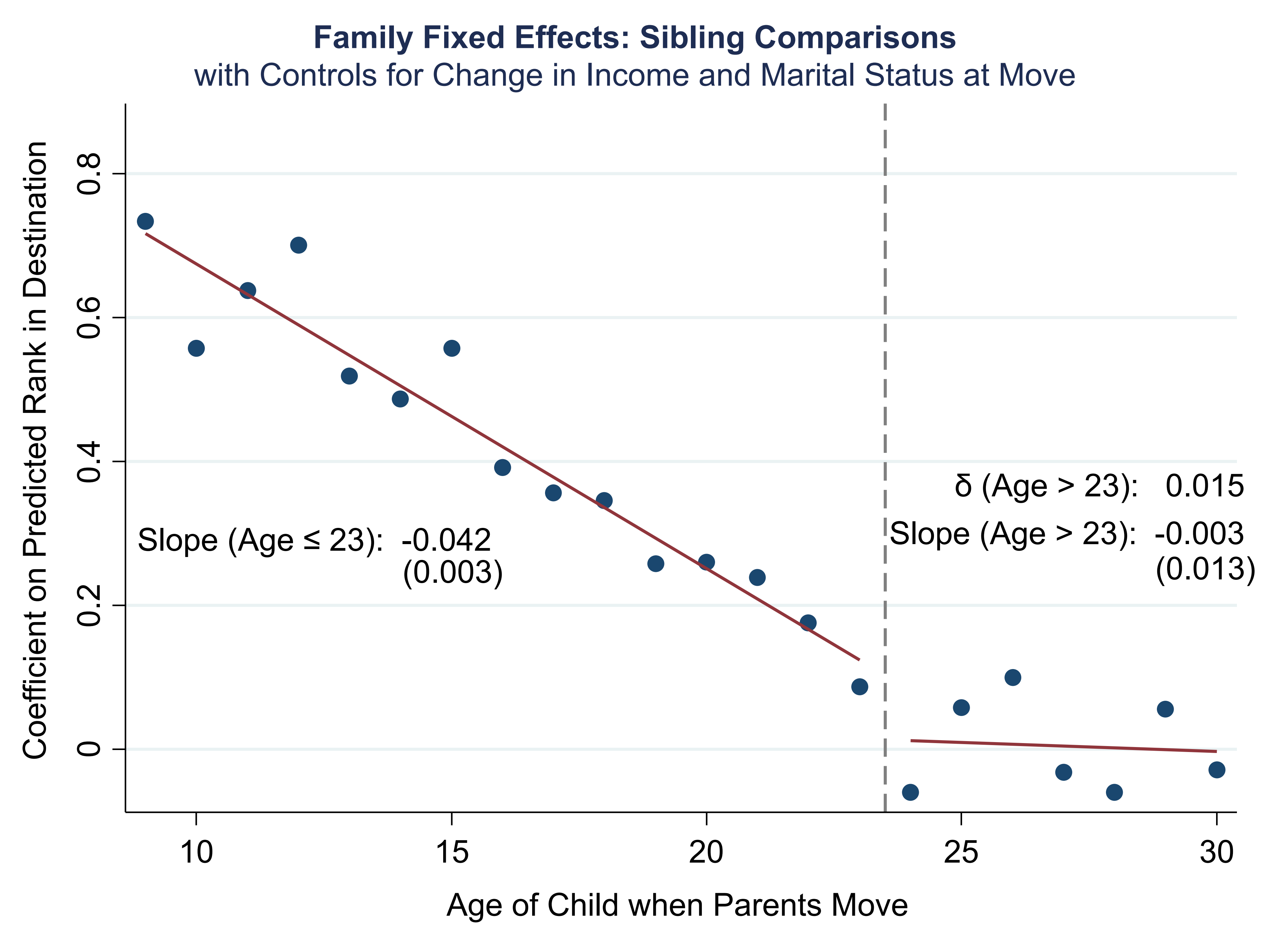

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Age = 24
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
Slope: -0.038
(0.002)
δ: 0.226
Slope: -0.002
(0.011)
10
15
20
25
30
Age of Child when Parents Move



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




Family Fixed Effects: Sibling Comparisons
with Controls for Change in Income and Marital Status at Move
Coefficient on Predicted Rank in Destination
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Slope (Age ≤ 23): -0.042
(0.003)
δ (Age > 23): 0.015
Slope (Age > 23): -0.003
(0.013)

Time-Varying Unobservables

- 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. Experimental/quasi-experimental variation from displacement shocks or randomized incentives to move

Outcome-Based Placebo Tests

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

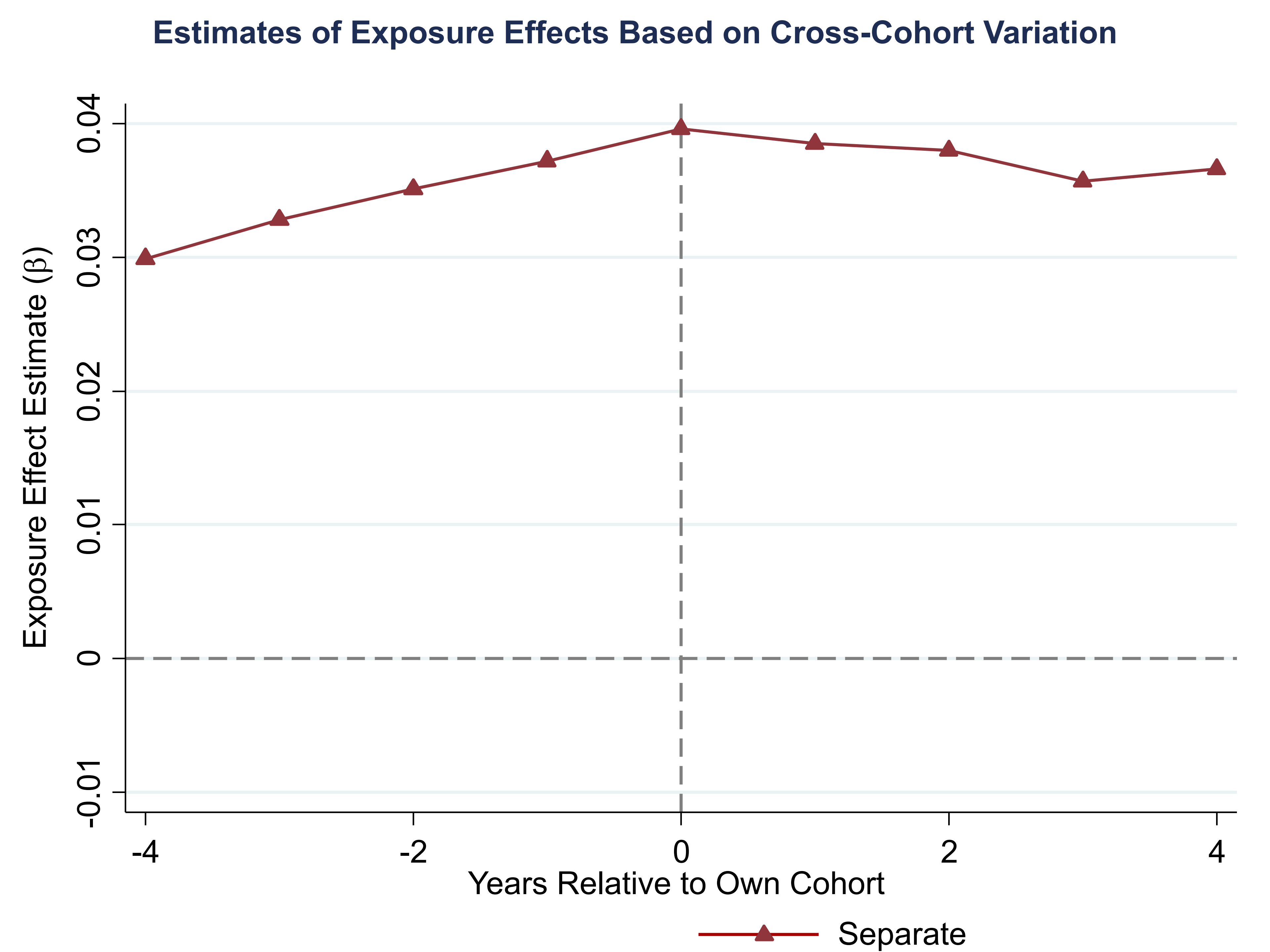
- Start with variation in place effects across birth cohorts
  - Some areas are getting better over time, others are getting worse
  - Causal effect of neighborhood on a child who moves in to an area should depend on properties of that area while he is growing up

Outcome-Based Placebo Tests

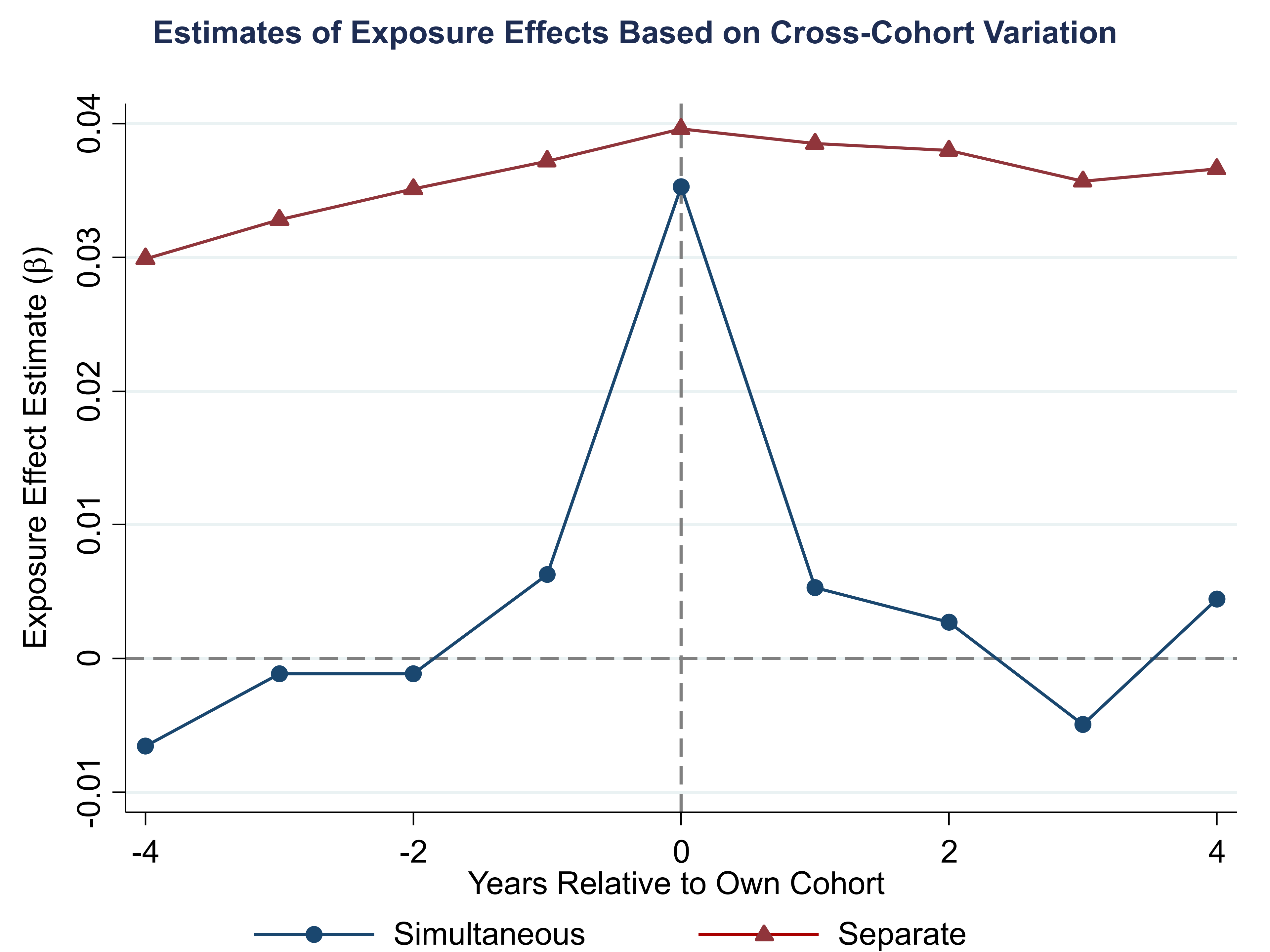
- Parents choose neighborhoods based on their preferences and information set at time of move
  - Difficult to predict high-frequency differences that are realized 15 years later → hard to sort on this dimension
- Key assumption: if unobservables θ_i correlated with exposure effect for cohort *s*, then correlated with exposure effects for surrounding cohorts s′ as well

$$Cov(\theta_i, m\Delta_{odp,s(i)}|X) > 0 \Rightarrow Cov(\theta_i, m\Delta_{odps'}|X, m\Delta_{odp,s(i)}) > 0$$

- Under this assumption, selection effects will be manifested in correlation with place effects for surrounding cohorts



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

- Next, implement an analogous set of placebo tests by exploiting heterogeneity across realized distribution of incomes
- 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

Distributional Convergence

- 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
- Difficult to know exactly where in the income distribution your child will fall as an adult when moving with a 10 year old
  - Also unlikely that unobserved factor θ_i would replicate distribution of outcomes in destination area in proportion to exposure time
- Does greater exposure to areas that produce stars increase probability of becoming a star, controlling for mean predicted rank?

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 Unemployed		
	(1)	(2)	(3)	(4)	(5)	(6)
Distributional Prediction	0.043		0.040	0.041		0.043
	(0.002)		(0.003)	(0.003)		(0.004)
Mean Rank Prediction (Placebo)		0.024	0.003		0.018	-0.002
		(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. More segregation (concentrated poverty)
  2. Higher rates of crime
  3. Lower marriage rates [Autor and Wasserman 2013]

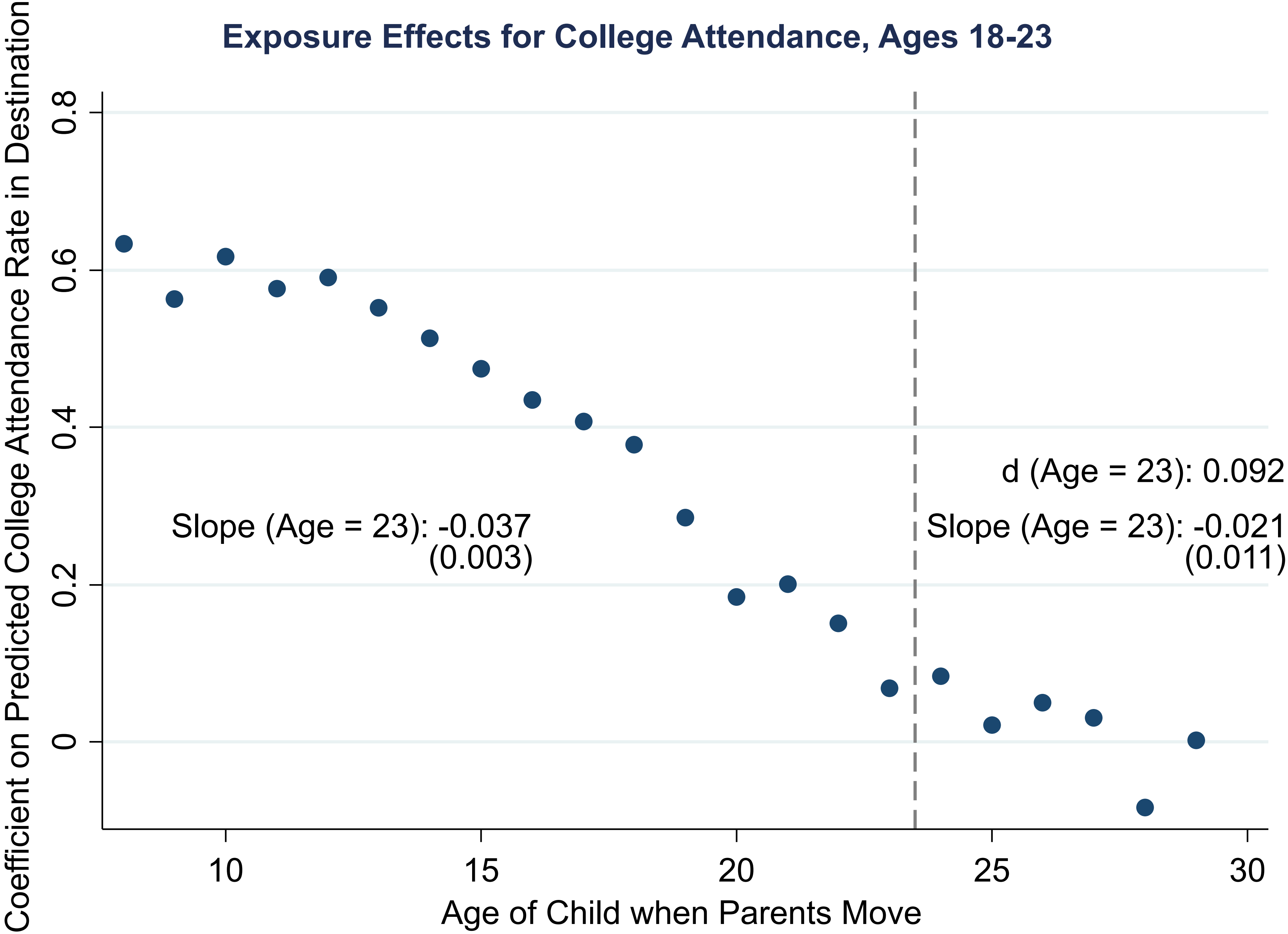
- If unobservable input θ_i does not covary with gender-specific neighborhood effect, can use gender differences to conduct a placebo test

Exposure Effect Estimates: Gender-Specific Predictions

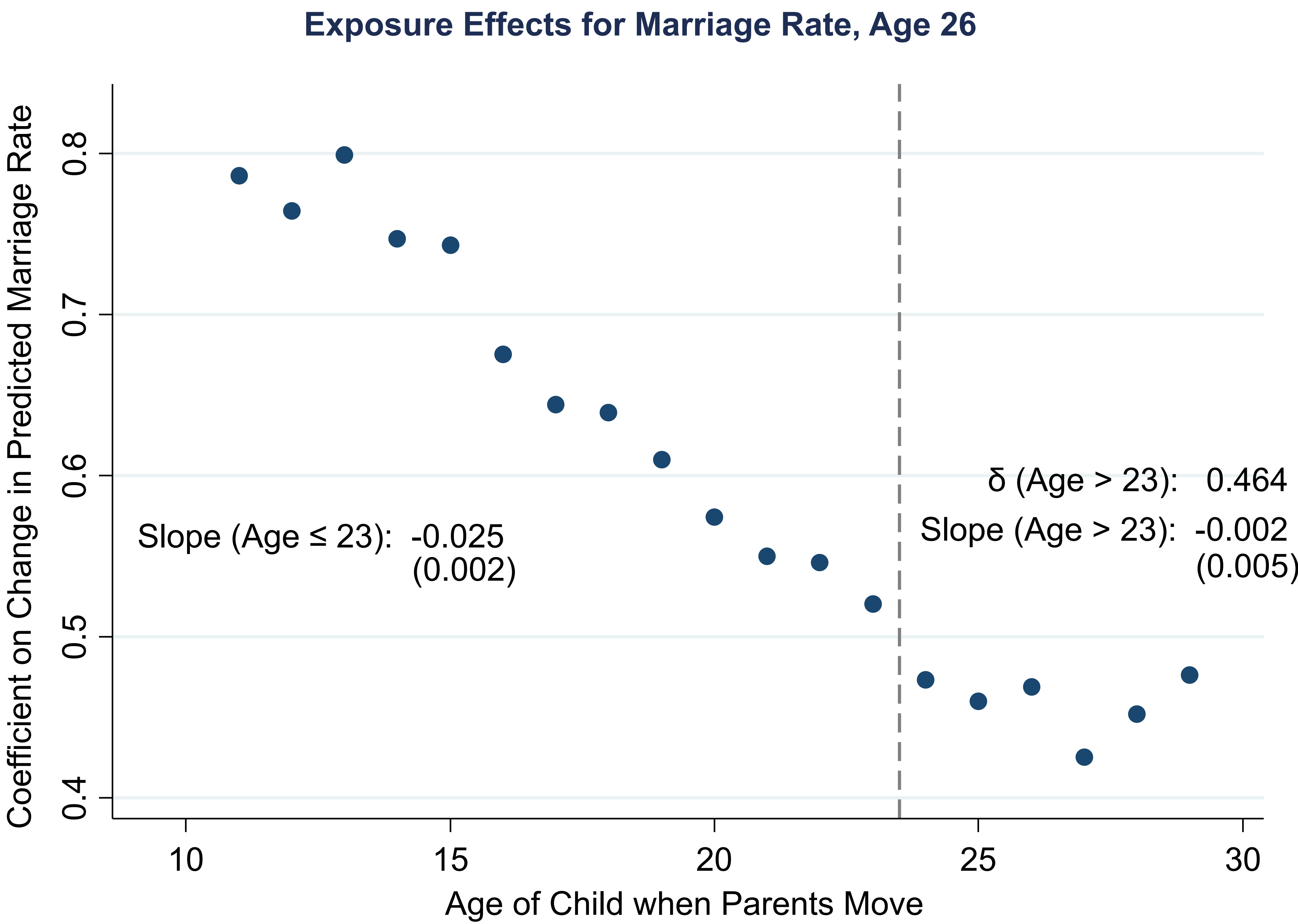
	No Family Fixed Effects			Family Fixed Effects
	(1)	(2)	(3)	(4)
Own Gender Prediction	0.038		0.030	**0.030**
	(0.002)		(0.003)	(0.007)
Other Gender Prediction (Placebo)		0.031	0.010	**0.009**
		(0.002)	(0.003)	(0.007)
Sample		Full Sample		2-Gender HH

Neighborhood Effects on Other Outcomes

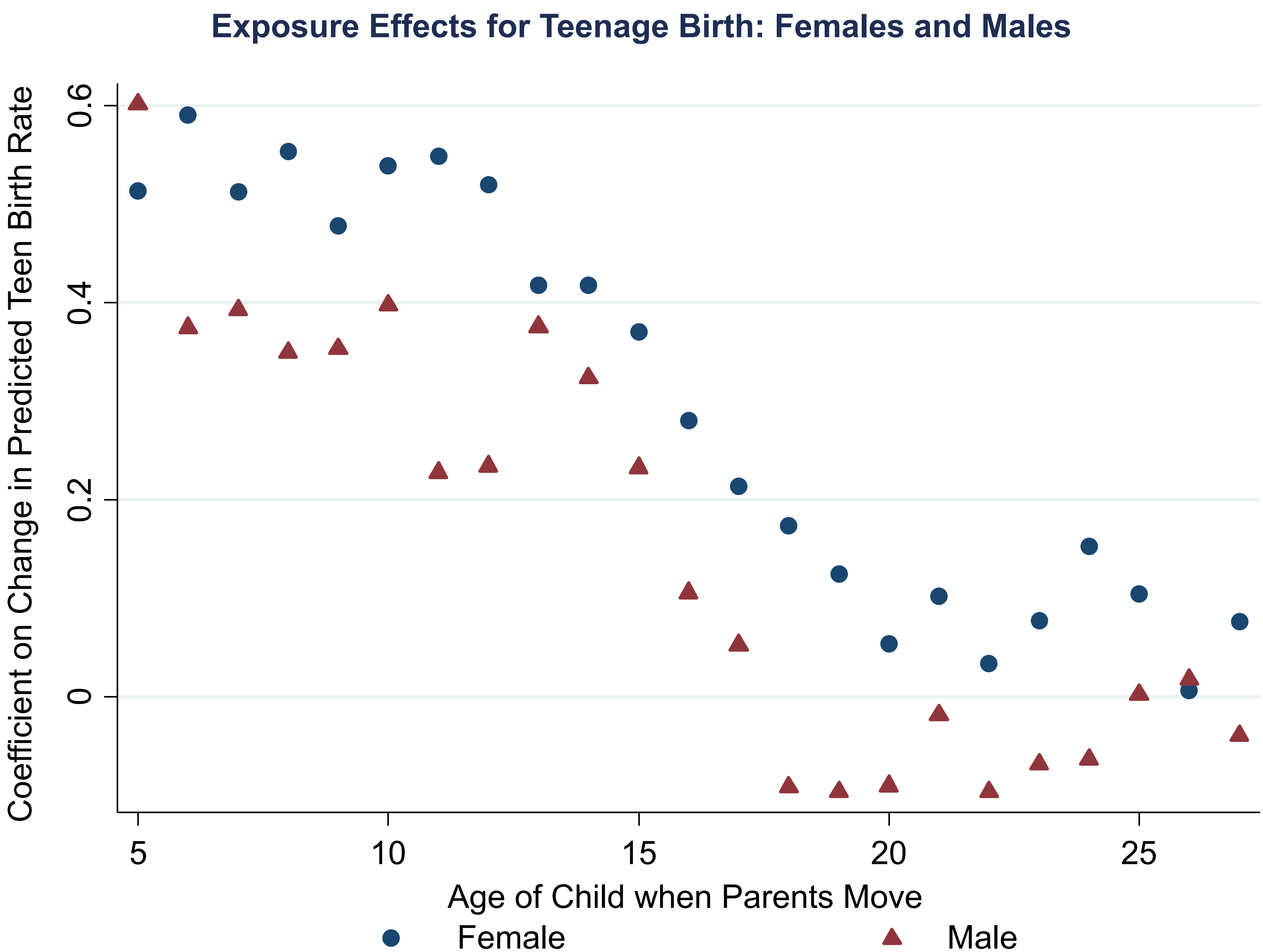
- We also find similar exposure effects for other outcomes:
  - College attendance (from 1098-T forms filed by colleges)
  - Teenage birth (from birth certificate data)
  - Teenage employment (from W-2 forms)
  - Marriage



Exposure Effects for College Attendance, Ages 18-23
Coefficient on Predicted College Attendance Rate in Destination
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Slope (Age = 23): -0.037
(0.003)
d (Age = 23): 0.092
Slope (Age = 23): -0.021
(0.011)



Exposure Effects for Marriage Rate, Age 26
Coefficient on Change in Predicted Marriage Rate
0.4
0.5
0.6
0.7
0.8
10
15
20
25
30
Age of Child when Parents Move
Slope (Age ≤ 23): -0.025
(0.002)
δ (Age > 23): 0.464
Slope (Age > 23): -0.002
(0.005)



Exposure Effects for Teenage Birth: Females and Males
Coefficient on Change in Predicted Teen Birth Rate
0
0.2
0.4
0.6
5
10
15
20
25
Age of Child when Parents Move
Female
Male

Identification of Exposure Effects: Summary

- Any omitted variable θ_i that generates bias in the exposure effect estimates would have to:

  1. Operate within family in proportion to exposure time

  2. Be orthogonal to changes in parent income and marital status

  3. Replicate prior residents' outcomes by birth cohort, quantile, and gender in proportion to exposure time

  4. Replicate impacts across outcomes (income, college attendance, teen labor, marriage)

→ We conclude that baseline design exploiting variation in timing of move yields unbiased estimates of neighborhoods' causal effects

Experimental Variation

- We also validate this quasi-experimental design using experimental variation where we know what triggers the move

- We consider two such subsets of moves:

  1. Displacement shocks such as plant closures and natural disasters

  2. Moving to Opportunity Experiment

- Both induce families to move for reasons known to be unrelated to child's age and potential outcomes

- Focus on the MTO results here in the interest of time

  - MTO also provides insights at finer geographies

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
- 48% of eligible households in experimental voucher group “complied” and took up voucher

Most Common MTO Residential Locations in New York

MTO Experiment: Exposure Effects?

- Prior research on MTO has found little impact of moving to a better area on earnings and other economic outcomes

  - This work has focused on adults and older youth at point of move
    [e.g., Kling, Liebman, and Katz 2007]

- In a companion paper (joint with Larry Katz), we test for childhood exposure effects in MTO experiment:

Chetty, Hendren, Katz. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment"

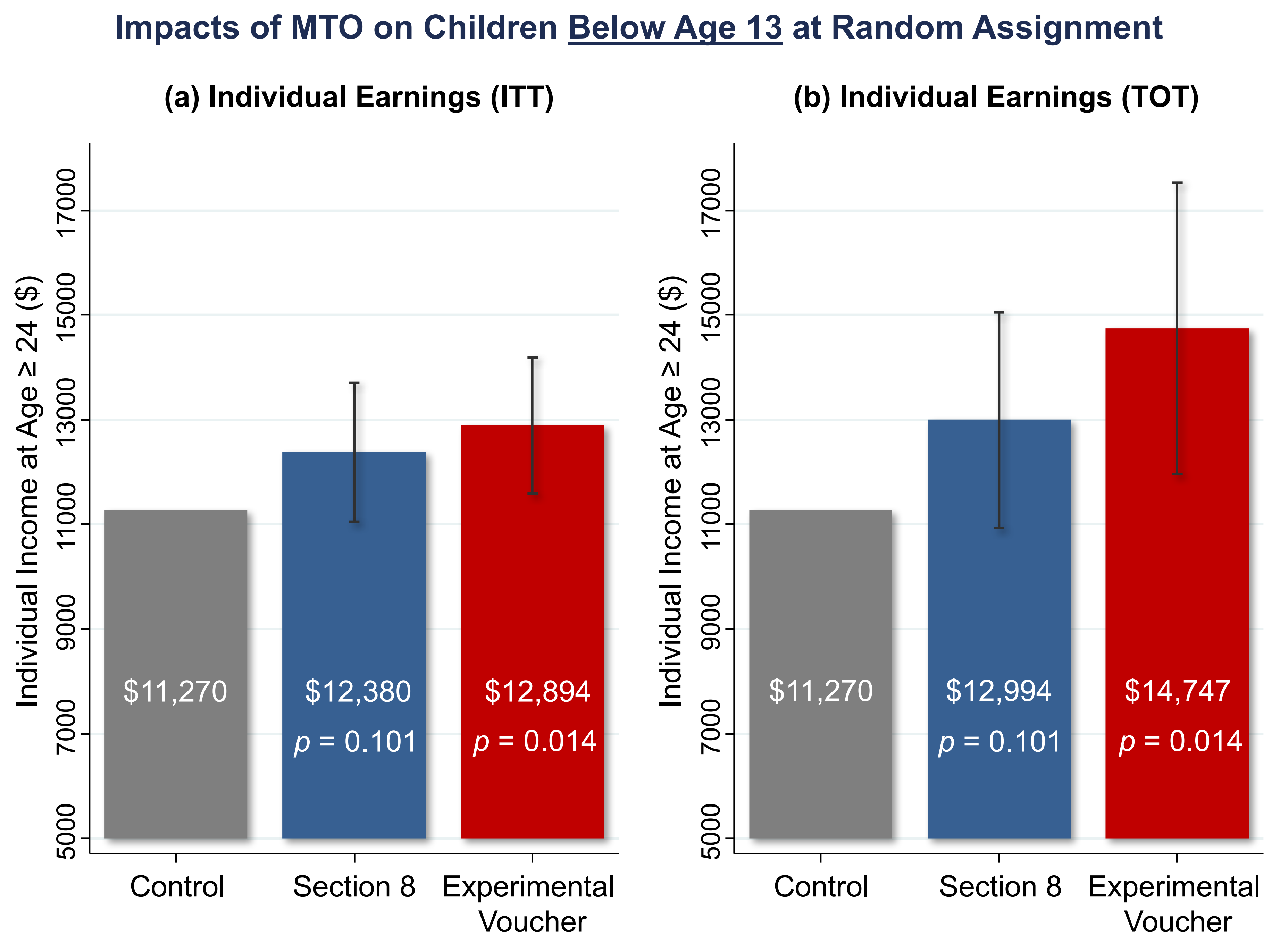
- Does MTO improve outcomes for children who moved when young?

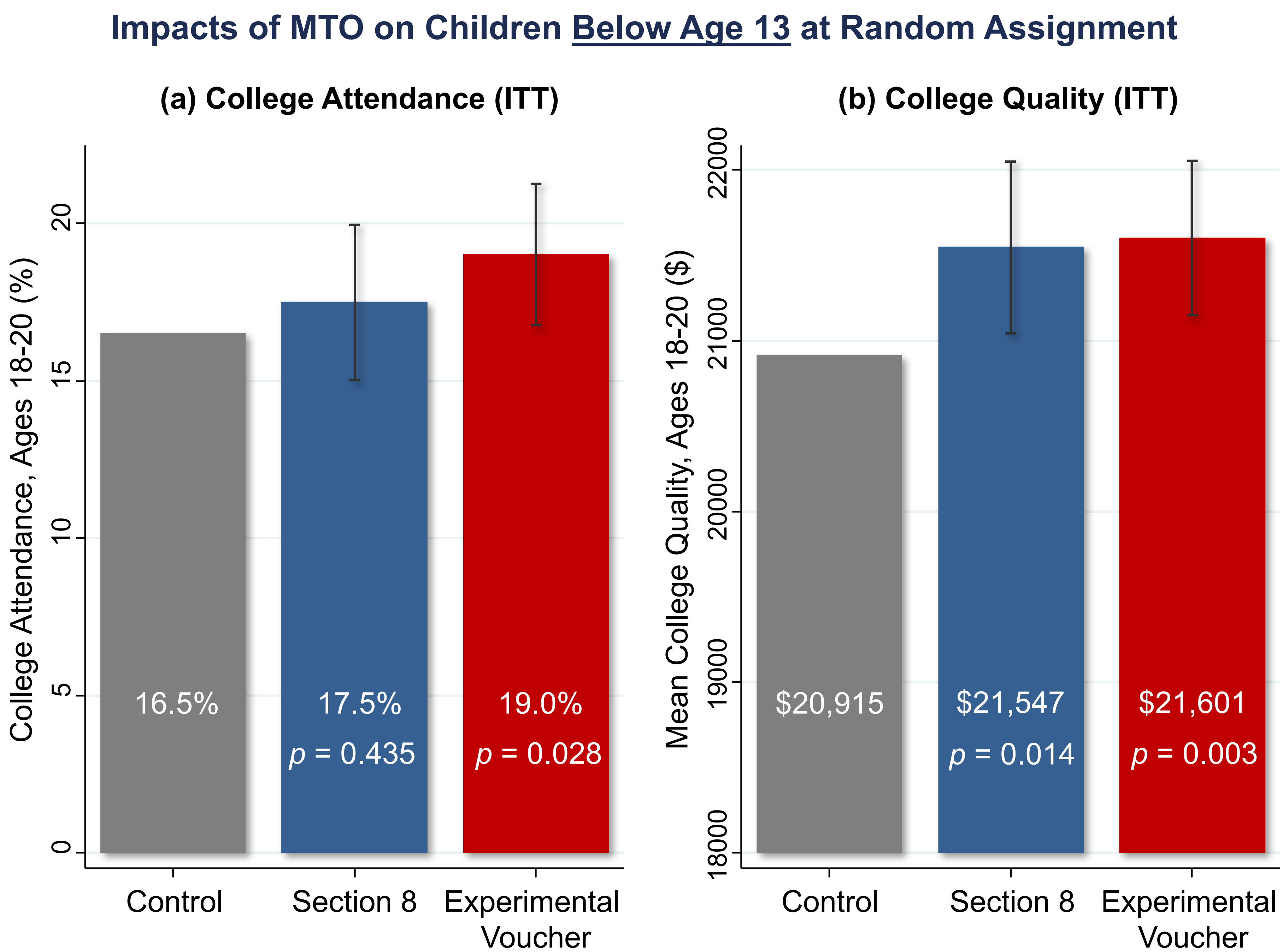
  - Link MTO data to tax data to study children's outcomes in mid-20's

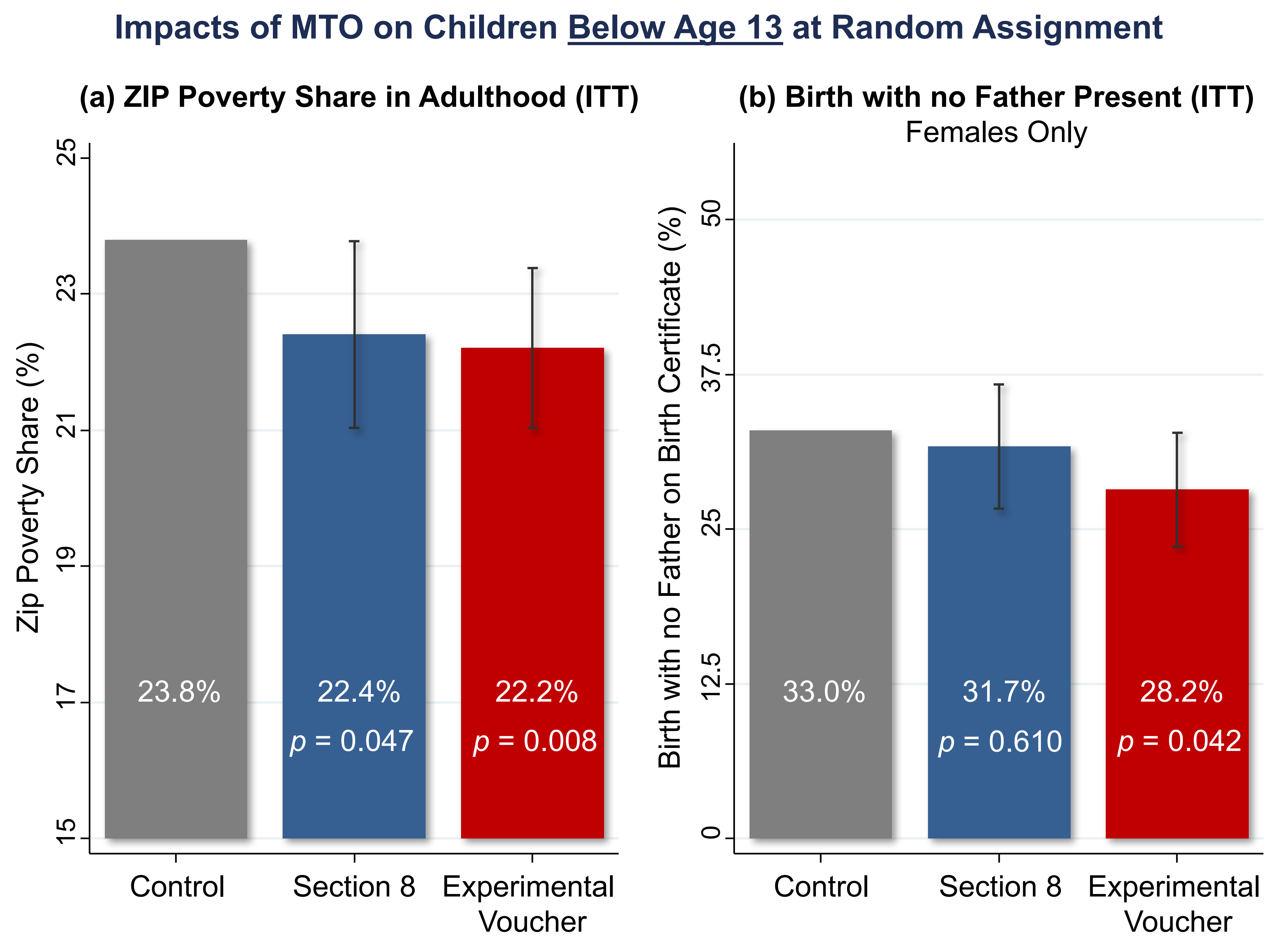
MTO vs. Quasi-Experiment

Differences between MTO and quasi-experimental designs:

1. Different set of compliers who identify LATE
   - MTO identified from moves induced by vouchers
   - Quasi-experiment from moves that families chose in equilibrium
2. Inclusion of disruption effects from move
   - MTO compares movers to non-movers and therefore incorporates any disruption effect of move
   - Quasi-experimental design compares effect of moving to better vs. worse areas *conditional* on moving → fixed cost of move netted out

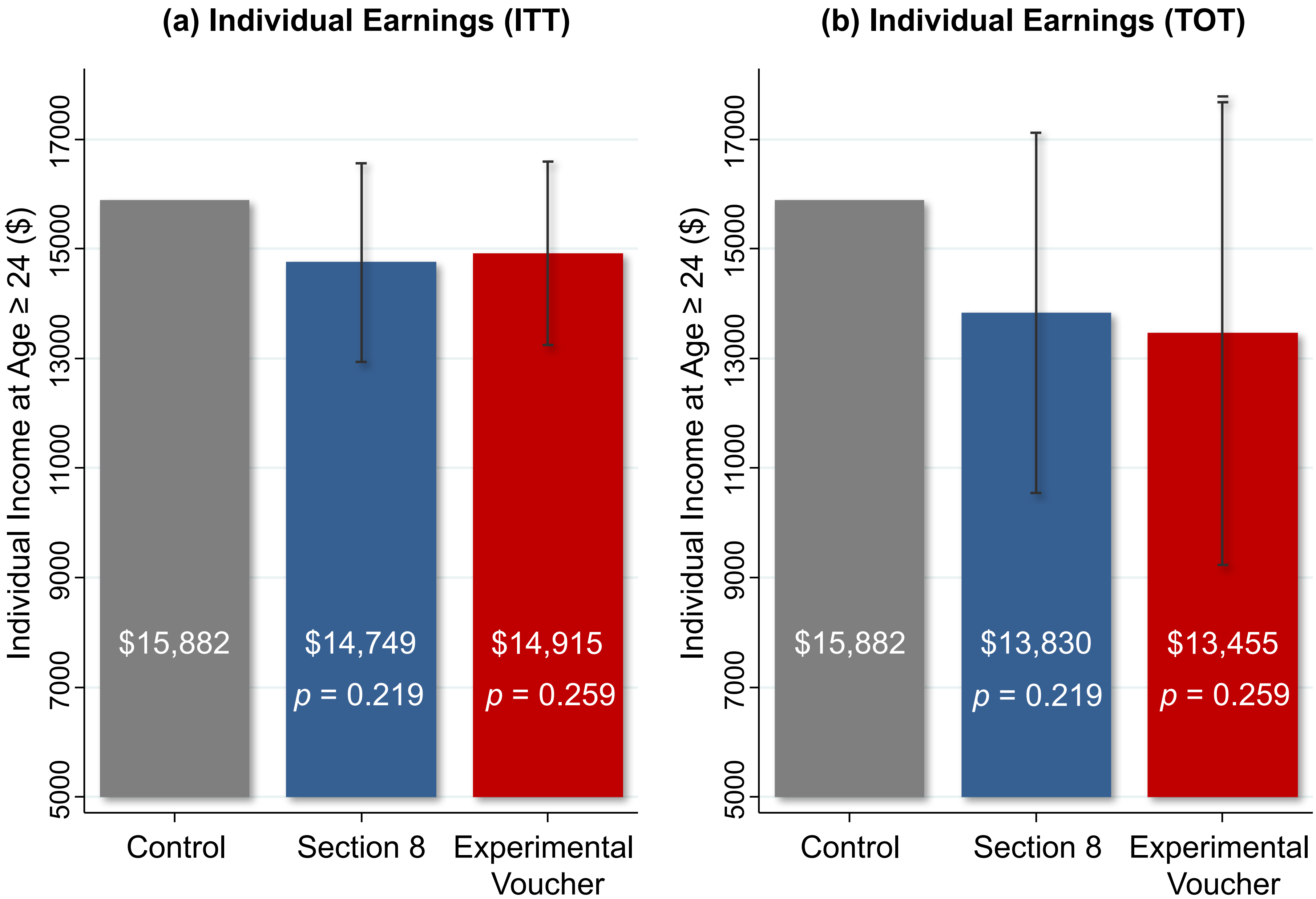

Impacts of MTO on Children Below Age 13 at Random Assignment
(a) Individual Earnings (ITT)
(b) Individual Earnings (TOT)
Individual Income at Age ≥ 24 ($)
5000
7000
9000
11000
13000
15000
17000
$11,270
$12,380
p = 0.101
$12,894
p = 0.014
$11,270
$12,994
p = 0.101
$14,747
p = 0.014
Control
Section 8
Experimental Voucher


Impacts of MTO on Children Below Age 13 at Random Assignment
(a) College Attendance (ITT)
College Attendance, Ages 18-20 (%)
0
5
10
15
20
16.5%
17.5%
p = 0.435
19.0%
p = 0.028
Control
Section 8
Experimental Voucher
(b) College Quality (ITT)
Mean College Quality, Ages 18-20 ($)
18000
19000
20000
21000
22000
$20,915
$21,547
p = 0.014
$21,601
p = 0.003
Control
Section 8
Experimental Voucher



Impacts of MTO on Children Below Age 13 at Random Assignment
(a) ZIP Poverty Share in Adulthood (ITT)
Zip Poverty Share (%)
25
23
21
19
17
15
23.8%
22.4%
p = 0.047
22.2%
p = 0.008
Control
Section 8
Experimental Voucher
(b) Birth with no Father Present (ITT)
Females Only
Birth with no Father on Birth Certificate (%)
50
37.5
25
12.5
0
33.0%
31.7%
p = 0.610
28.2%
p = 0.042
Control
Section 8
Experimental Voucher

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



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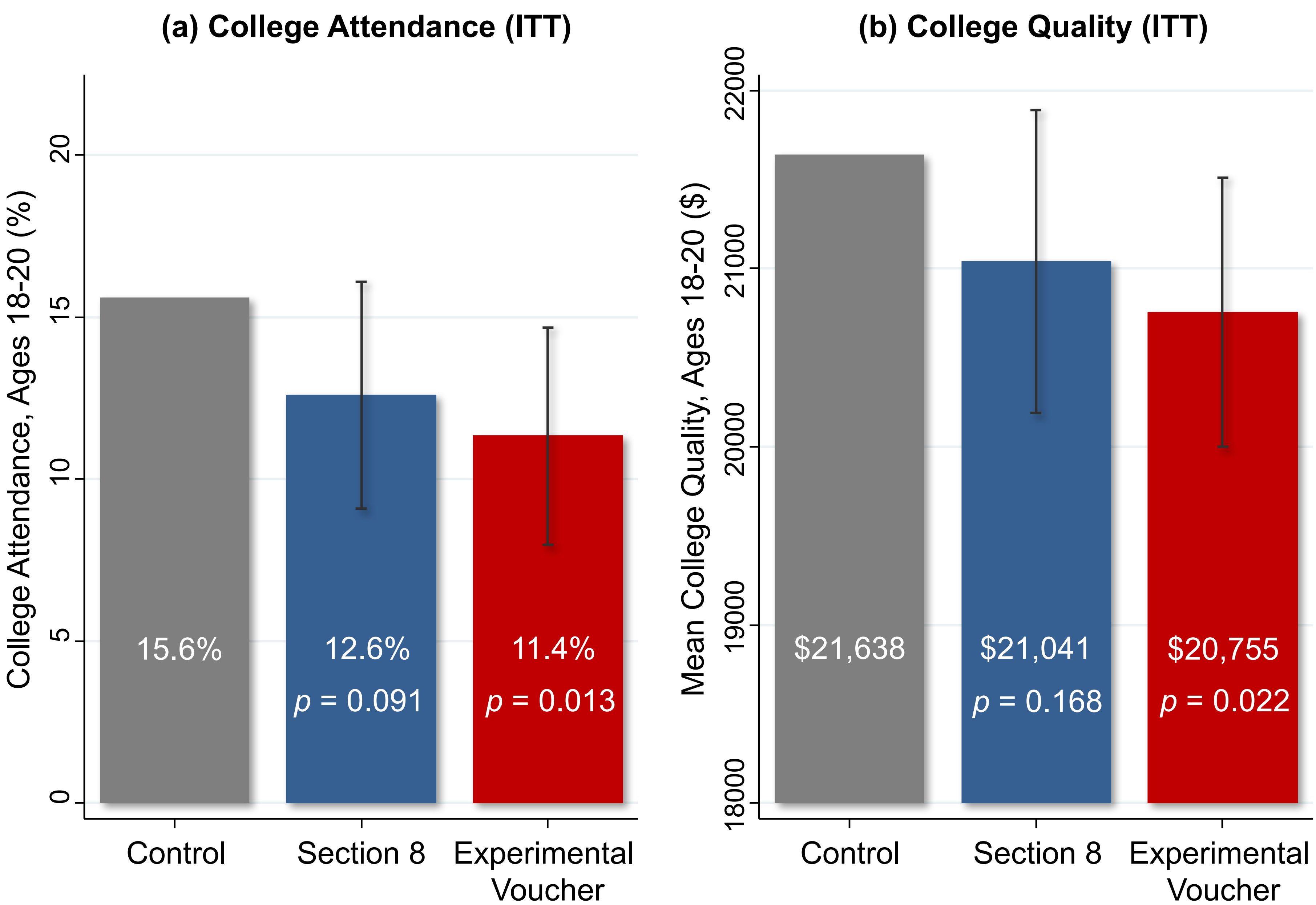
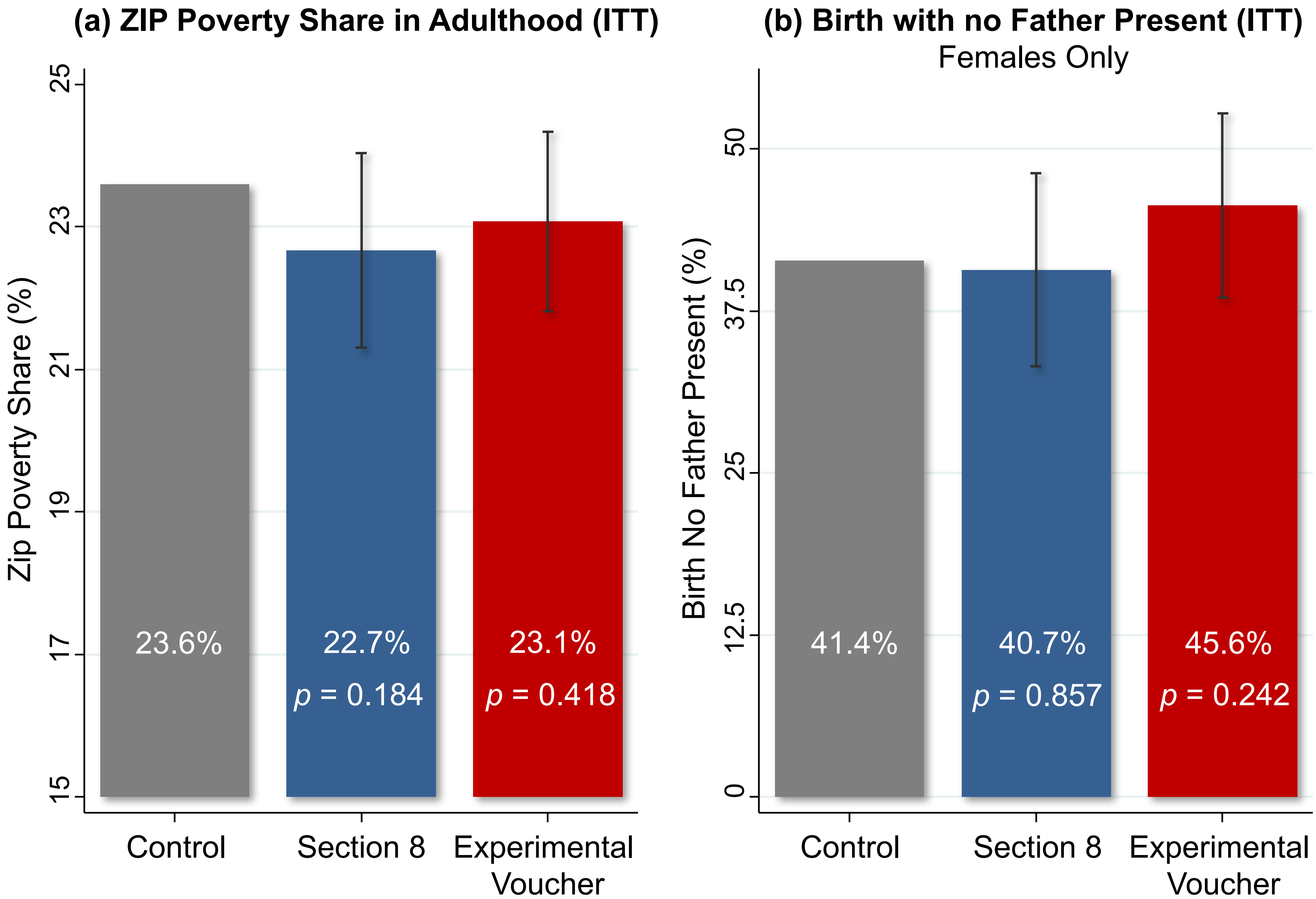
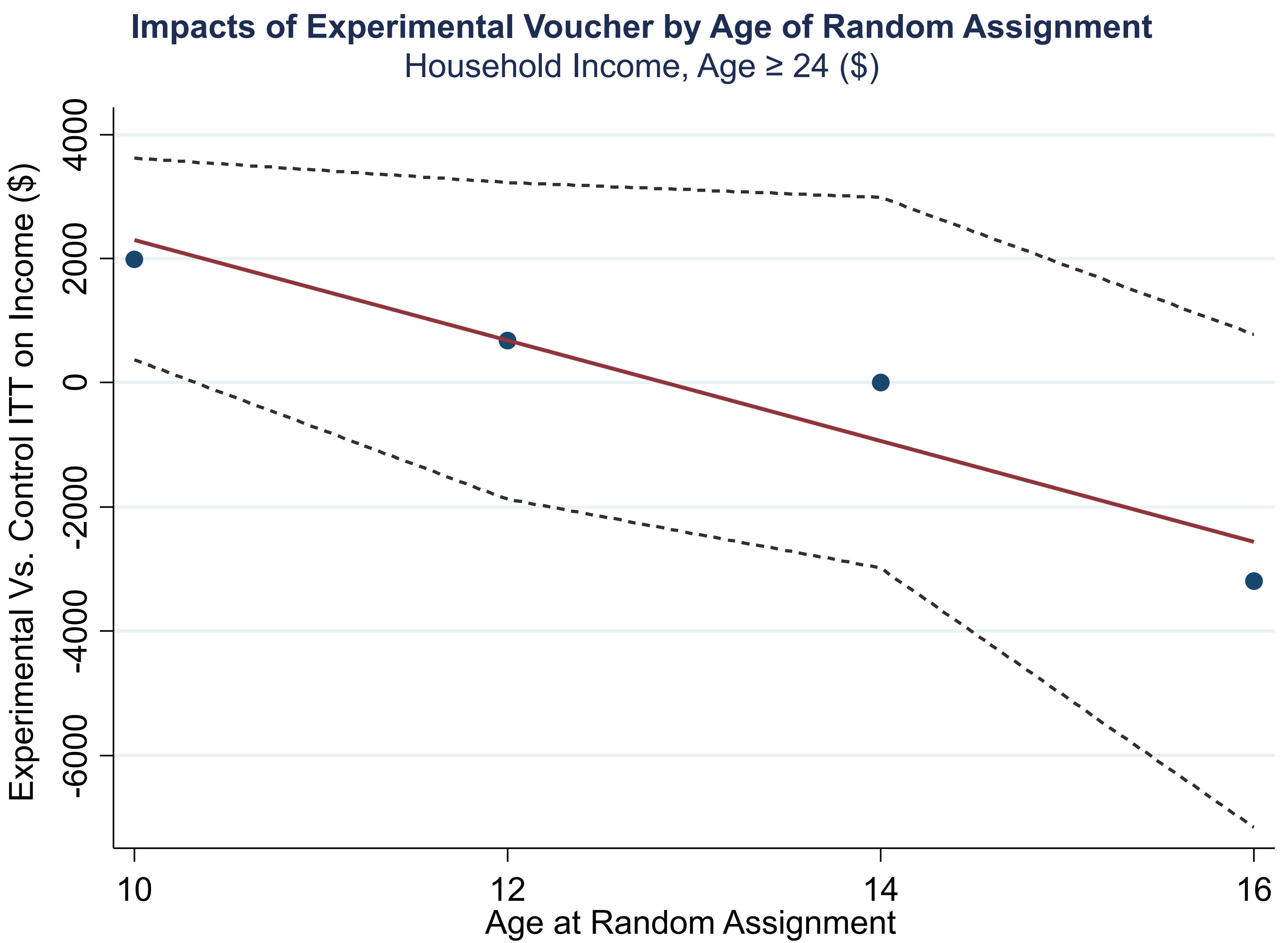


Impacts of MTO on Children Age 13-18 at Random Assignment




Impacts of Experimental Voucher by Age of 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

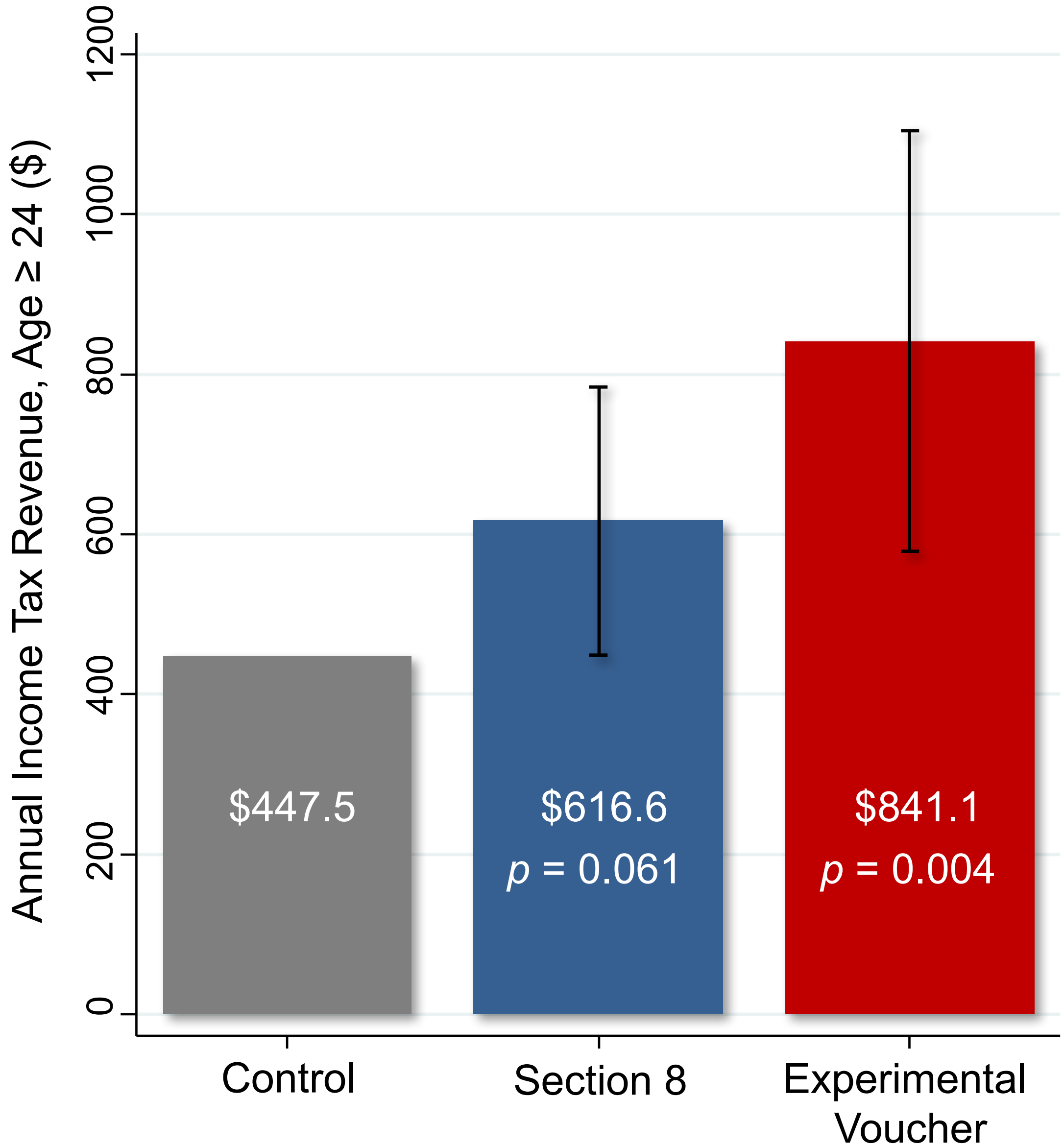
Conclusion: Policy Lessons

- 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

        - 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)



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- Key input for both policies:
  1. What are the best and worst places to grow up?
  2. What are the characteristics of places that improve children's outcomes?

- Developed in companion paper: "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates"

Download County-Level Data on Social Mobility in the U.S.

www.equality-of-opportunity.org/data