Part 2: Efficient Redistribution through Places/Mobility?

Nathaniel Hendren

(Based on joint work with Raj Chetty and Larry Katz)

Harvard University and NBER

August, 2015

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

- Part 1: Redistribution is not free
- Part 2: find the least expensive method of redistribution

- Two types of policies:
  - Ex-post "redistributive" policies targeted towards adults
    - EITC, income tax
    - Food Stamps
    - Job Training
    - Etc.
  - Ex-ante "mobility" policies targeted towards children
    - Public schools, S-Chip, Harlem Children's Zone, etc.

Introduction

- Growing evidence that may be more efficient to promote redistribution through mobility / investment in children
    - **Health.** Medicaid to children decreases long-run public expenditure on health transfers (Wherry et al. 2015)
    - **Education.** Impact of teachers on long-run earnings (Chetty et al. 2013)
- **This lecture: Place.**
    - Theory of how neighborhood environments play role in persistent inequality and immobility: Durlauf (1996)
    - Observational evidence 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)
    - Empirical evidence: Chetty and Hendren (2015)
        - Neighborhoods have significant childhood exposure effects

Outline of Lecture

- Background: Geographical variation in intergenerational mobility in the U.S. [Chetty, Hendren, Kline, Saez QJE 2014]

- Part 1: Childhood Exposure Effects
  - Estimate fraction of variance across areas due to causal effects of place

- Part 2: Causal Estimates by County
  - Decompose variation across areas into sorting and causal effect of each county

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

The Geography of Intergenerational Mobility in the U.S.

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]

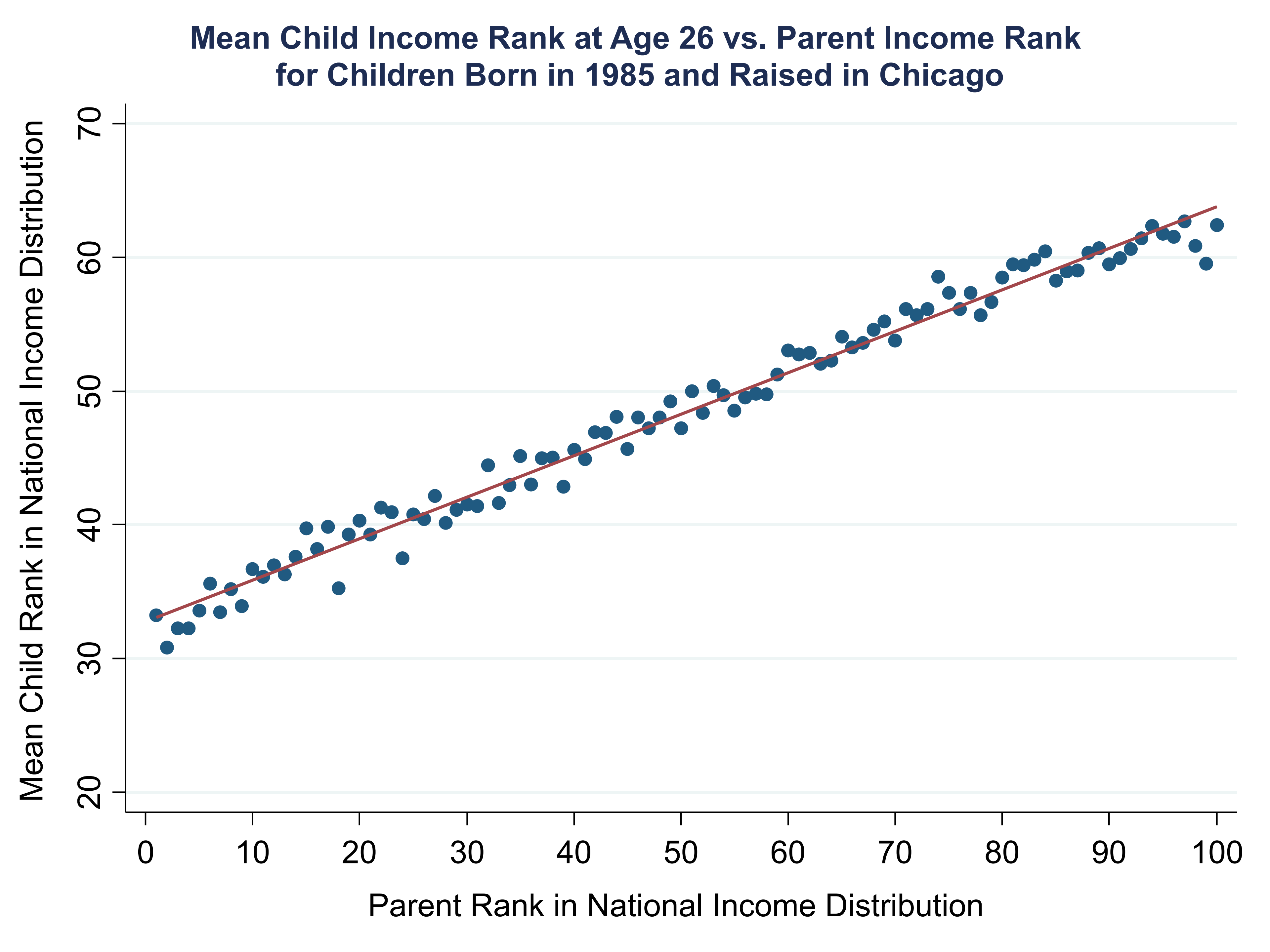
- Variance of place effects at broad geographies is a lower bound for total variance of neighborhood effects

Intergenerational Mobility by CZ

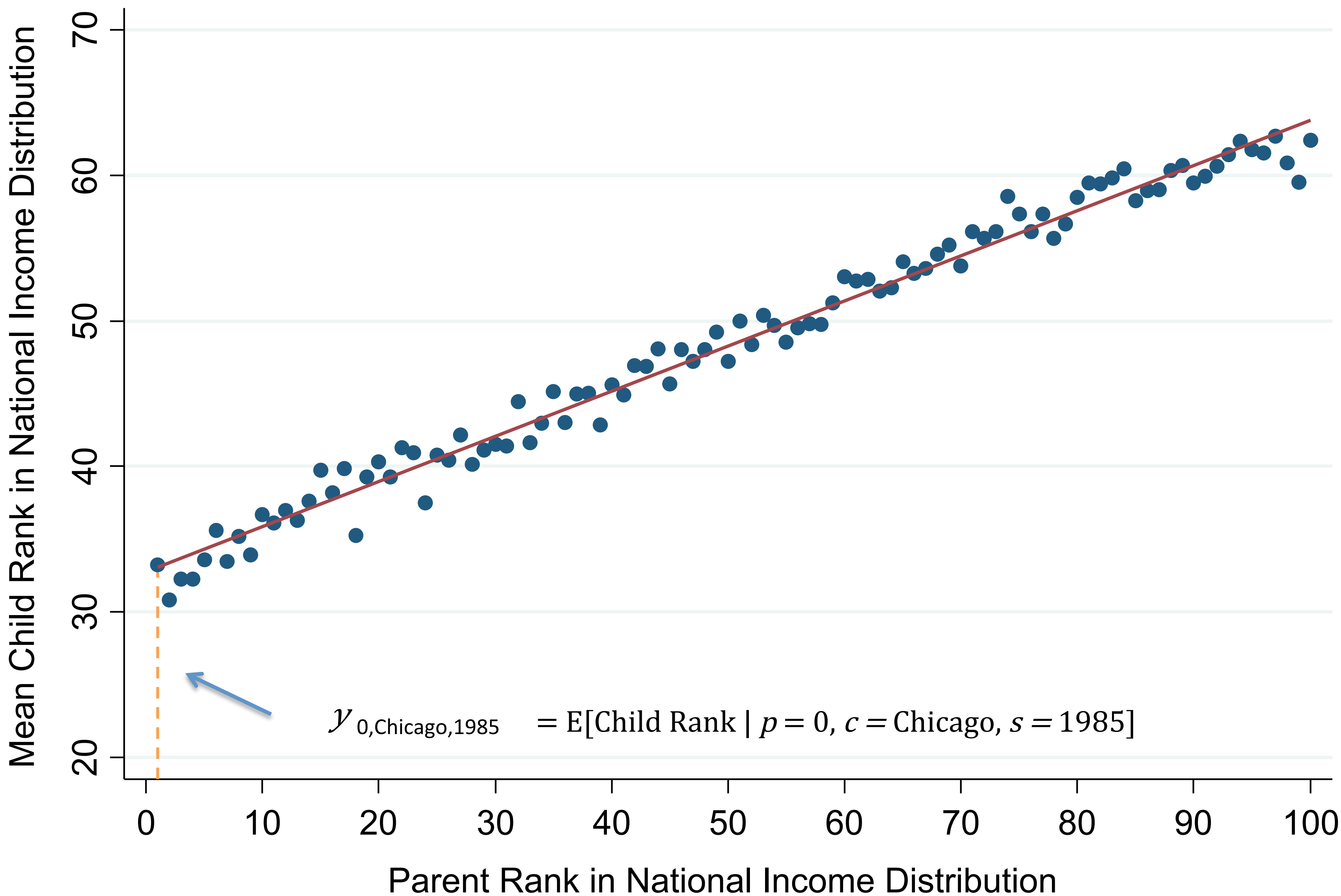
- Begin with a descriptive characterization of children's outcomes in each CZ

- 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

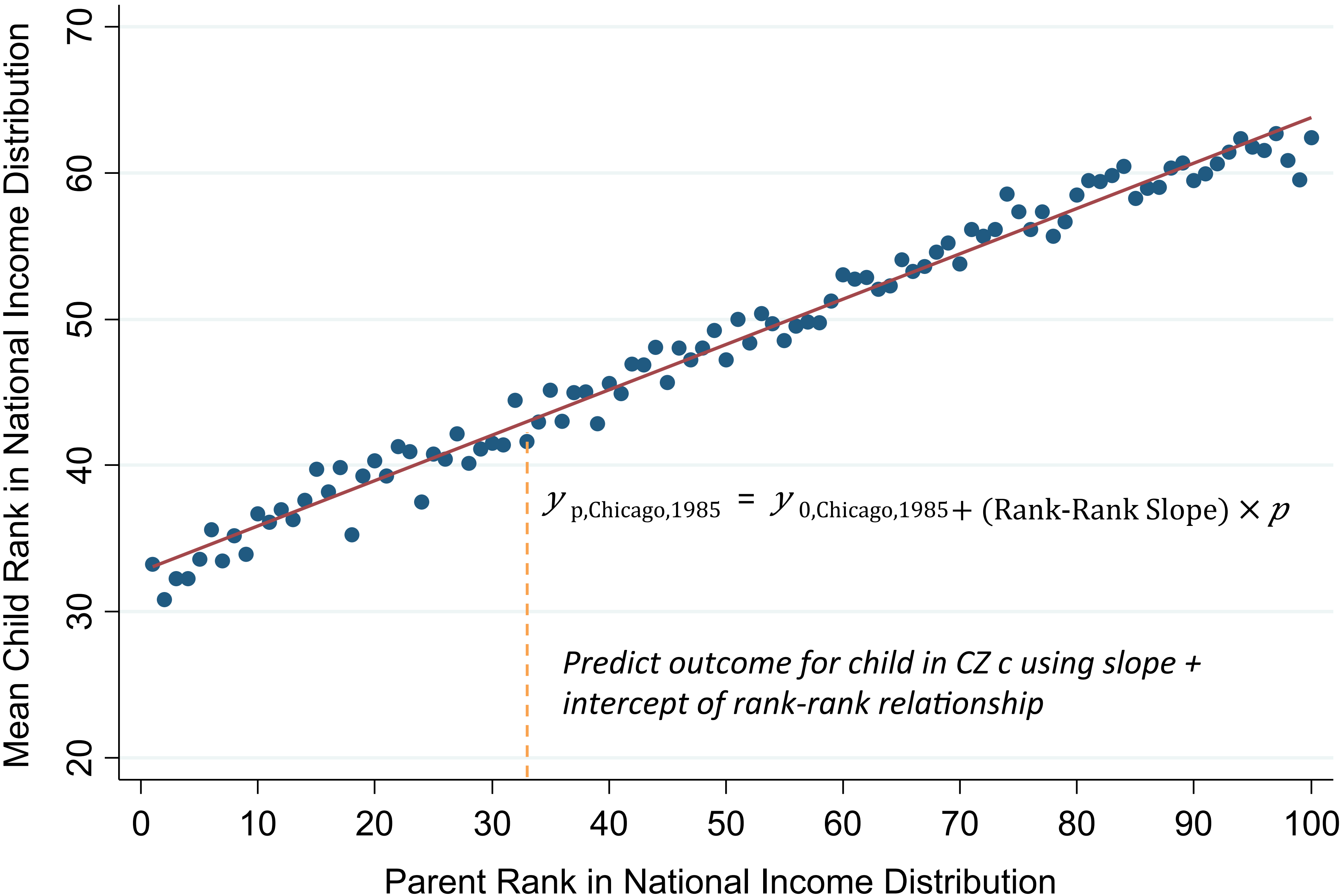
- Characterize relationship between child's income rank and parent's income rank *p* for each CZ *c* and birth cohort *s*


Mean Child Income Rank at Age 26 vs. Parent Income Rank
for Children Born in 1985 and Raised in Chicago
Mean Child Rank in National Income Distribution
20
30
40
50
60
70
0
10
20
30
40
50
60
70
80
90
100
Parent Rank in National Income Distribution

Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago

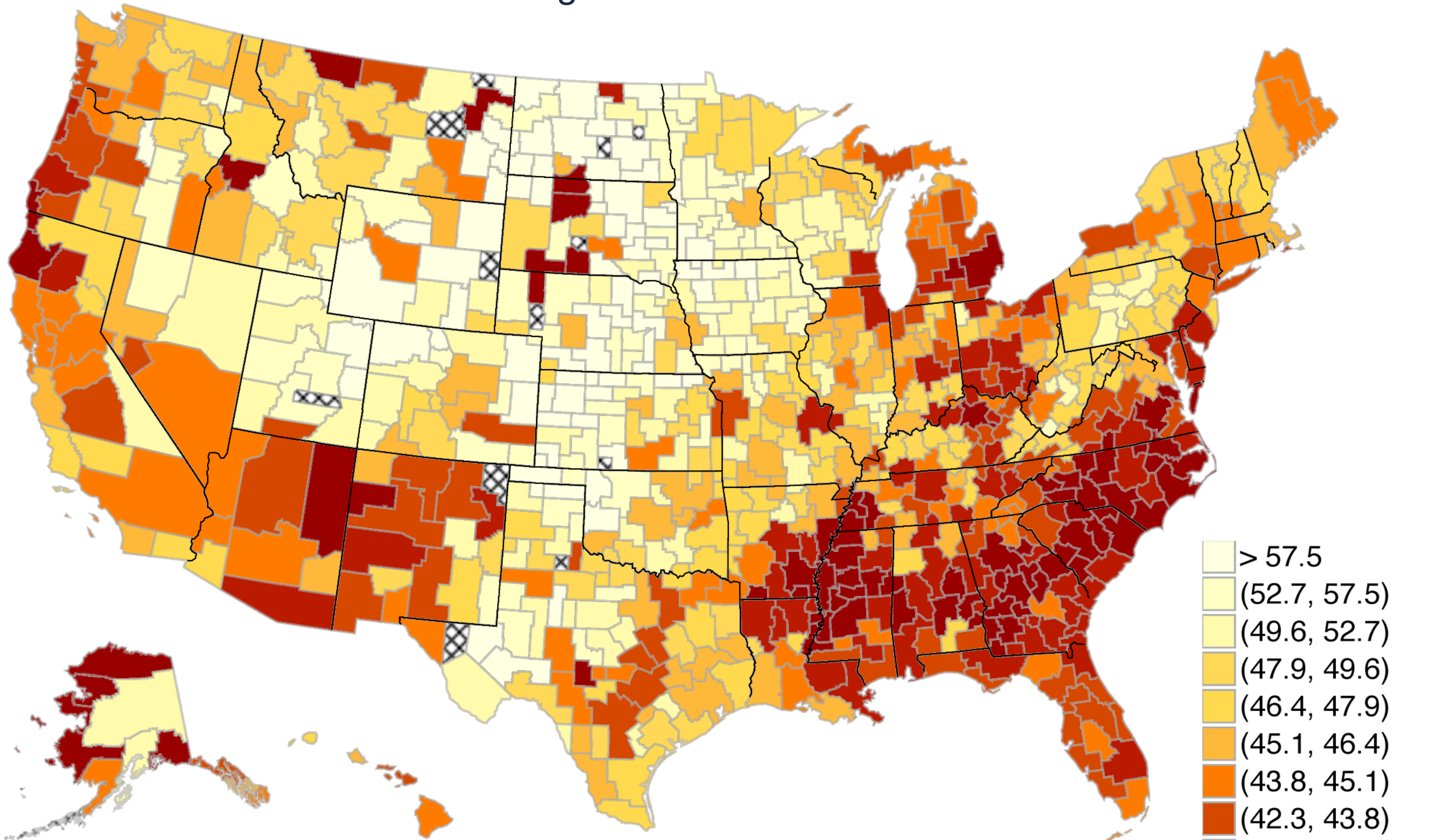


Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago



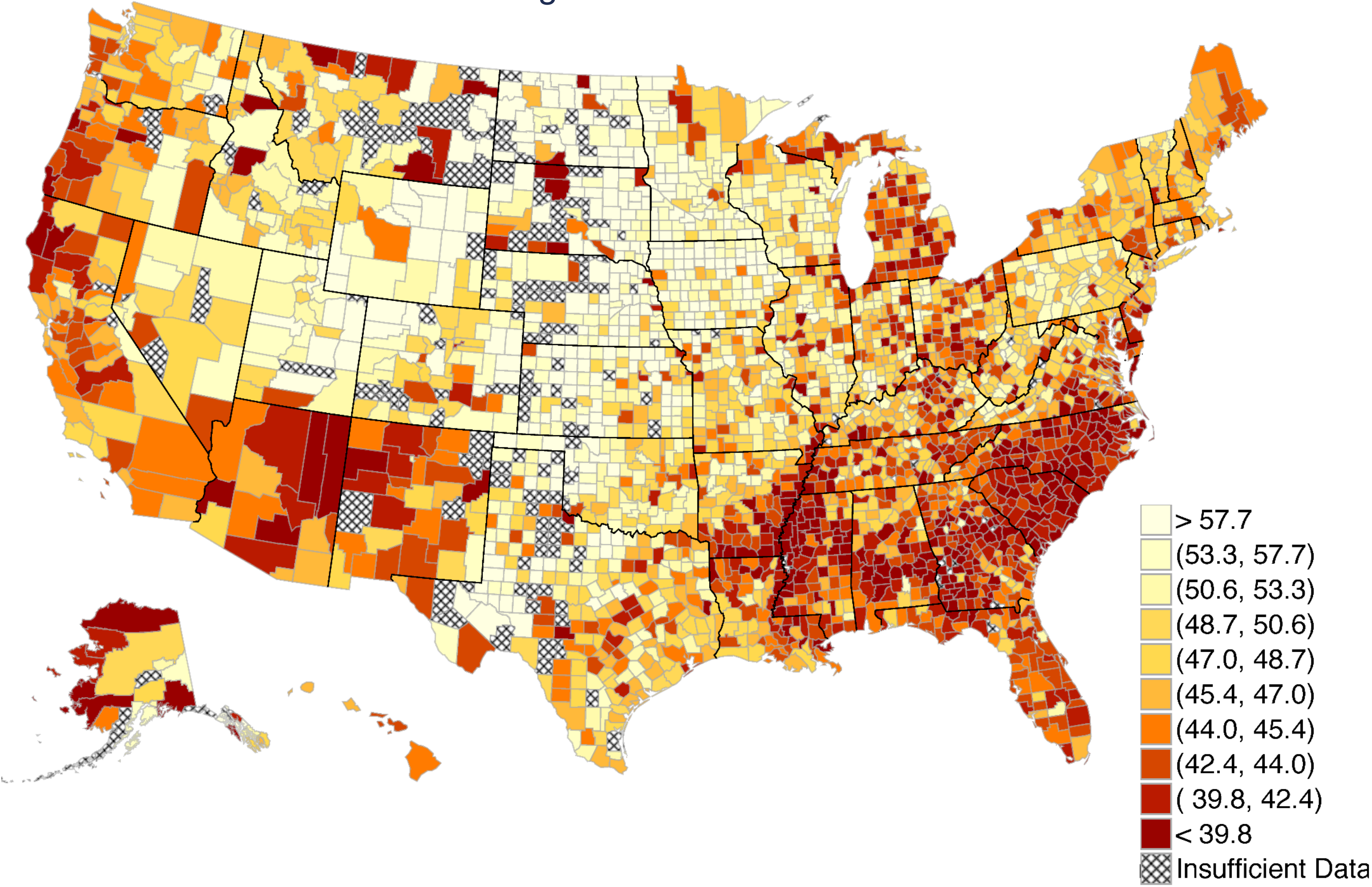
The Geography of Intergenerational Mobility in the United States

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



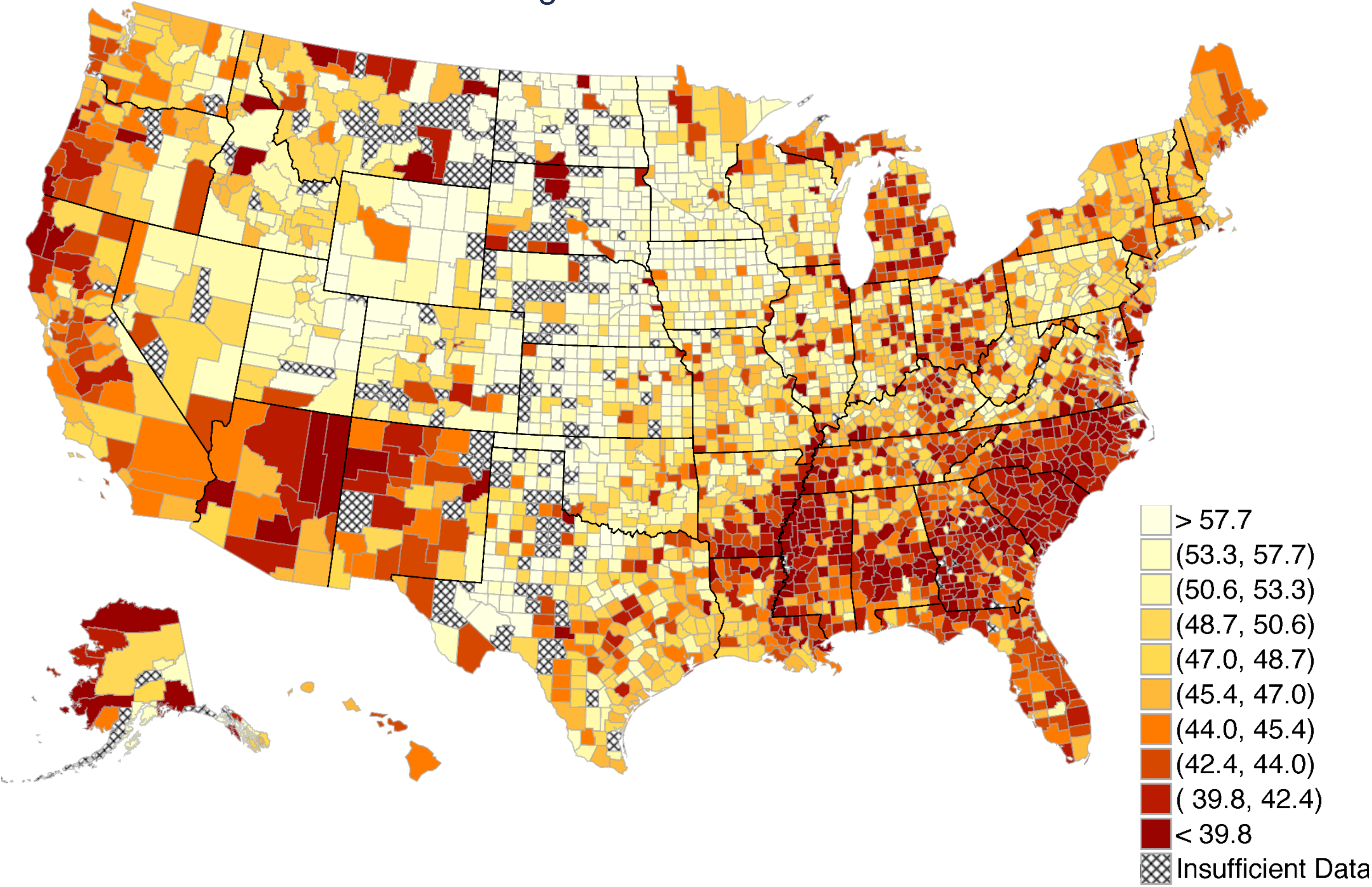
The Geography of Intergenerational Mobility in the United States

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



The Geography of Intergenerational Mobility in the United States

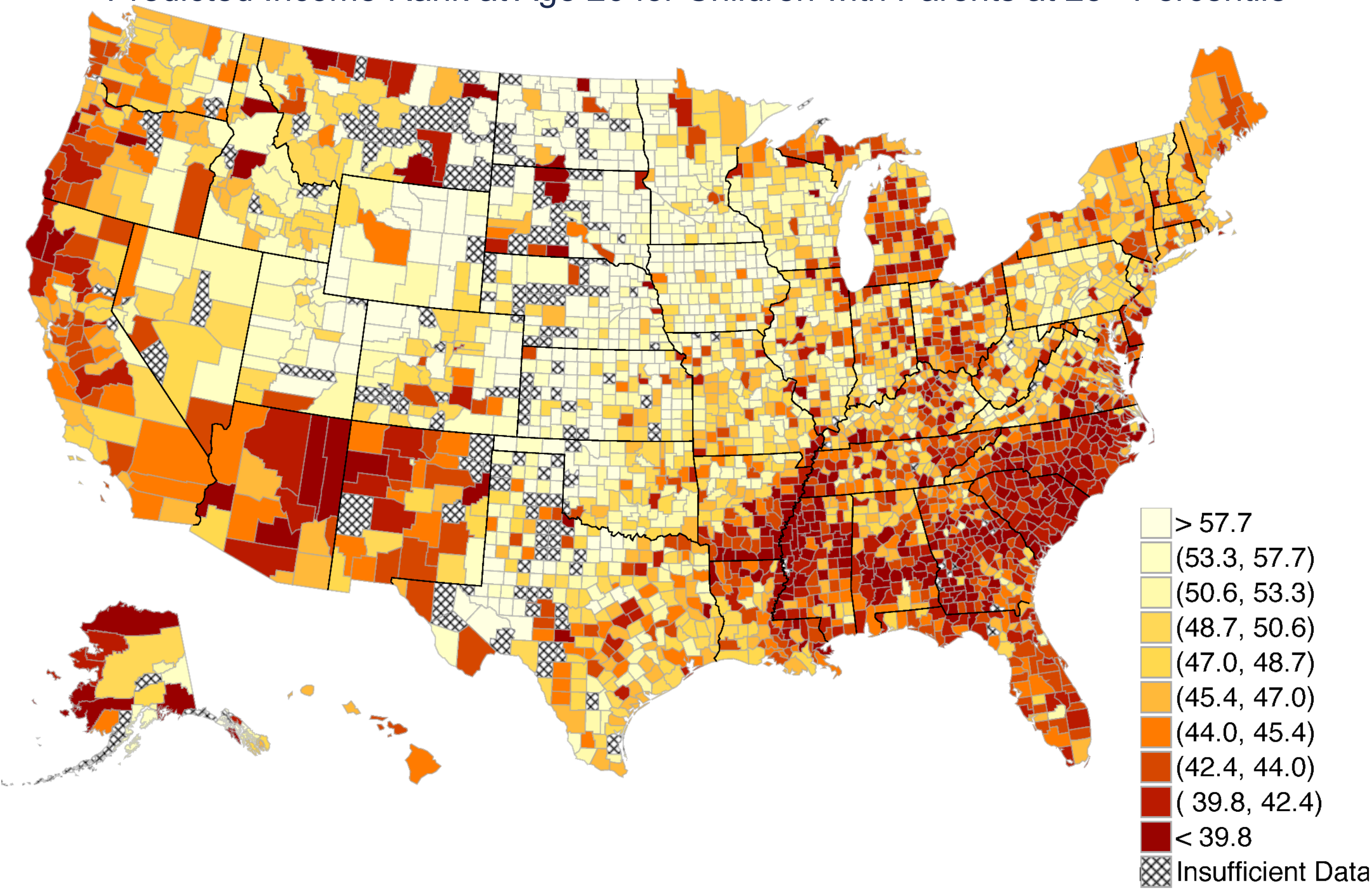
Predicted Income Rank at Age 26 for Children with Parents at 25th Percentile



Part 1: What happens if you move to a lighter county?

The Geography of Intergenerational Mobility in the United States

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



Part 2: Decompose map into sorting and causal effect for <u>each</u> county

Part 1
Impact of Exposure to a Better Neighborhood

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

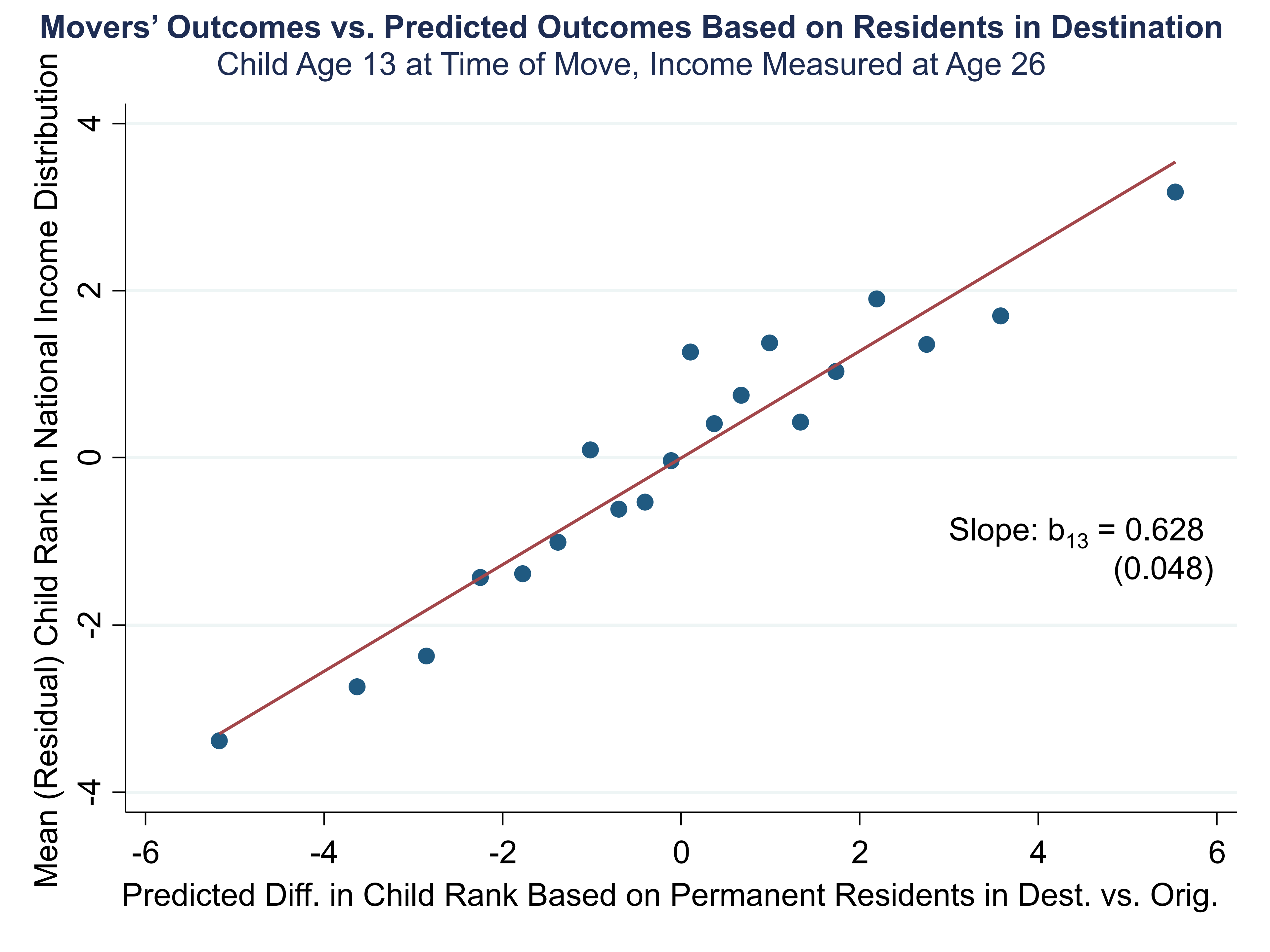
Estimating Exposure Effects in Observational Data

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

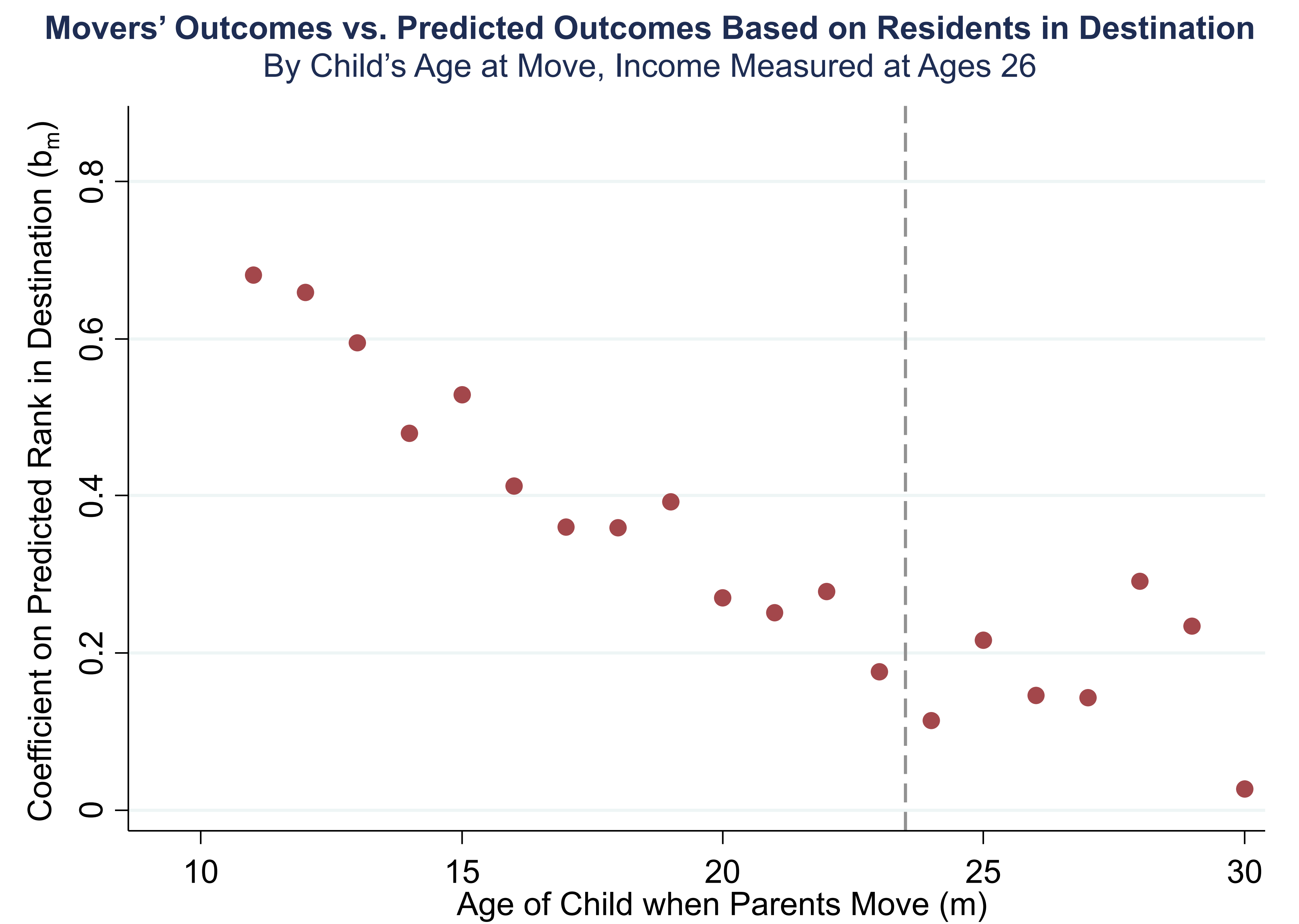
- Regress child's income rank at age 26 y_i on predicted outcome of permanent residents in destination:

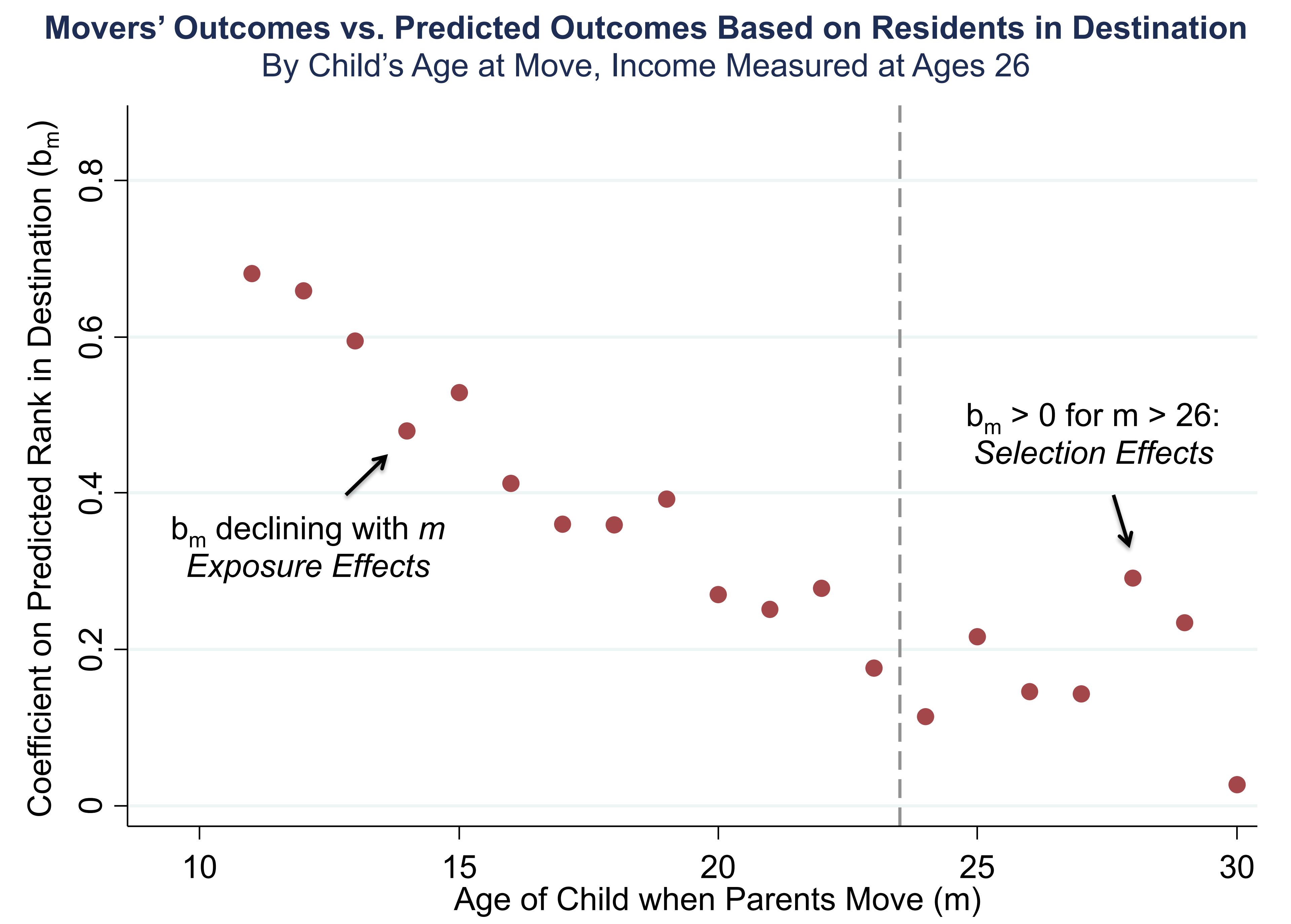
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

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

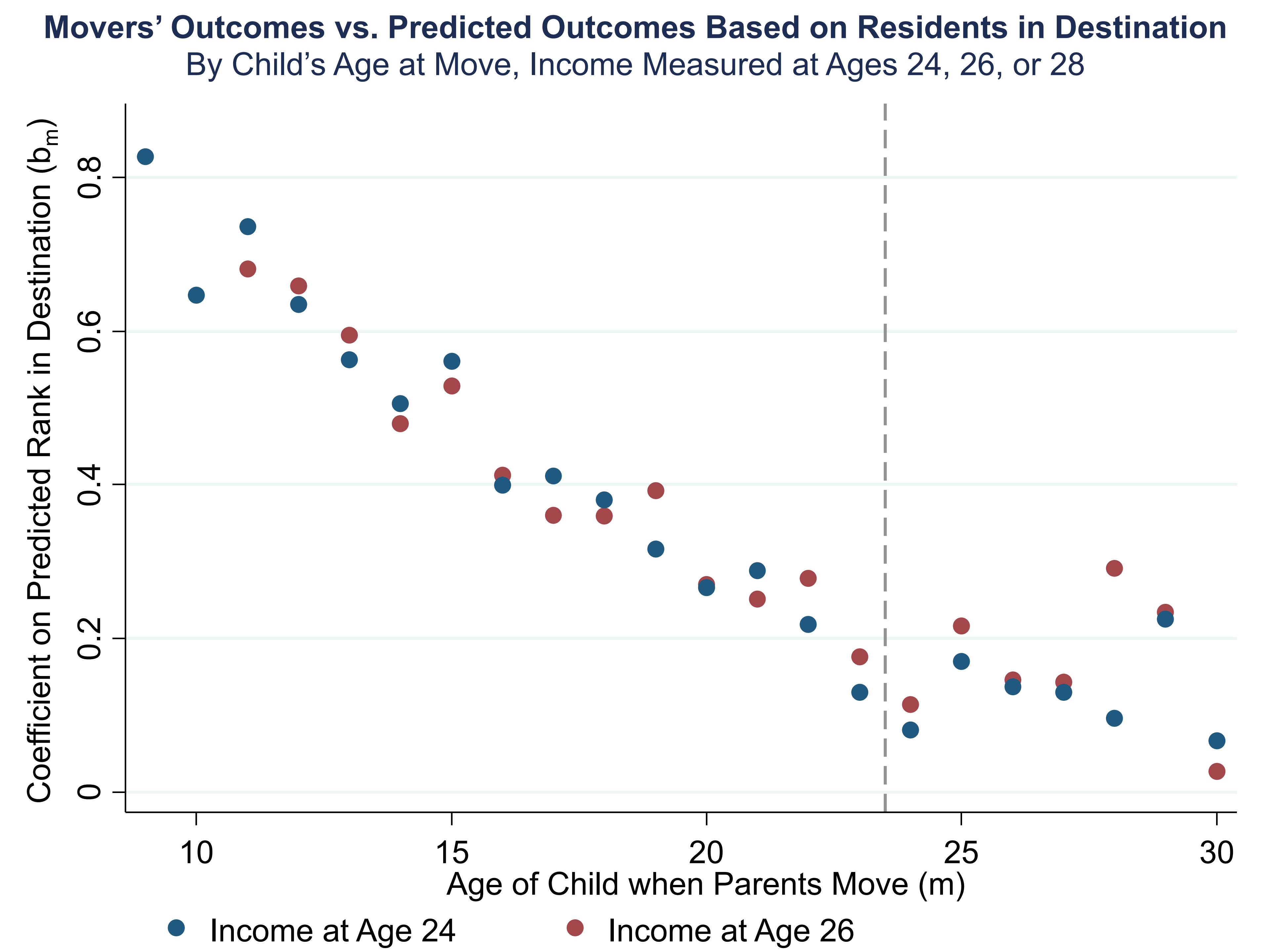


Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
Child Age 13 at Time of Move, Income Measured at Age 26
Mean (Residual) Child Rank in National Income Distribution
Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.
Slope: b_{13} = 0.628
(0.048)
-4
-2
0
2
4
-6
-4
-2
0
2
4
6


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



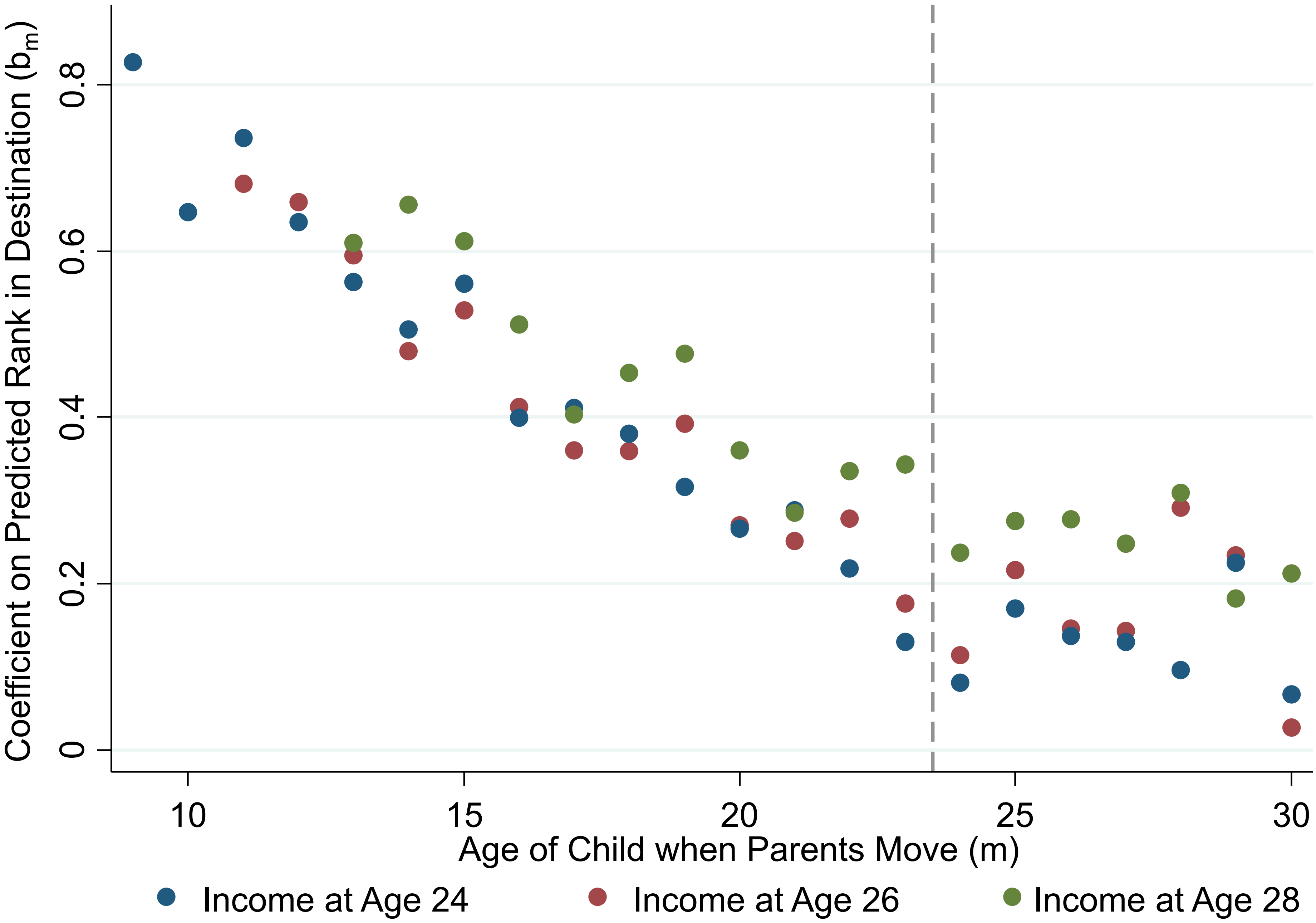
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 26
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)
b_m declining with *m*
Exposure Effects
$b_m > 0$ for $m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

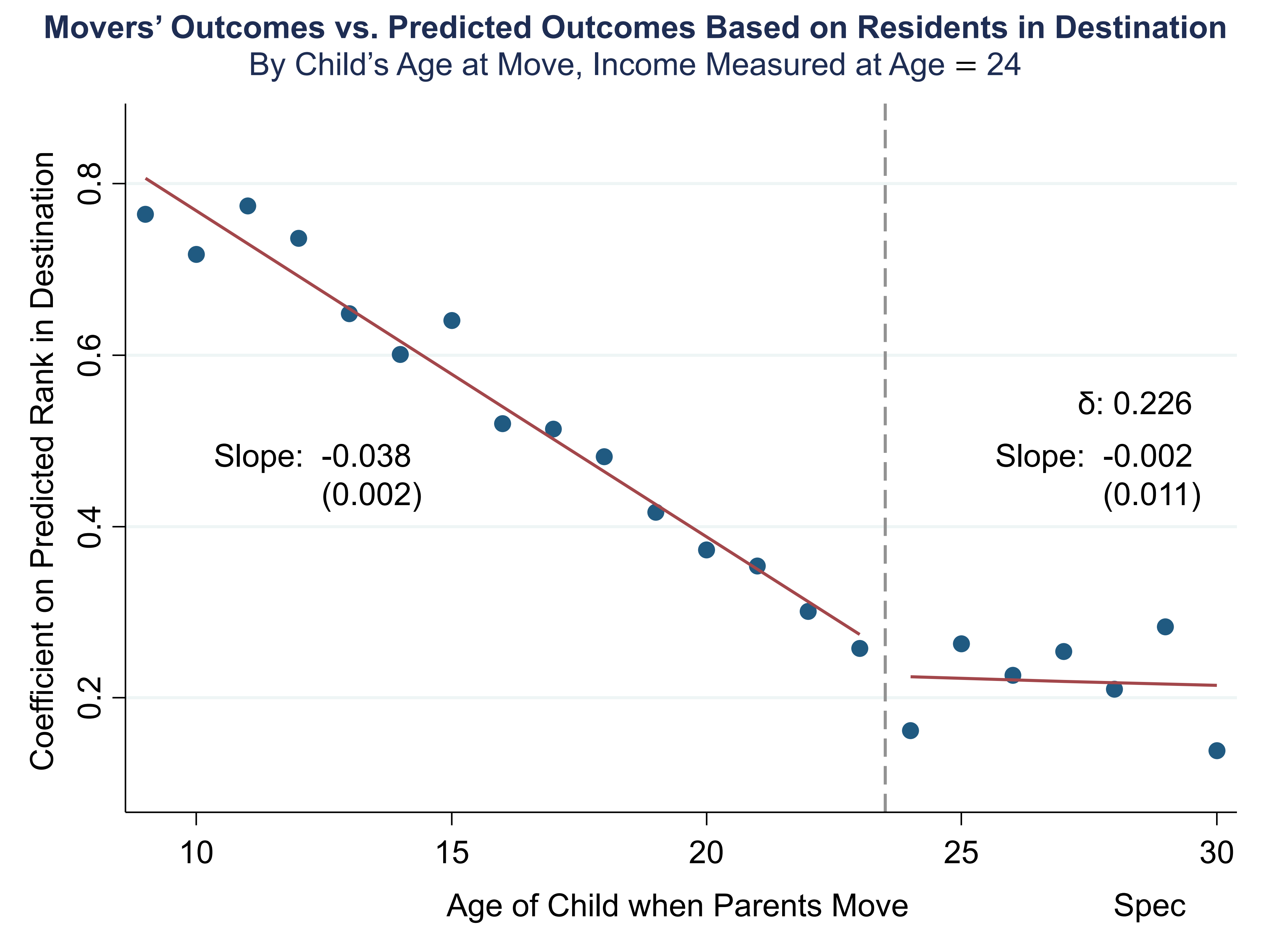


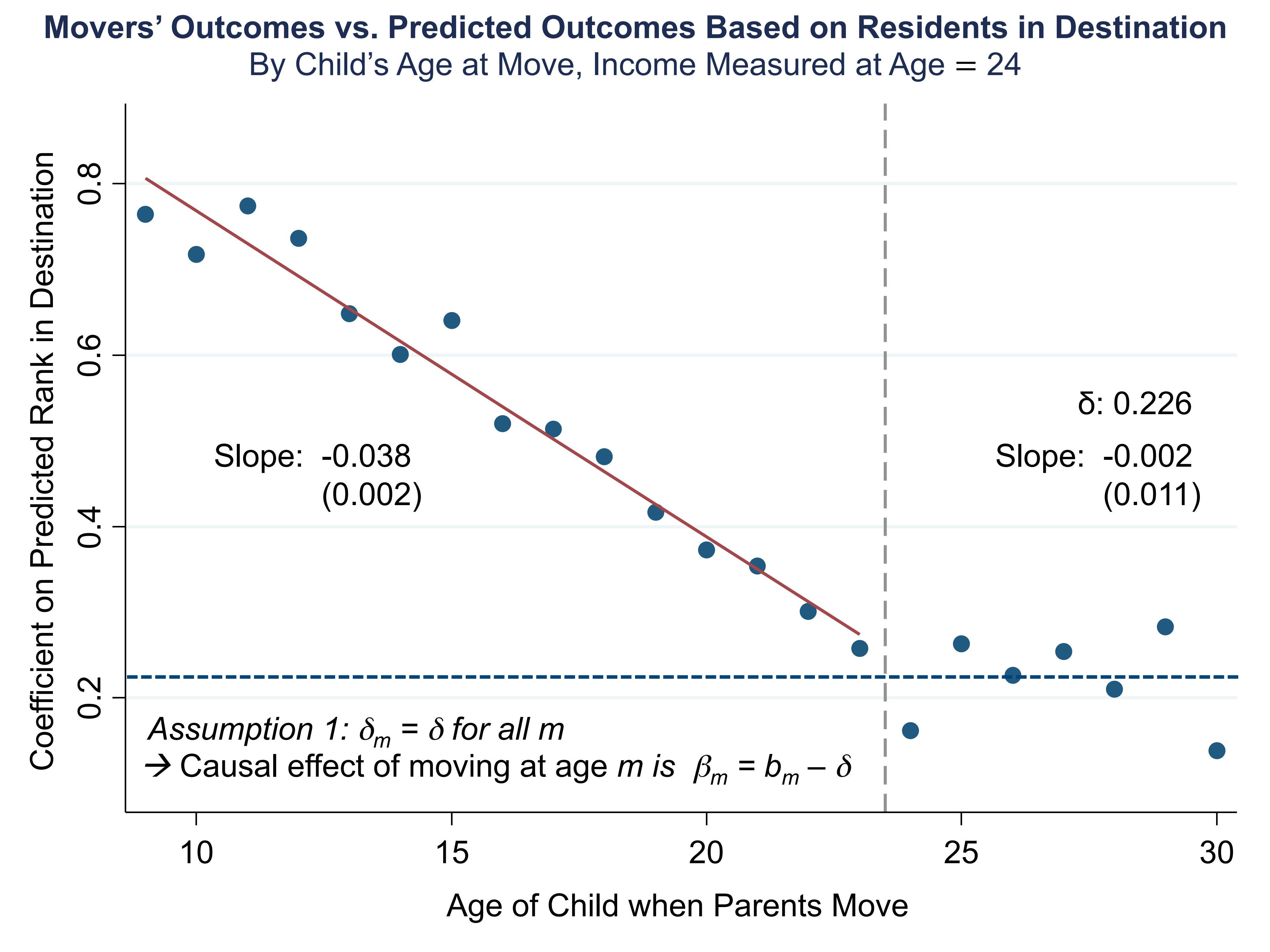
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 24, 26, or 28
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)
Income at Age 24
Income at Age 26

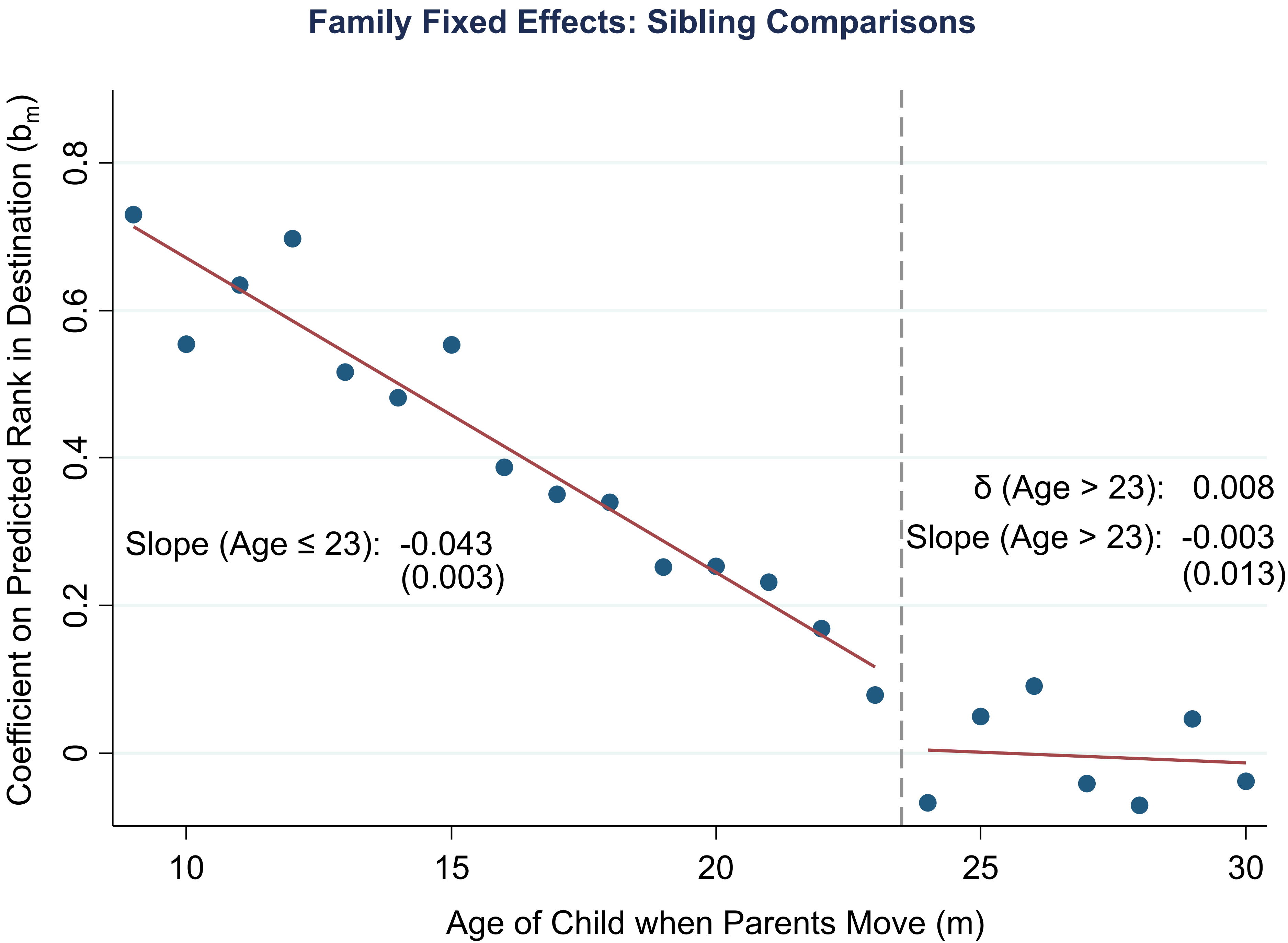
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination

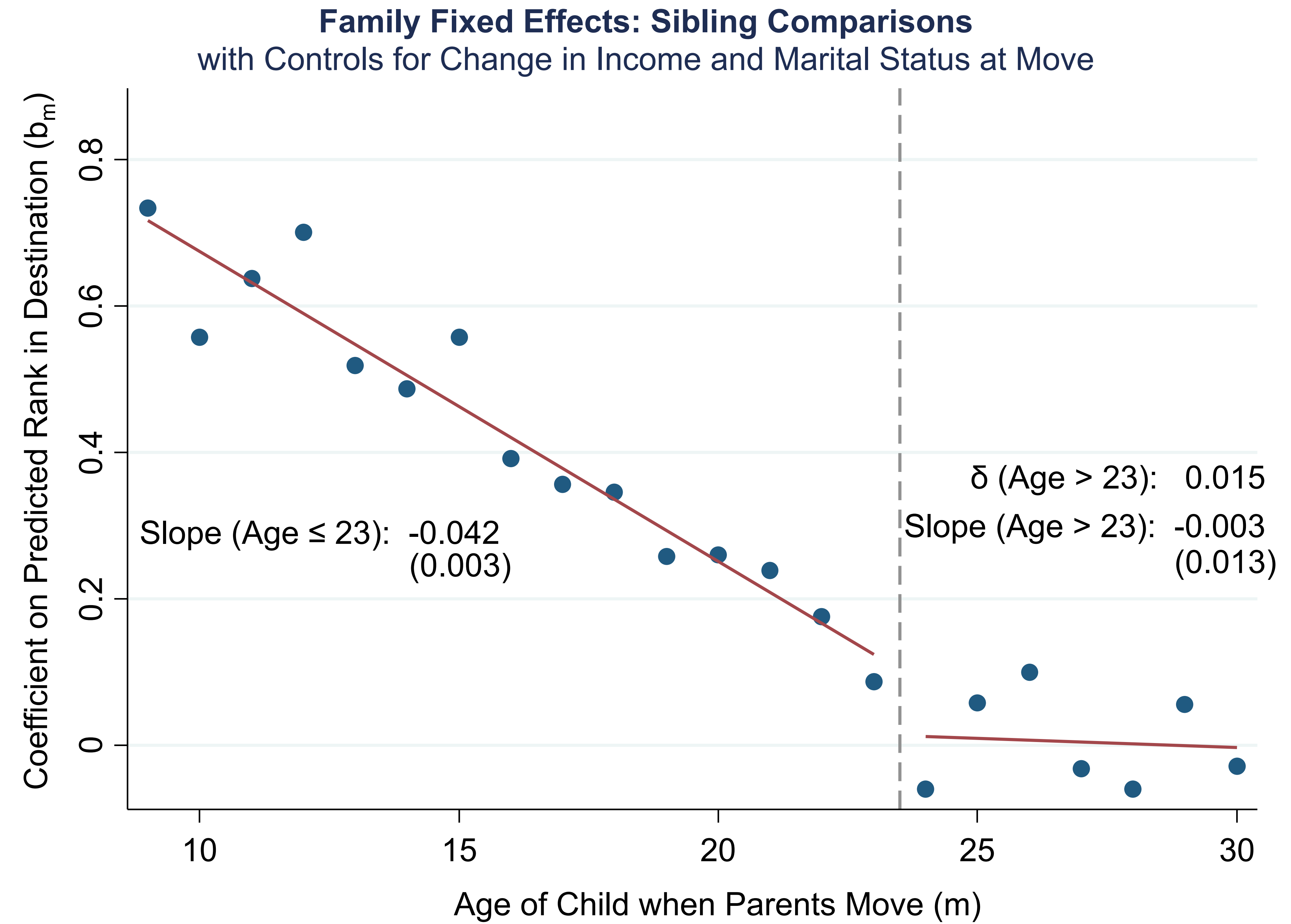
By Child's Age at Move, Income Measured at Ages 24, 26, or 28




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
0.8
0.6
0.4
0.2
Slope: -0.038
(0.002)
δ: 0.226
Slope: -0.002
(0.011)
10
15
20
25
30
Age of Child when Parents Move
Spec


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
0.8
0.6
0.4
0.2
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 $\beta_m = b_m - \delta$
10
15
20
25
30
Age of Child when Parents Move


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)



Family Fixed Effects: Sibling Comparisons
with Controls for Change in Income and Marital Status at Move
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): -0.042
(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
  - Core problem: we do not know what triggered the move

- Two approaches to evaluate such confounds:

  1. Experimental variation: Moving to Opportunity experiment
  2. Outcome-based placebo (overidentification) tests

Outcome-Based Placebo Tests

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

- For example, exposure model predicts convergence to permanent residents' outcomes not just on means but across *entire* distribution

  - Variance of earnings for children of permanent residents in SF is higher than for children of permanent residents in Boston

  - Exposure model predicts that 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 child will fall as an adult when moving

  - Unlikely that unobserved factor θ_i would replicate distribution of outcomes in destination area in proportion to exposure time

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)

Outcome-Based Placebo Tests

- We implement similar placebo tests using variation in place effects across birth cohorts and across genders
  - Exposure effect is fully determined by *own-cohort* and *own-gender* place effect
  - When a family with a daughter and son moves to a place where boys do especially well, son does better in proportion to exposure but daughter does not

→ We conclude based on these tests that timing-of-move design yields unbiased estimates of neighborhoods' causal exposure effects

- How do these findings fit with results from MTO experiment?

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

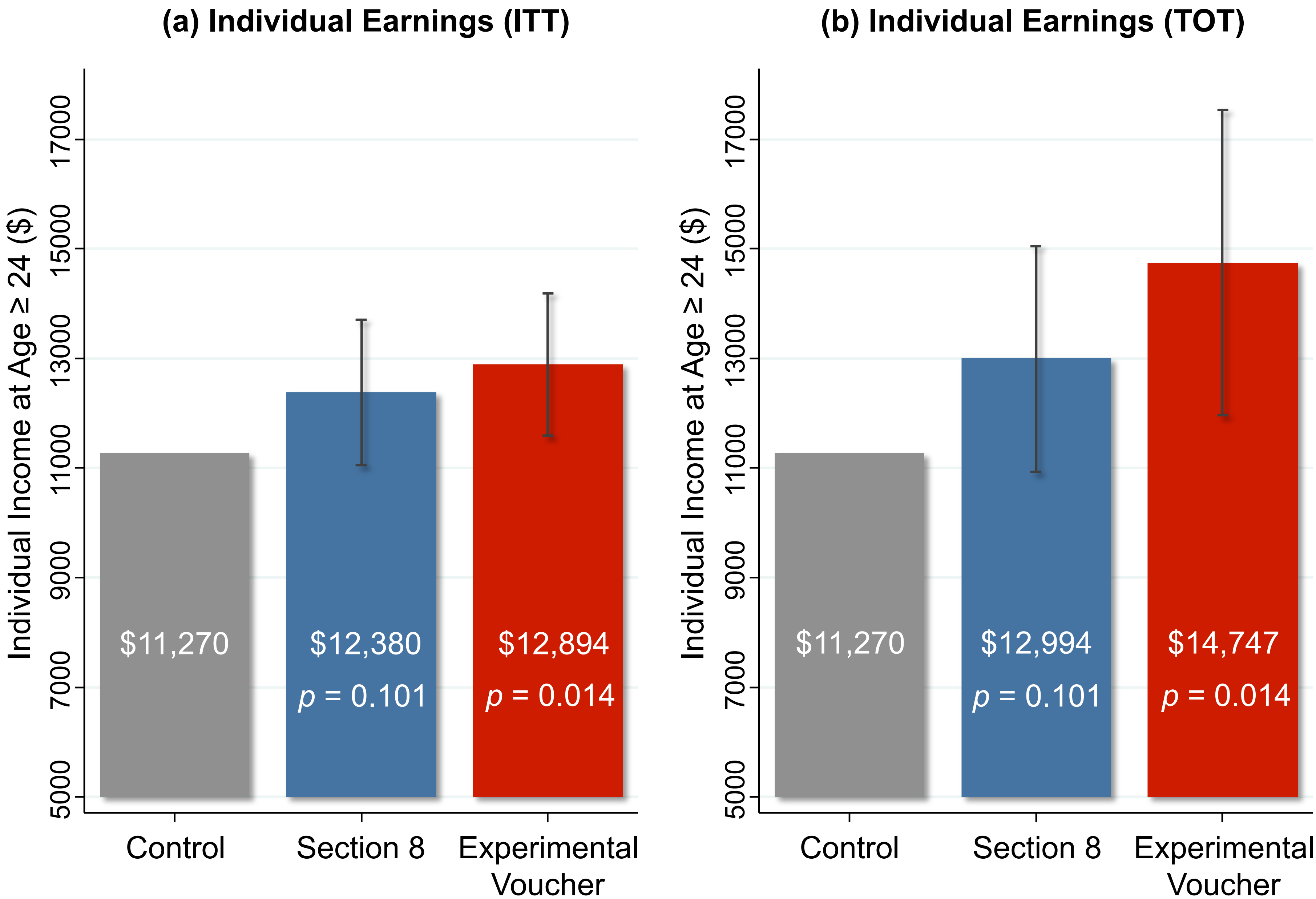
MTO Experiment: Exposure Effects?

- Existing research on MTO:
  - Little impact of moving to a better area on earnings and other economic outcomes
  - Work has focused on adults and older youth at point of move [e.g., Kling, Liebman, and Katz 2007]
- What about the young kids?

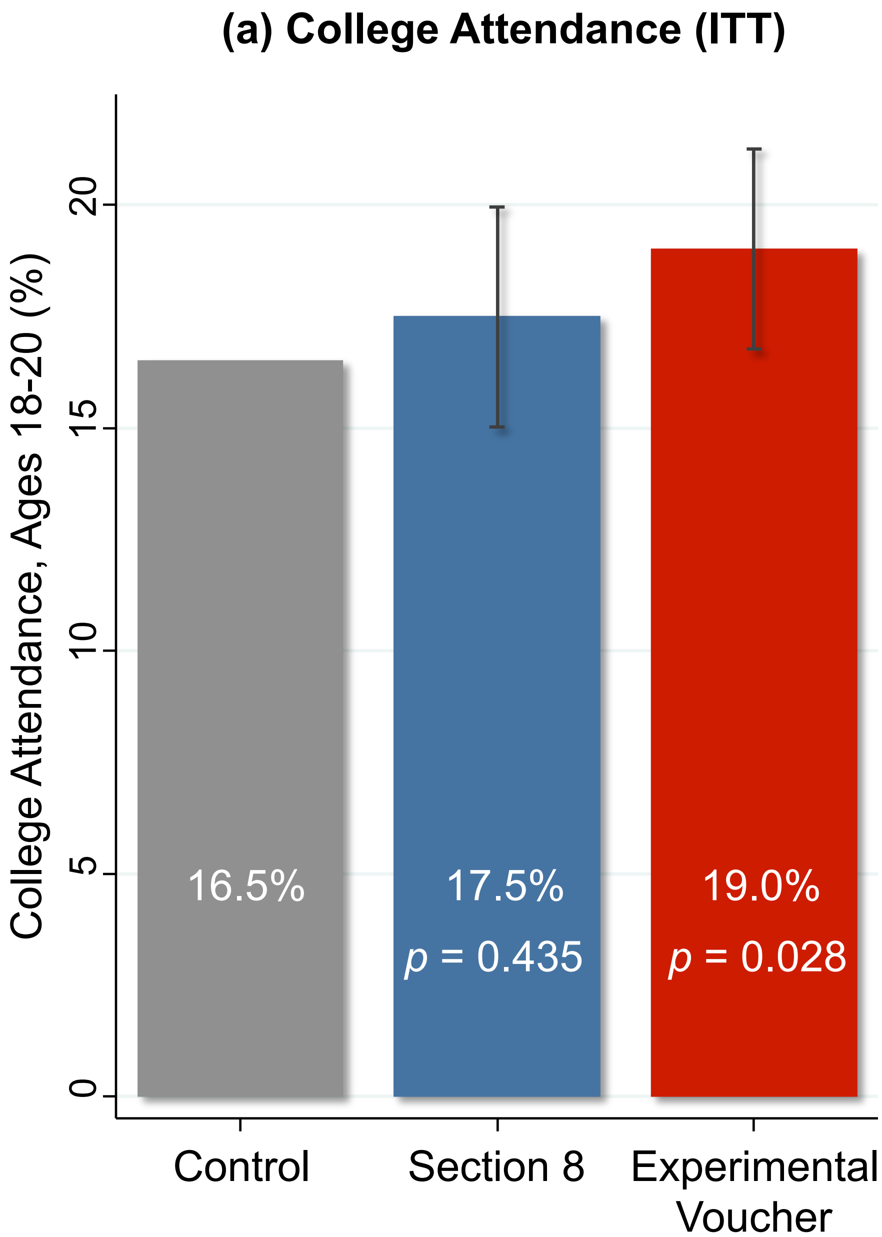
Chetty, Hendren, Katz. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment"

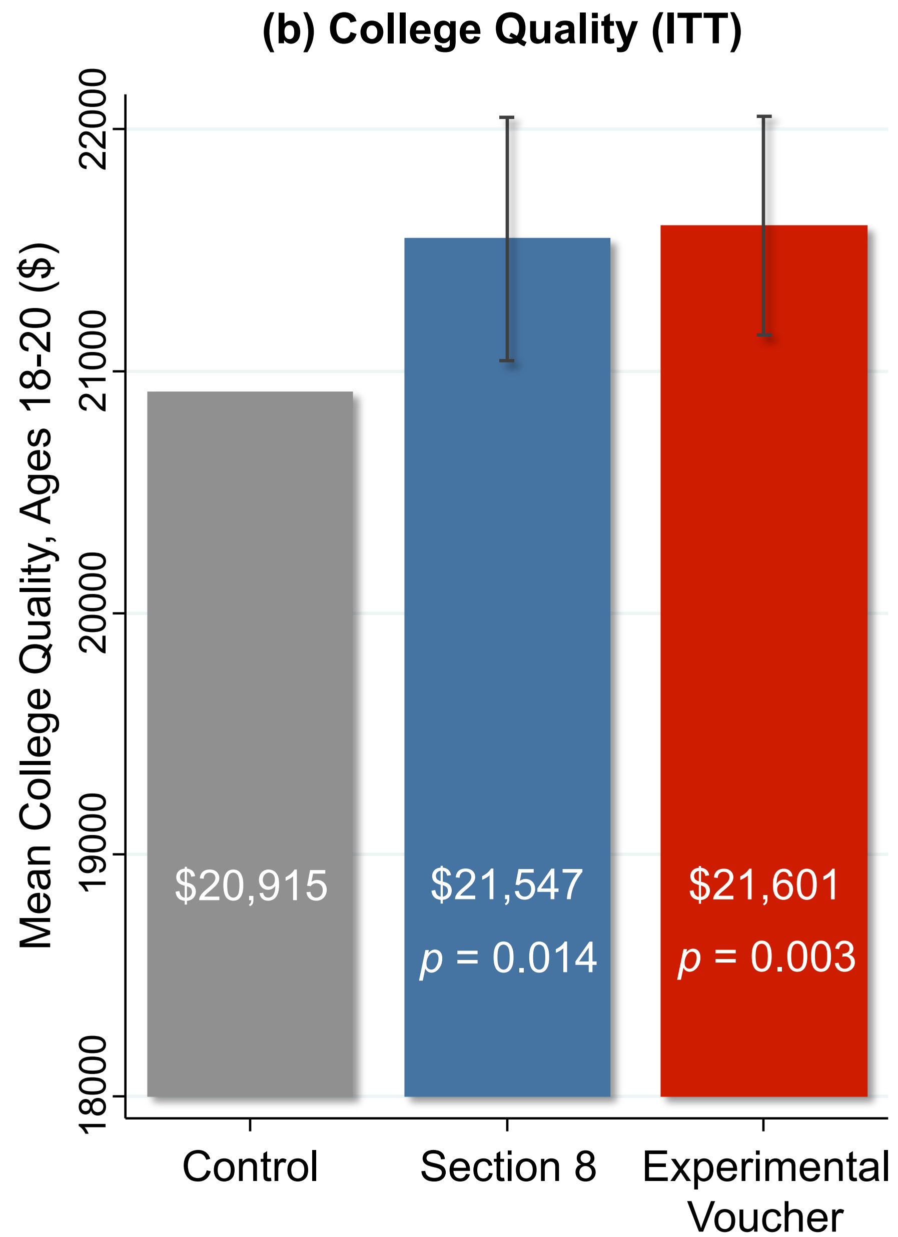
- Does MTO improve outcomes for children who moved when young?
  - Link MTO data to tax data to study children's outcomes in mid-20's

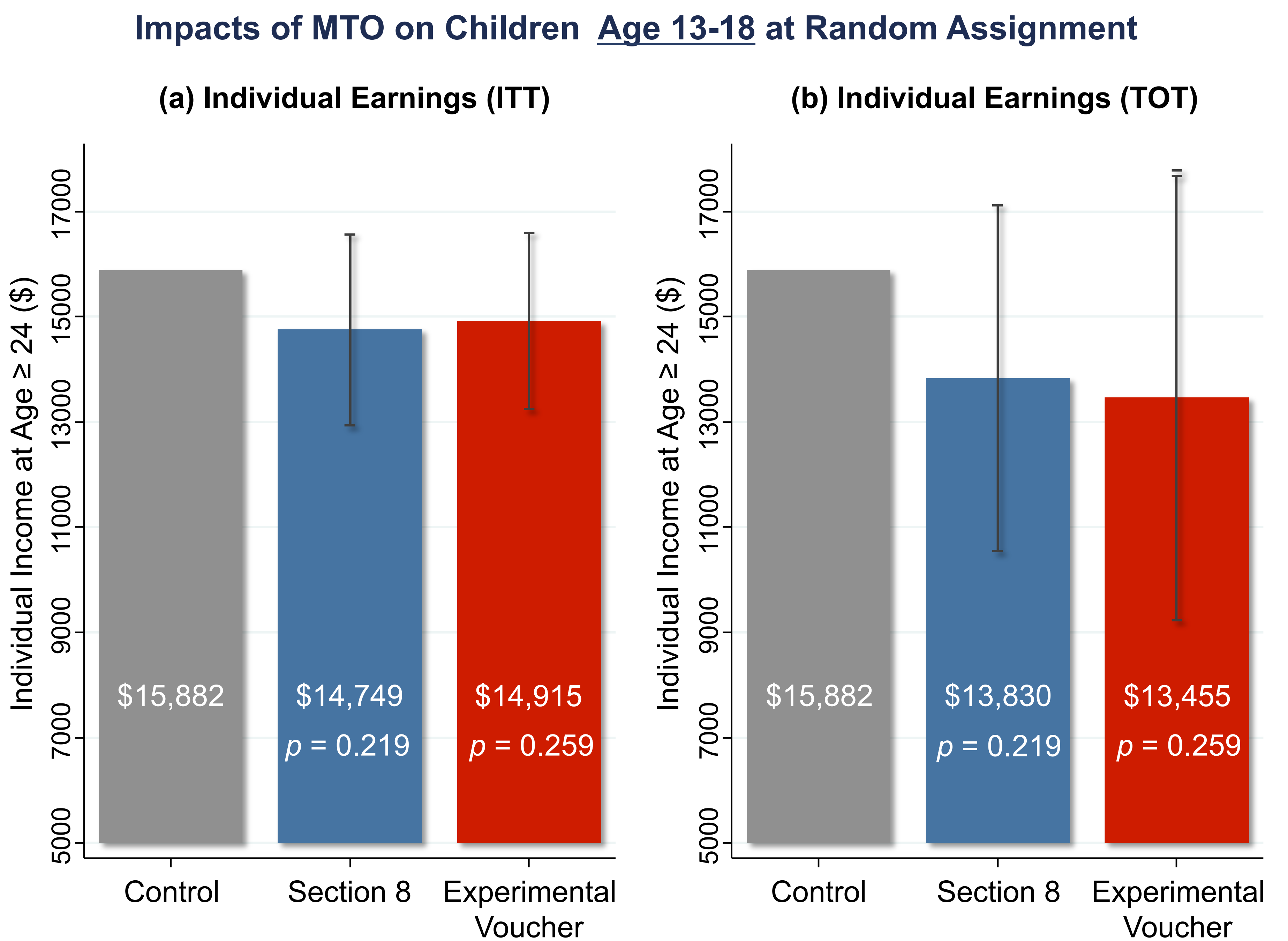
Impacts of MTO on Children Below Age 13 at Random Assignment



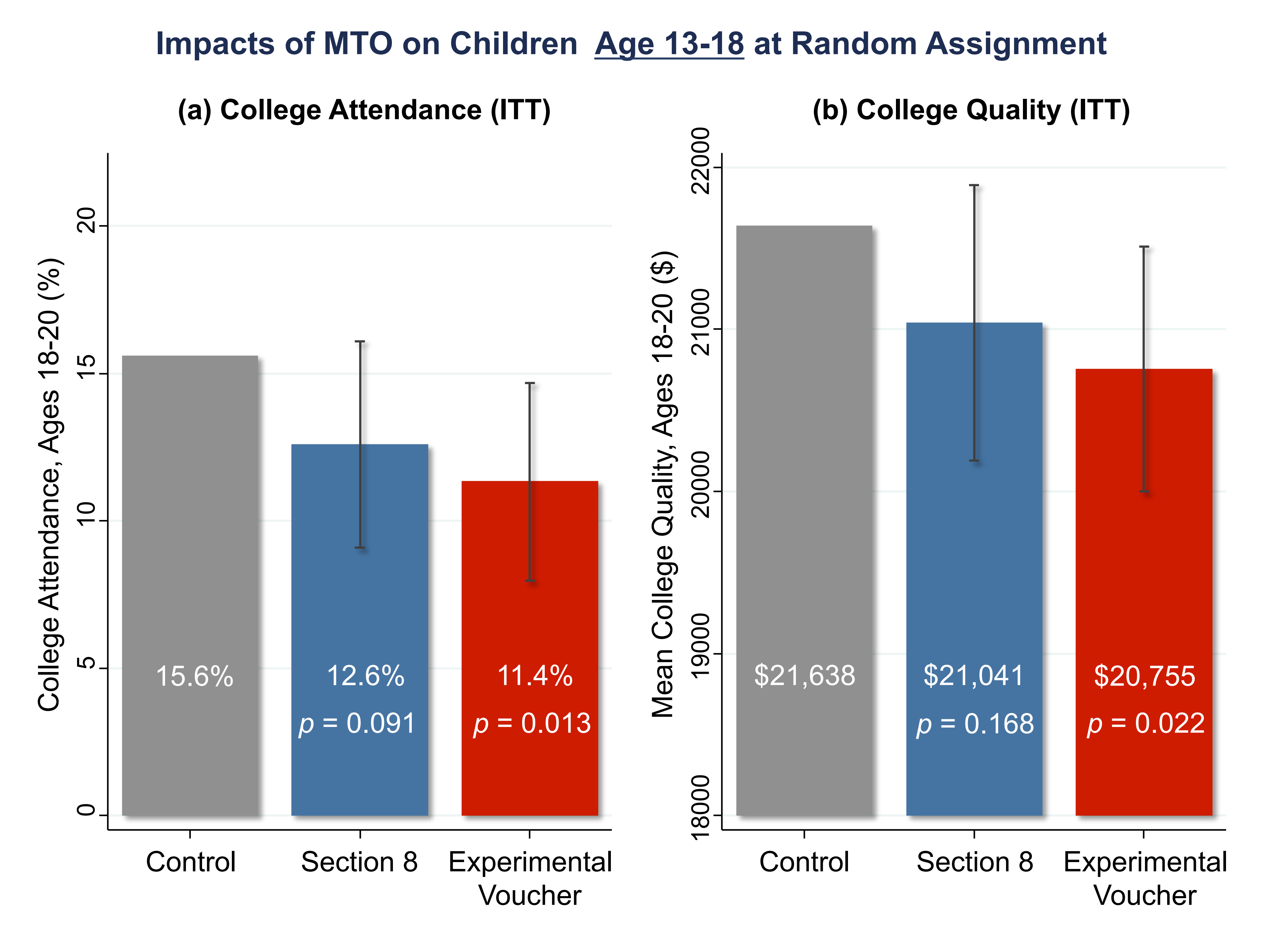
Impacts of MTO on Children Below Age 13 at Random Assignment





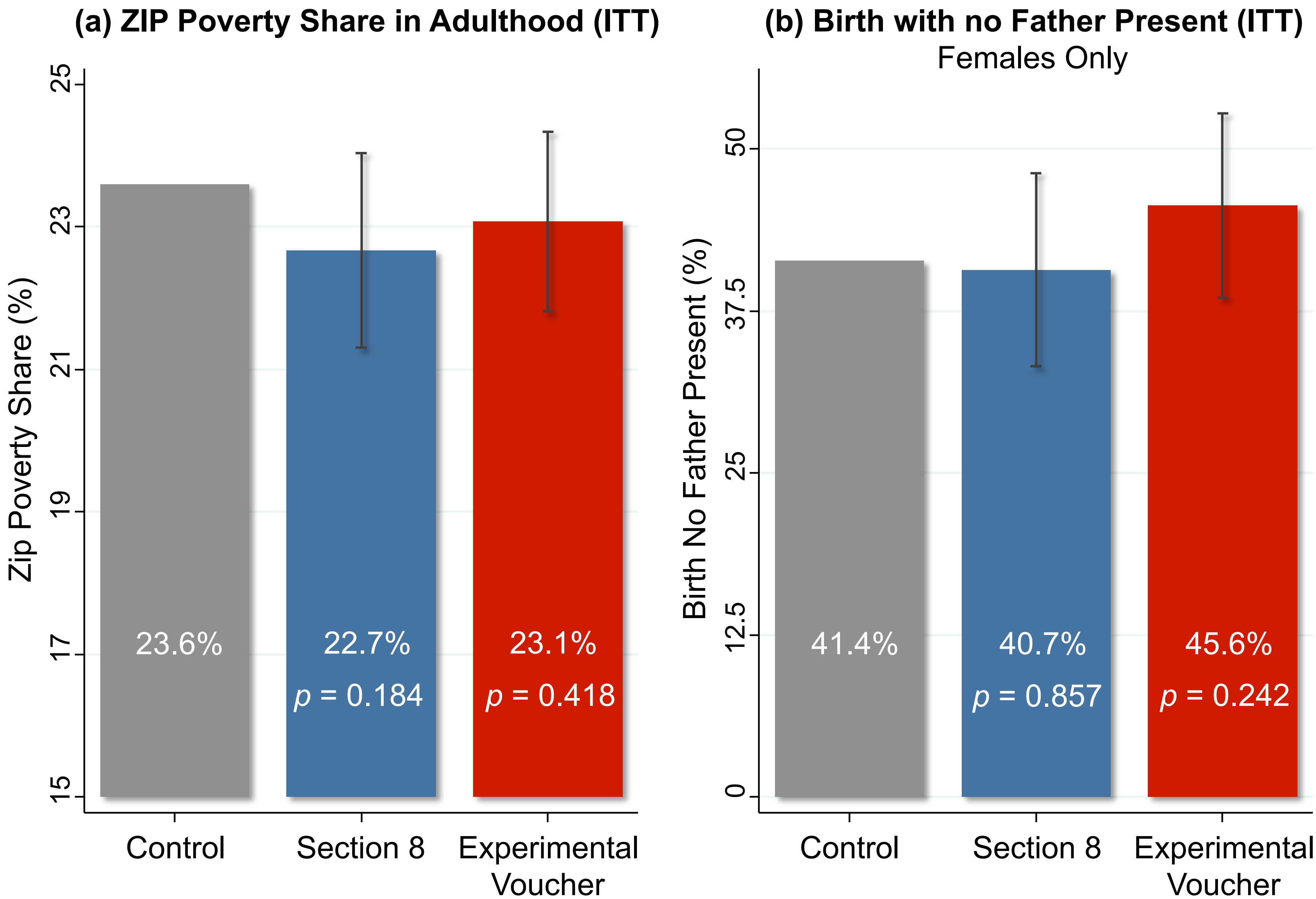


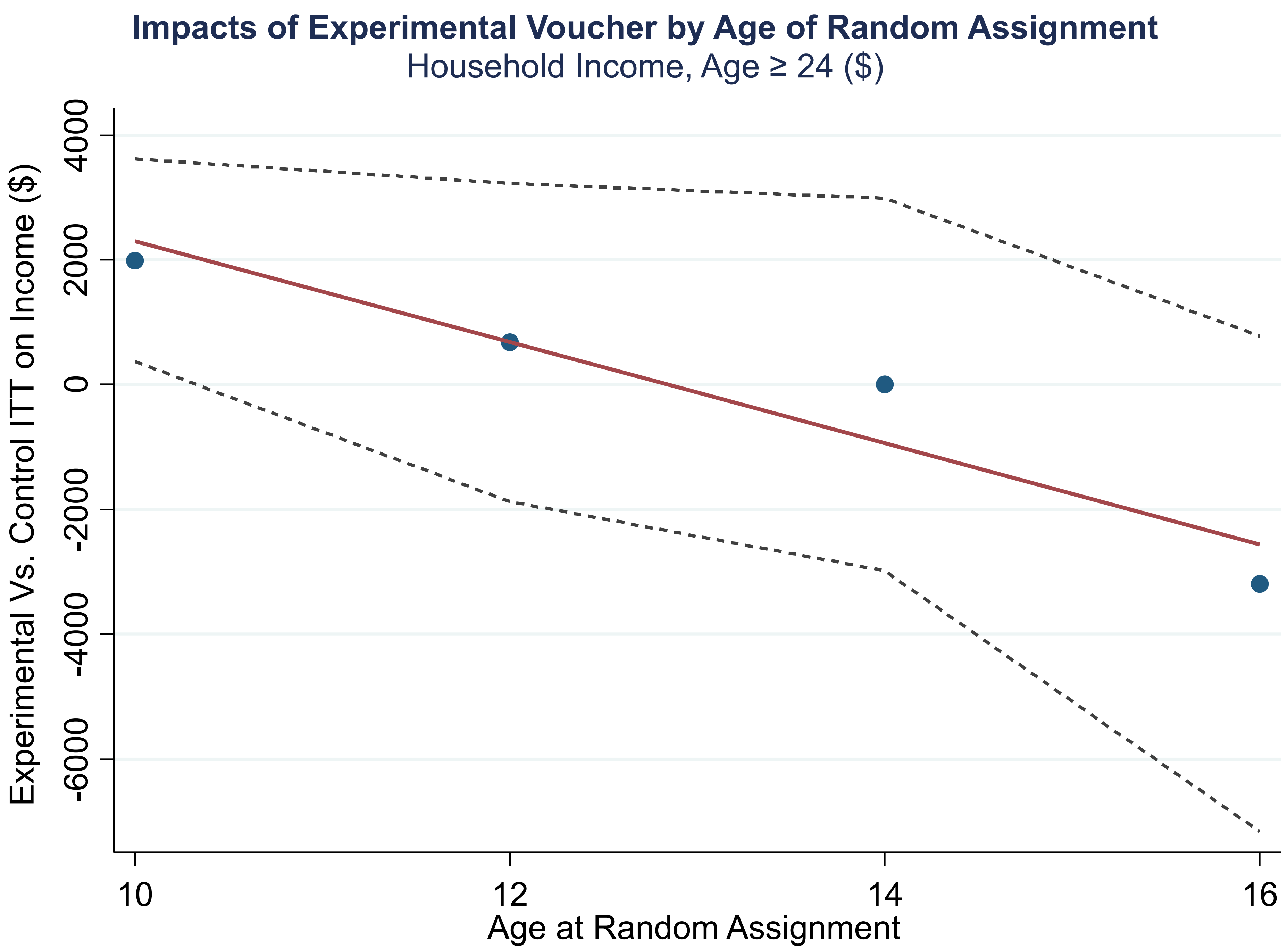
Impacts of MTO on Children Age 13-18 at Random Assignment
(a) Individual Earnings (ITT)
(b) Individual Earnings (TOT)
Individual Income at Age ≥ 24 ($)
5000
7000
9000
11000
13000
15000
17000
$15,882
$14,749
p = 0.219
$14,915
p = 0.259
$15,882
$13,830
p = 0.219
$13,455
p = 0.259
Control
Section 8
Experimental Voucher



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





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

Part 2
Estimates of Causal Place Effects

Estimating Causal Effects of Each County

- Part 1 of our analysis establishes that neighborhoods matter, but it does not tell us which places are good and which are not

- Part 2: estimate causal effects of each county and CZ in the U.S. on children’s earnings in adulthood

County-Level Estimates: Four Steps

- We characterize each county and CZ’s causal effect in four steps

1. Estimate fixed effects of each county using movers
2. Estimate variance components of latent variable model of nbhd. effects
3. Construct optimal predictors (shrunk estimates) of each county’s effect
4. Characterize features of areas that produce high vs. low levels of mobility

Step 1: Fixed Effects Estimation

- 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

Fixed Effects Model

- Estimate place effects $\mu = (\mu_1,\ldots,\mu_N)$ using fixed effects for origin and destination interacted with exposure time:

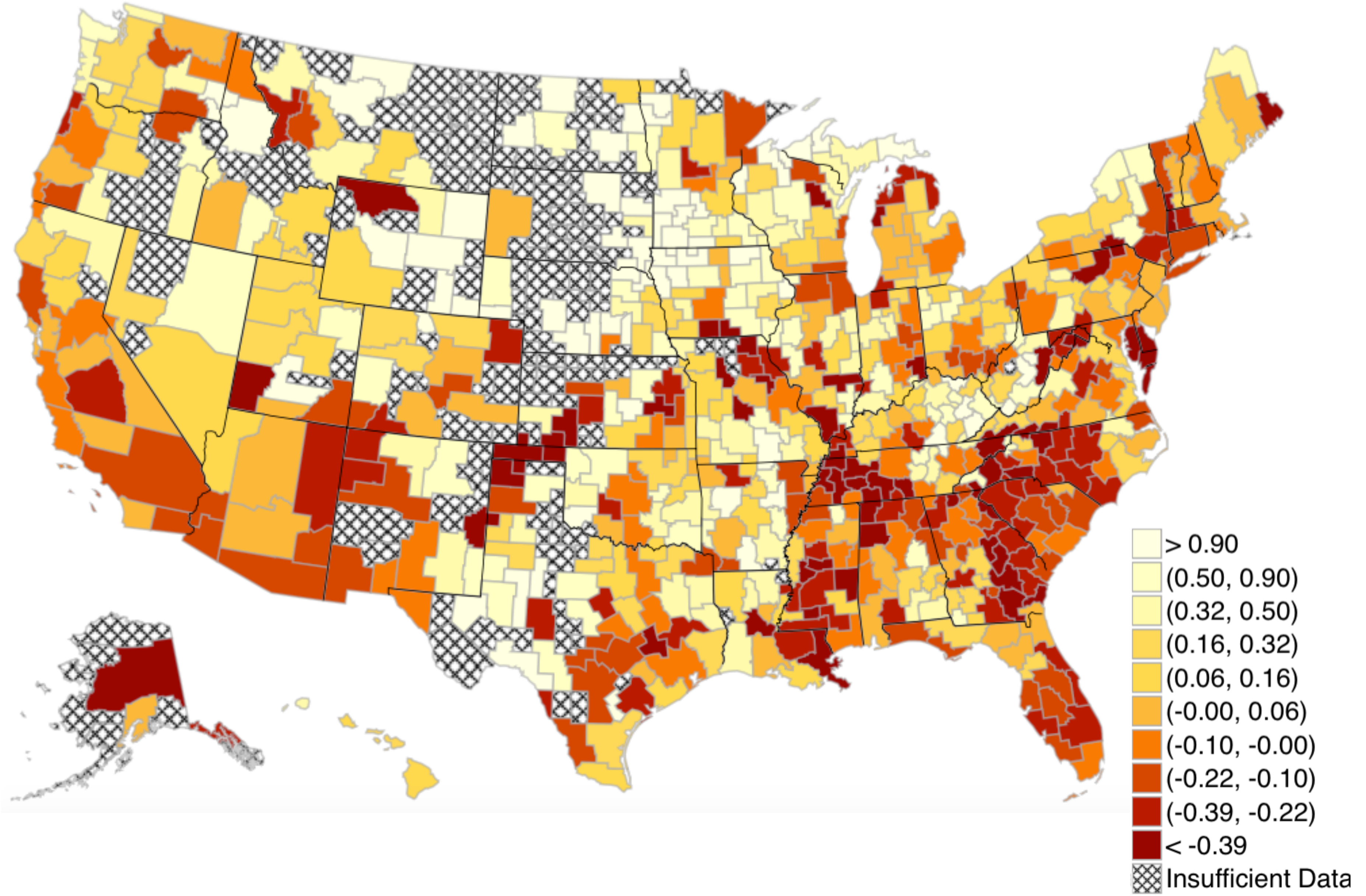
$$y_i = \underbrace{(T_c - m)}_{\text{Exposure}} \left[\underbrace{\mu_d 1\{d(i) = d\}}_{\text{Dest. FE}} - \underbrace{\mu_o 1\{o(i) = o\}}_{\text{Orig. FE.}} \right] + \underbrace{\alpha_{odps}}_{\text{orig x Dest FE}} + \eta_i$$

- Place effects are allowed to vary linearly with parent income rank:

$$\mu_c = \mu_c^0 + \mu_c^P p$$

- Include origin-by-destination fixed effects (to isolate variation in exposure) and quadratic birth cohort controls (to eliminate time trends)

CZ Fixed Effect Estimates for Child's Income Rank at Age 26
For Children with Parents at 25th Percentile of Income Distribution



Note: Estimates represent annual exposure effects on child's rank in income distribution at age 26

Step 2: Estimation of Variance Components

- Fixed effect estimates are the sum of latent causal effect of each place μ_{pc} and estimation error ε_{pc}
  - Variance of fixed effects therefore overstates true variance of causal effects of place
- Estimate magnitude of neighborhood effects by subtracting noise variance (due to sampling error) from total variance

Estimation of Variance Components

- Signal SD of annual exposure effect is σ_μ = 0.17 percentiles = 0.5% across counties for parents at 25th percentile
  - 1 SD better county from birth → 10% earnings gain
  - 1/3 as large as 1 SD increase in parent income
- For children at p75 (high-income families), signal SD of annual exposure effects = 0.16 percentiles = 0.3% effect on mean earnings
- Correlation of place effects for p25 and p75 across counties is +0.3
  - Places that are better for the poor are not worse for the rich

Estimation of Variance Components

- Variance components allow us to quantify degree of signal vs. noise in each fixed effect estimates
  - In largest counties, signal accounts for 75% of variance
  - In smaller counties, more than half of the variance is due to noise
  - Therefore raw fixed effect estimates do not provide reliable predictions of each county’s causal effect on a given child

Step 3: Optimal Forecasts of Place Effects

- Construct more reliable forecasts using a simple shrinkage estimator

- Goal: forecast each county's causal effect, minimizing mean-squared-error of prediction

- Optimal forecast is a weighted average of raw fixed effect based on movers and prediction based on permanent residents

  - Permanent residents' effects are very precise (large samples) but are biased by selection

  - Fixed effect estimates based on movers are noisy but unbiased estimates of each county's causal effect

Optimal Forecasts of Place Effects

- To derive optimal forecast, consider hypothetical experiment of randomly assigning children from an average place to new places

- Regress outcomes y_i on fixed-effect estimate and stayers prediction:

$$y_{ipc} = \alpha + \rho_{1,pc}\bar{y}_{pc} + \rho_{2,pc}\hat{\mu}_{pc}$$

- This yields regression coefficients:

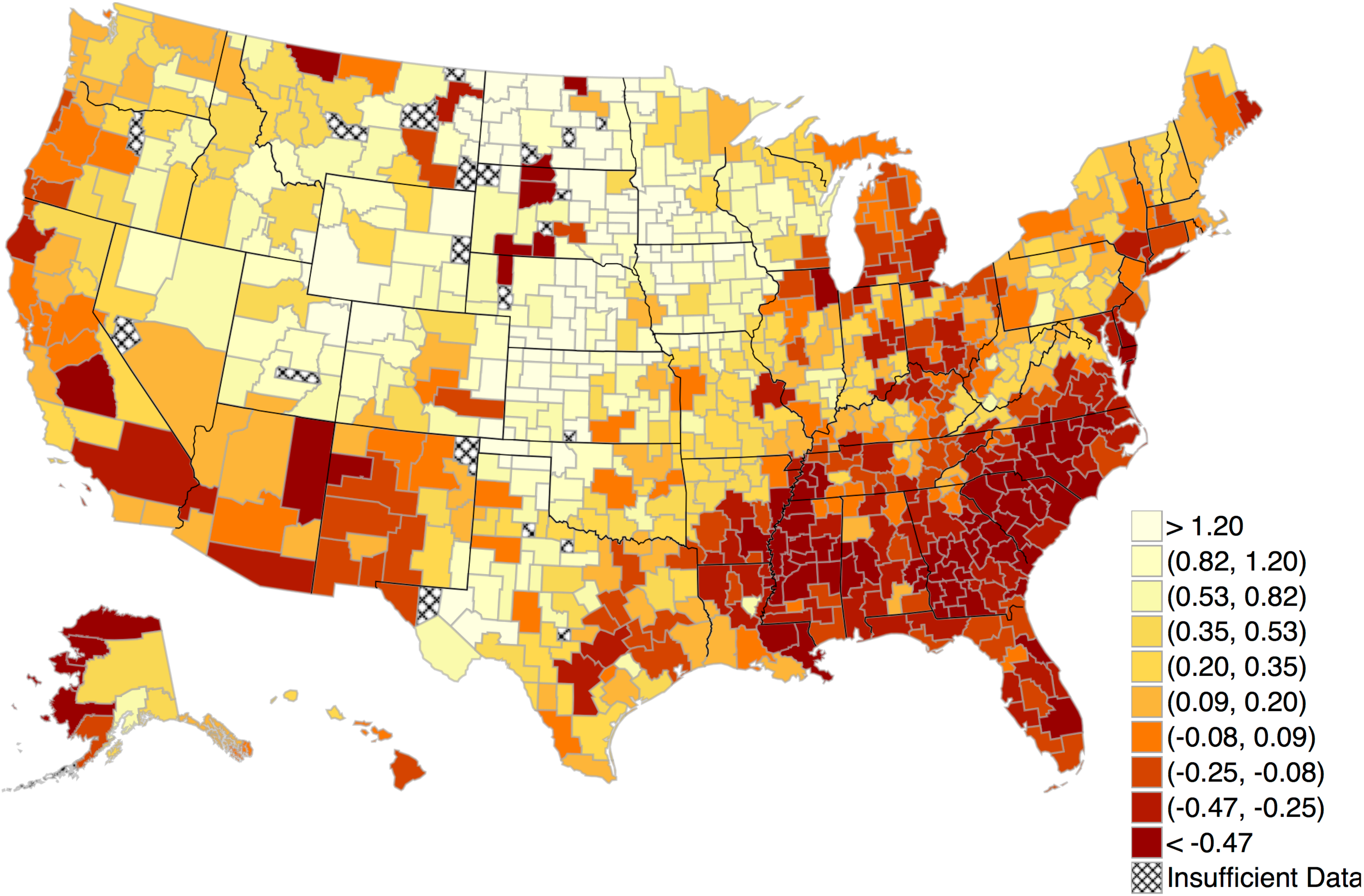
$$\rho_{1,pc} = \beta\frac{\sigma^2_{\varepsilon,pc}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}} \qquad \rho_{2,pc} = \frac{\sigma^2_{\nu,p}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}}$$

where σ_ν^2 is residual variance of fixed effects after regressing on stayers

- Optimal forecast weights movers fixed effect more heavily in large counties (less noise) and permanent residents more heavily in small counties

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

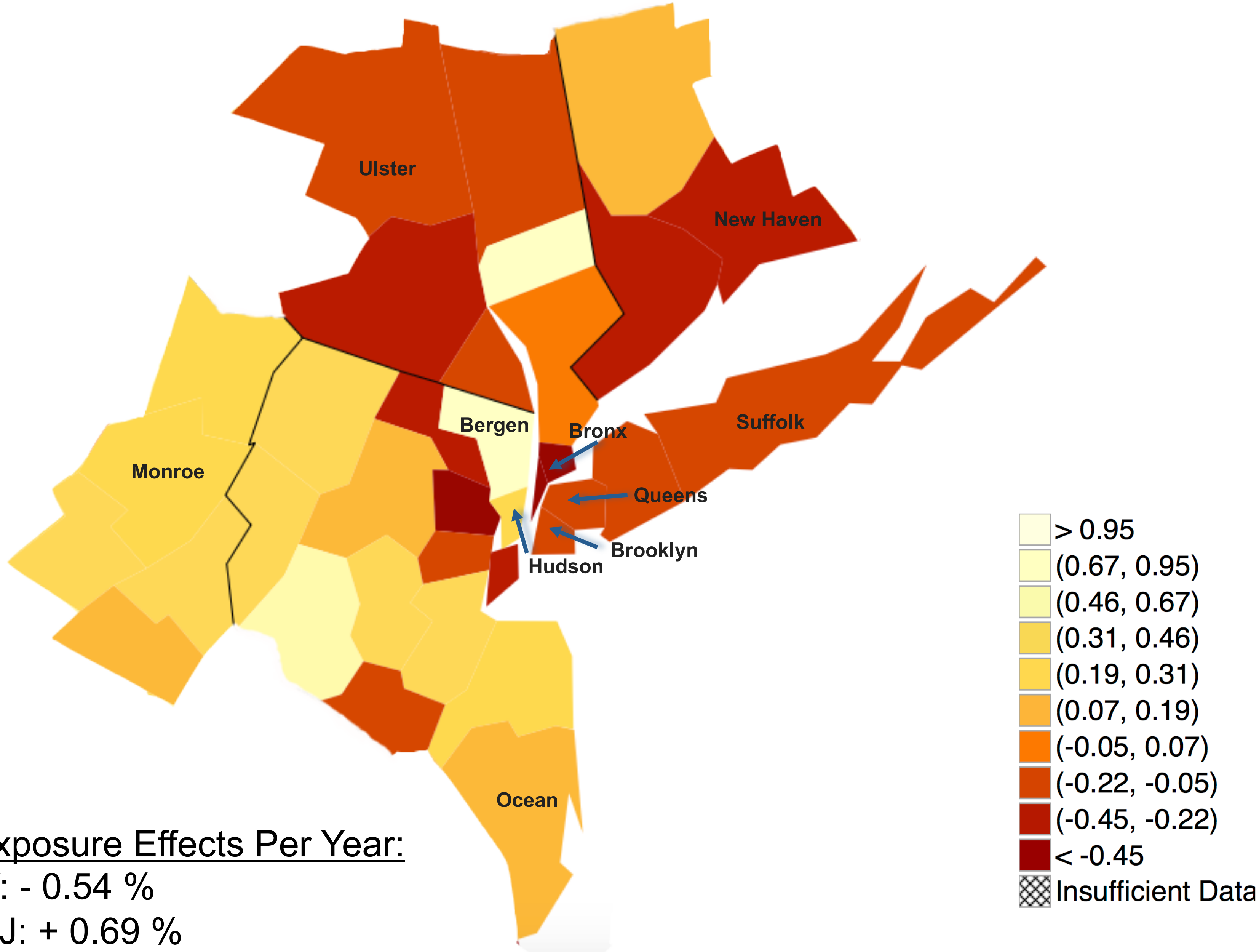
For Children with Parents at 25th Percentile of Income Distribution



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



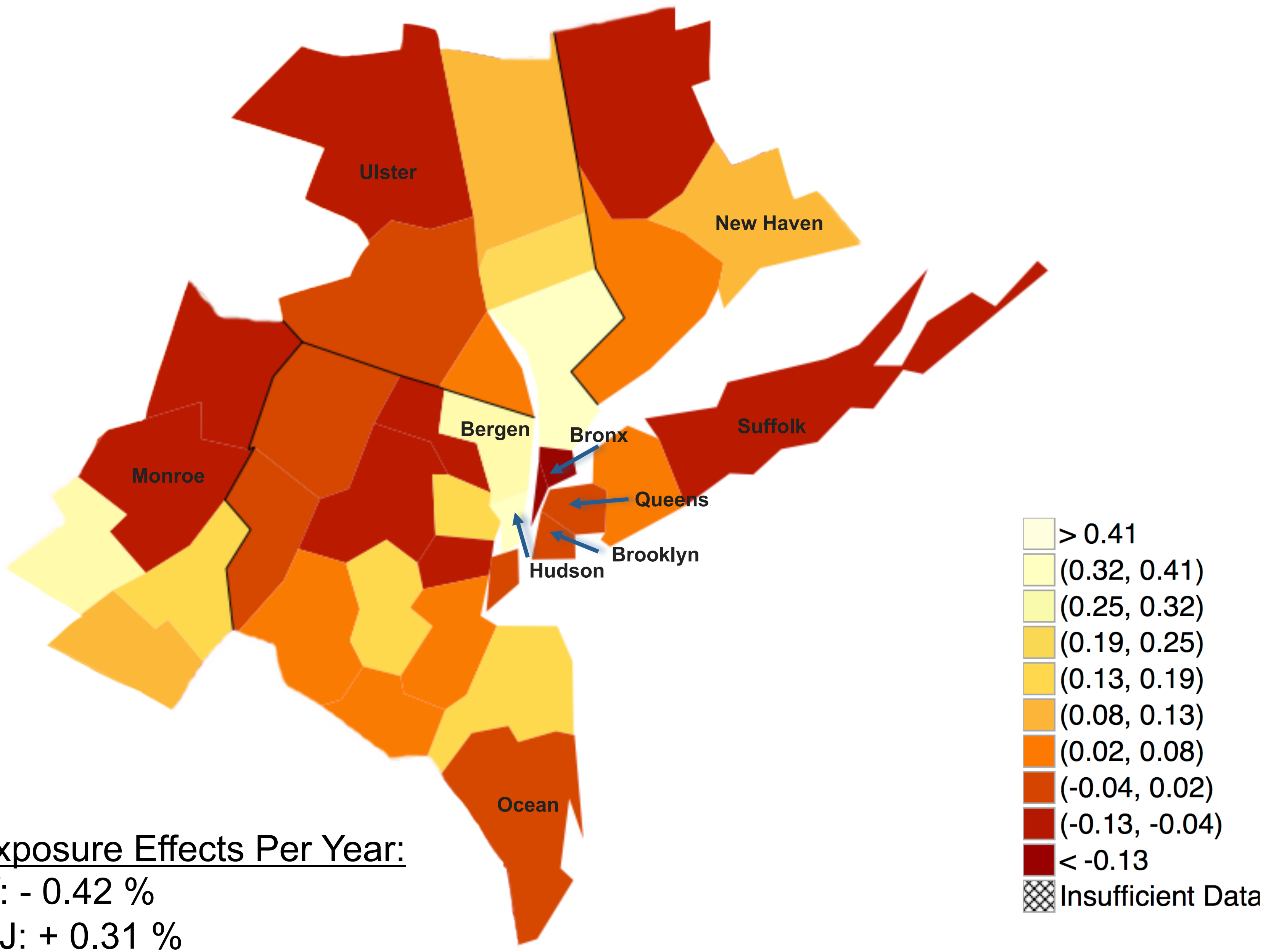
Causal Exposure Effects Per Year:

Bronx NY: - 0.54 %

Bergen NJ: + 0.69 %

Exposure Effects on Income in the New York CSA

For Children with Parents at 75th Percentile of Income Distribution

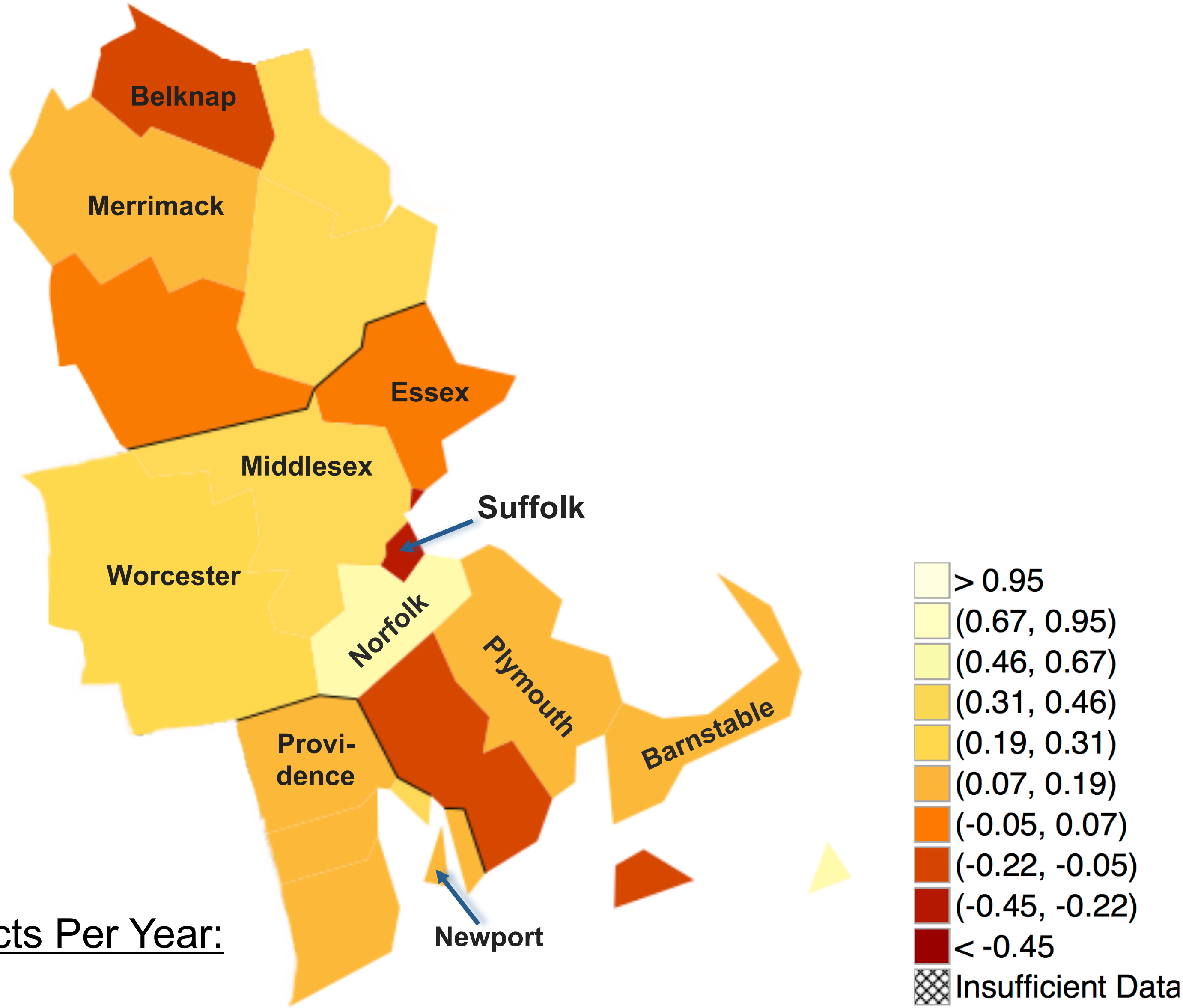


<u>Causal Exposure Effects Per Year:</u>

Bronx NY: - 0.42 %

Bergen NJ: + 0.31 %

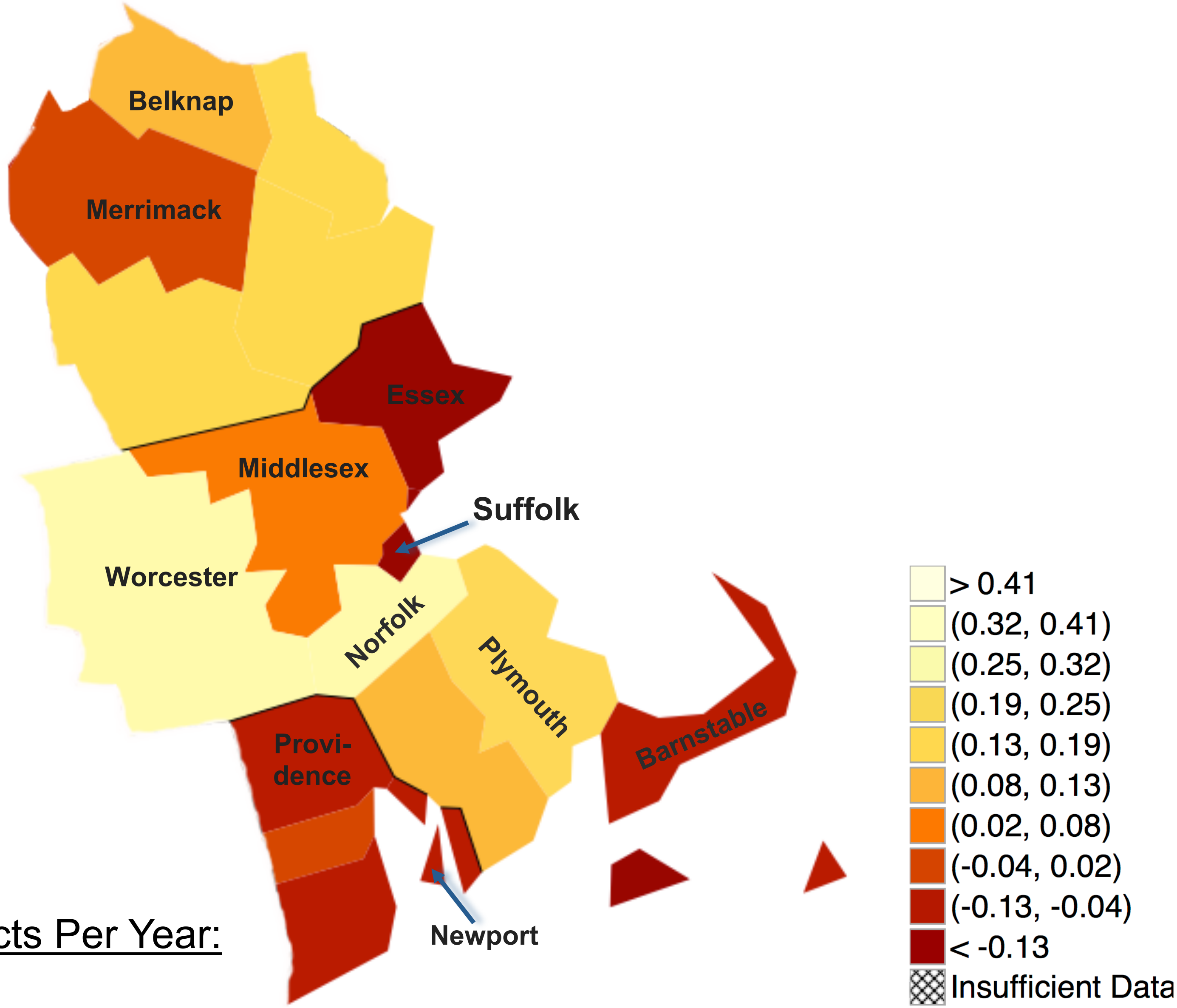
Exposure Effects on Income in the Boston CSA
For Children with Parents at 25th Percentile of Income Distribution



<u>Causal Exposure Effects Per Year:</u>
Suffolk MA: - 0.31 %
Middlesex MA: + 0.39 %

Exposure Effects on Income in the Boston CSA

For Children with Parents at 75th Percentile of Income Distribution



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

Suffolk MA: - 0.18 %

Middlesex MA: + 0.03 %

Annual Exposure Effects on Income for Children in Low-Income Families (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

Annual Exposure Effects on Income for Children in High-Income Families (p75)

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	Fairfax, VA	0.55	91	Hillsborough, FL	-0.40
2	Westchester, NY	0.34	92	Bronx, NY	-0.42
3	Hudson, NJ	0.33	93	Broward, FL	-0.46
4	Hamilton, OH	0.32	94	Dist. of Columbia, DC	-0.48
5	Bergen, NJ	0.31	95	Orange, CA	-0.49
6	Gwinnett, GA	0.31	96	San Bernardino, CA	-0.51
7	Norfolk, MA	0.31	97	Riverside, CA	-0.51
8	Worcester, MA	0.27	98	Los Angeles, CA	-0.52
9	Franklin, OH	0.24	99	New York, NY	-0.57
10	Kent, MI	0.23	100	Palm Beach, FL	-0.65

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

Annual Exposure Effects on Income for Children in Low-Income Families (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

Annual Exposure Effects on Income for Children in Low-Income Families (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

Step 4: Characteristics of Good Areas

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

- Observed upward mobility is strongly correlated with five factors [CHKS 2014]

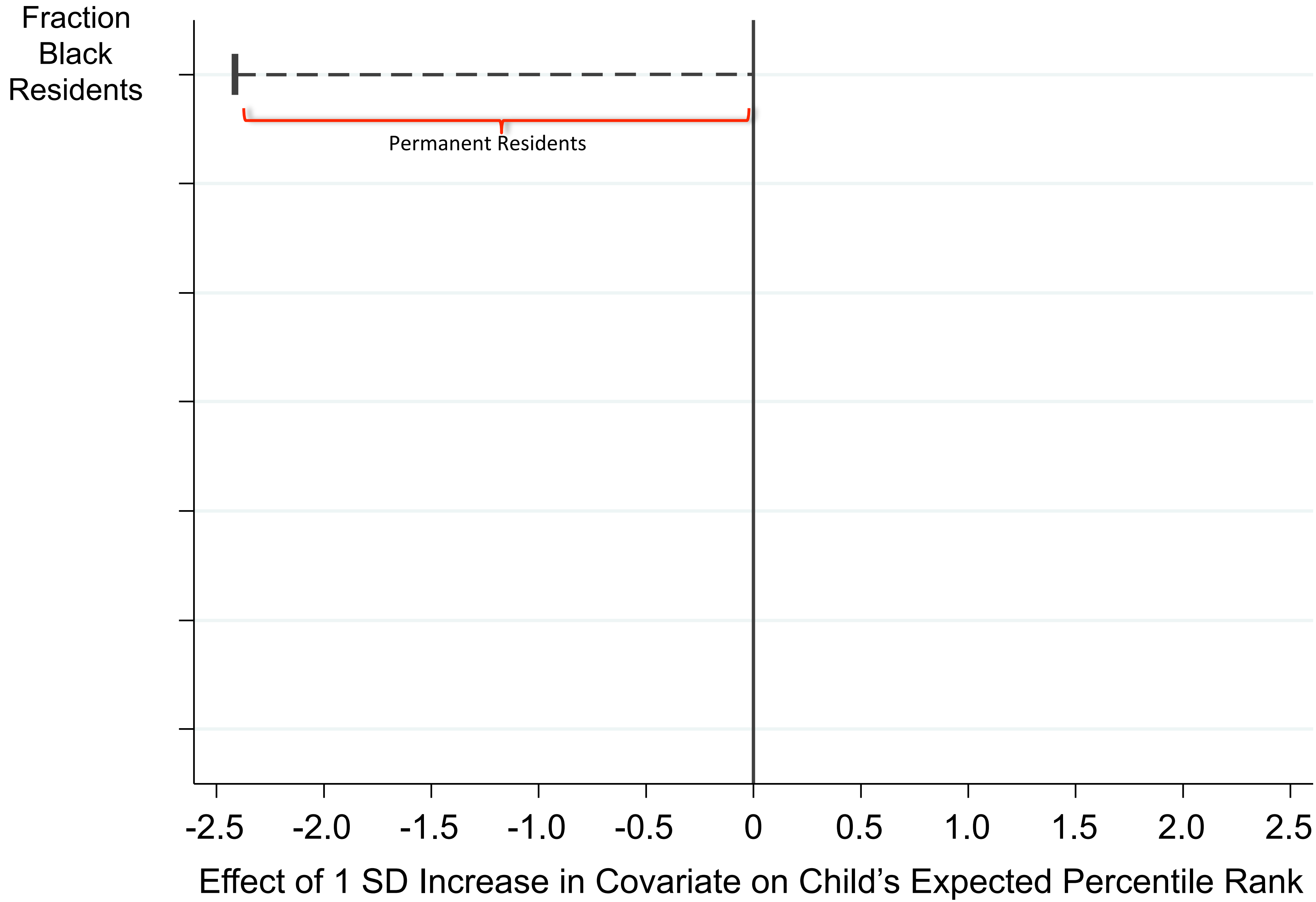
  - Segregation, Inequality, School Quality, Social Capital, Family Structure

- Are these characteristics of areas with positive causal effects (good places) or positive selection (good families)?

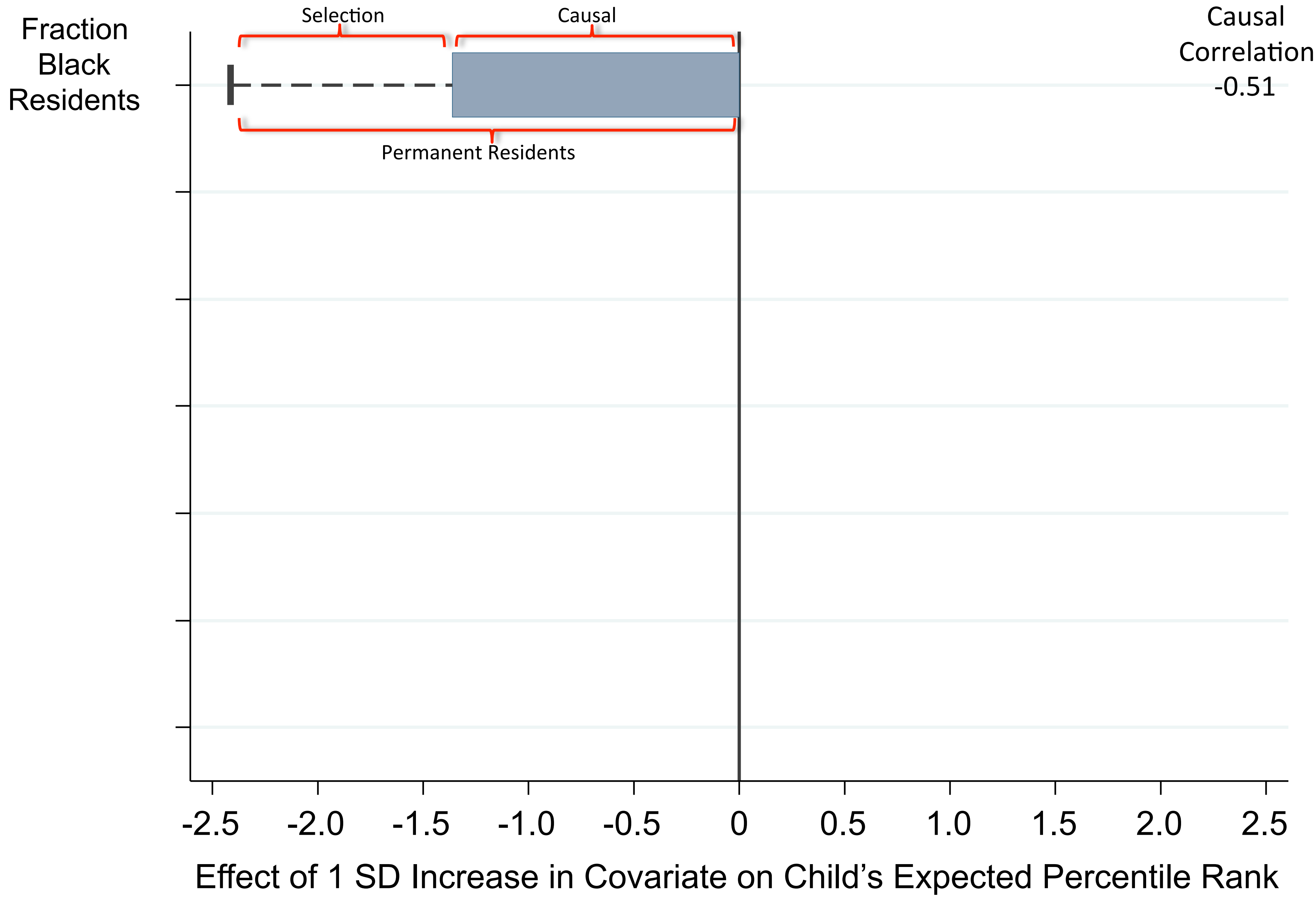
Step 4: Characteristics of Good Areas

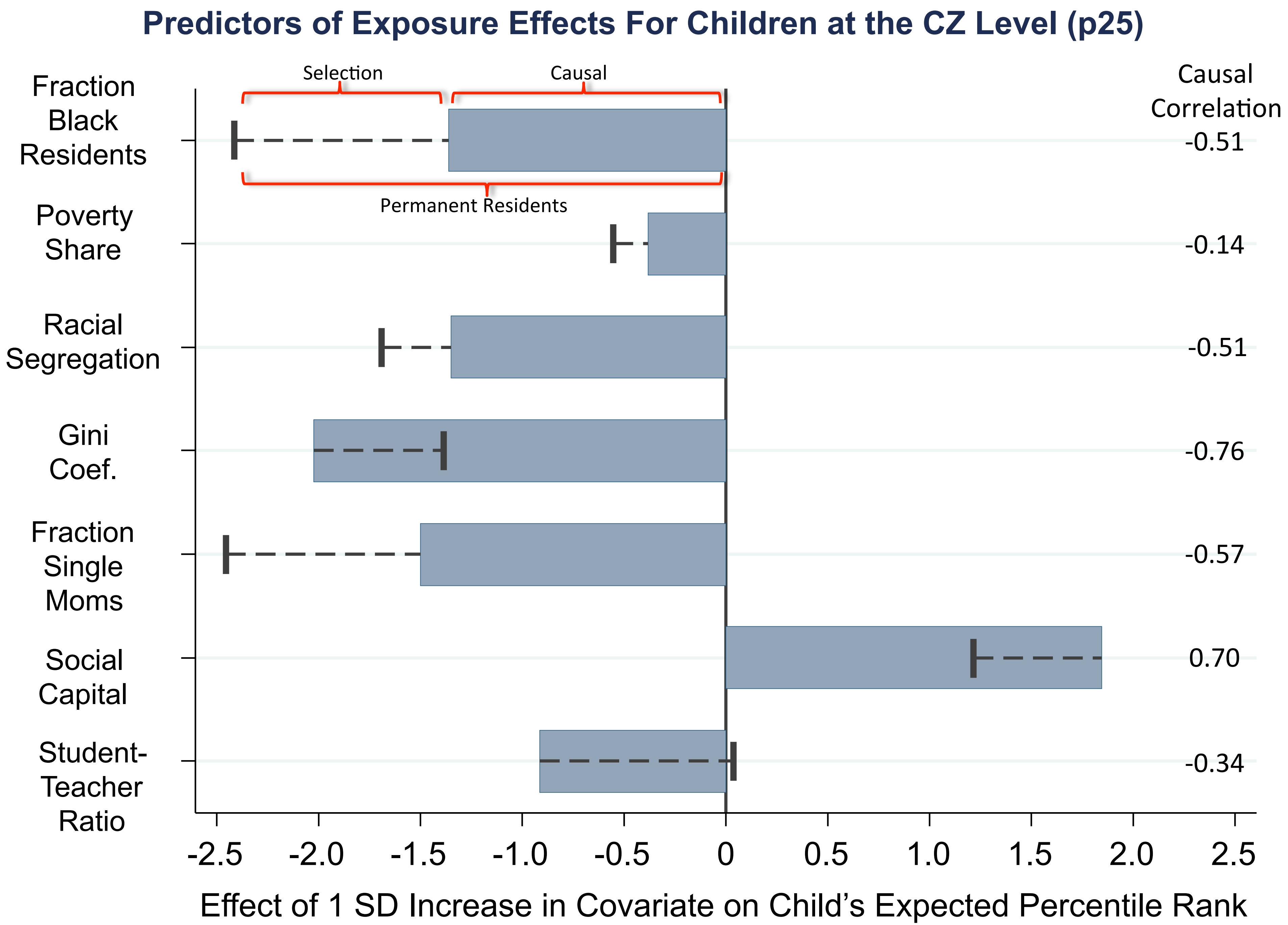
- Decompose observed rank for stayers (y_{pc}) into causal and sorting components by multiplying annual exposure effect μ_{pc} by 20:
  - Causal component = $20\mu_{pc}$
  - Sorting component = $y_{pc} – 20\mu_{pc}$
- Regress y_{pc}, causal, and sorting components on covariates
  - Standardize covariates so units represent impact of 1 SD change in covariate on child's percentile rank
    - Multiply by 3 to get percentage effects at p25

Predictors of Exposure Effects For Children at the CZ Level (p25)



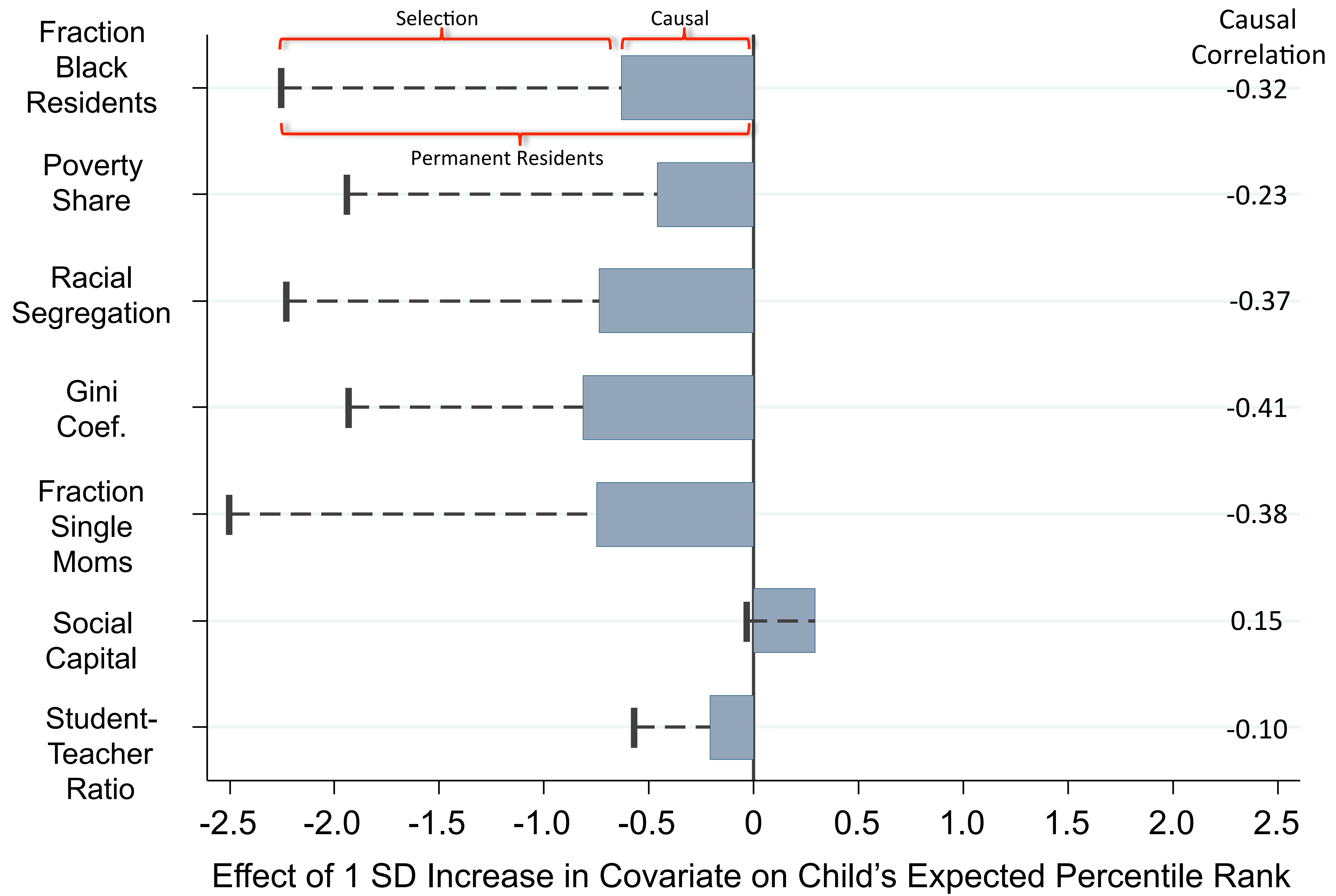
Predictors of Exposure Effects For Children at the CZ Level (p25)



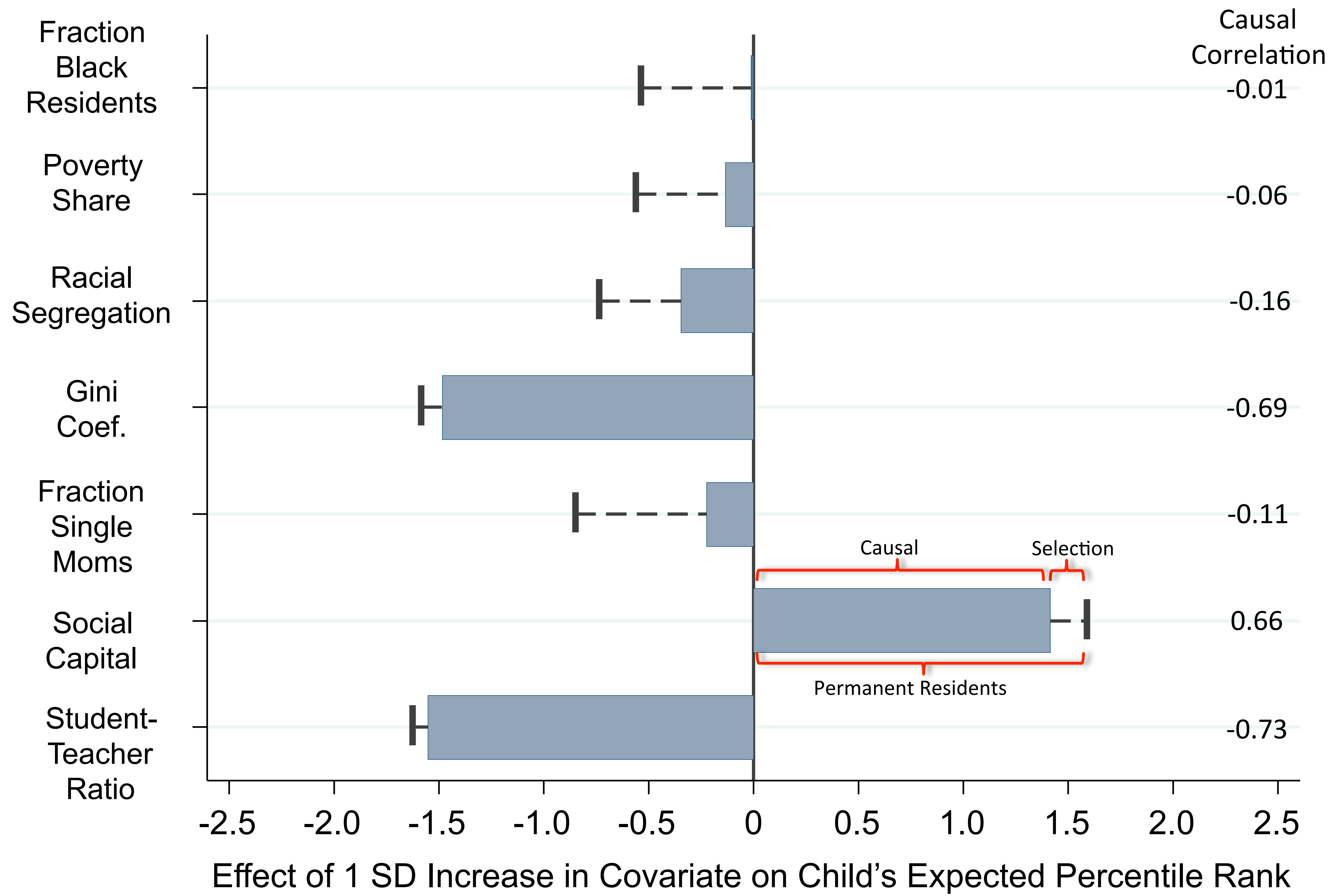


Predictors of Exposure Effects For Children at the CZ Level (p25)
Selection
Causal
Permanent Residents
Causal Correlation
Fraction Black Residents
-0.51
Poverty Share
-0.14
Racial Segregation
-0.51
Gini Coef.
-0.76
Fraction Single Moms
-0.57
Social Capital
0.70
Student-Teacher Ratio
-0.34
-2.5
-2.0
-1.5
-1.0
-0.5
0
0.5
1.0
1.5
2.0
2.5
Effect of 1 SD Increase in Covariate on Child's Expected Percentile Rank

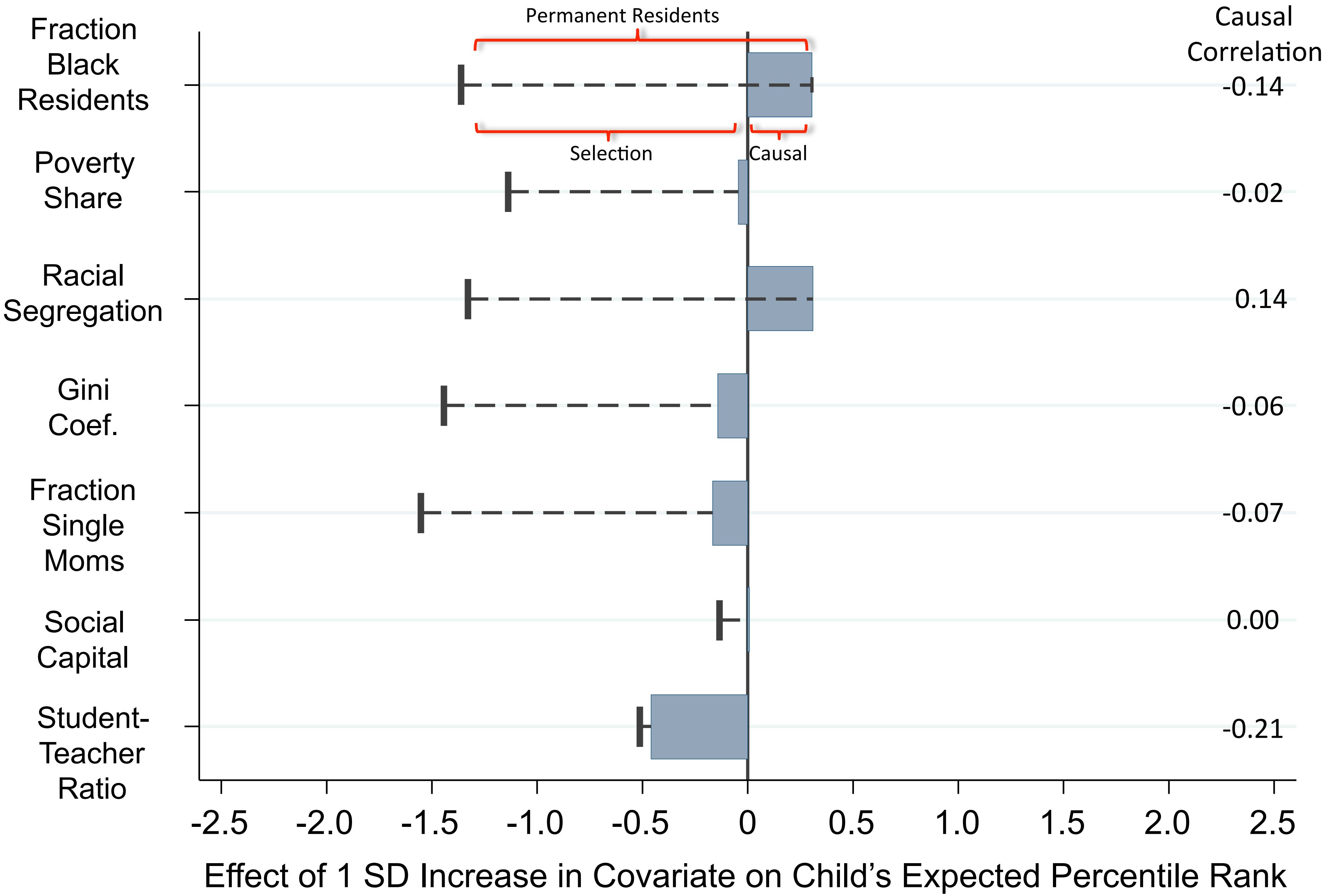
Predictors of Exposure Effects For Children at the County within CZ Level (p25)



Predictors of Exposure Effects For Children at the CZ Level (p75)



Predictors of Exposure Effects For Children at the County within CZ Level (p75)



Conclusion: Ex-ante versus Ex-post Policies

- Growing body of evidence suggests ex-ante policies targeted to children may be more efficient at providing redistribution

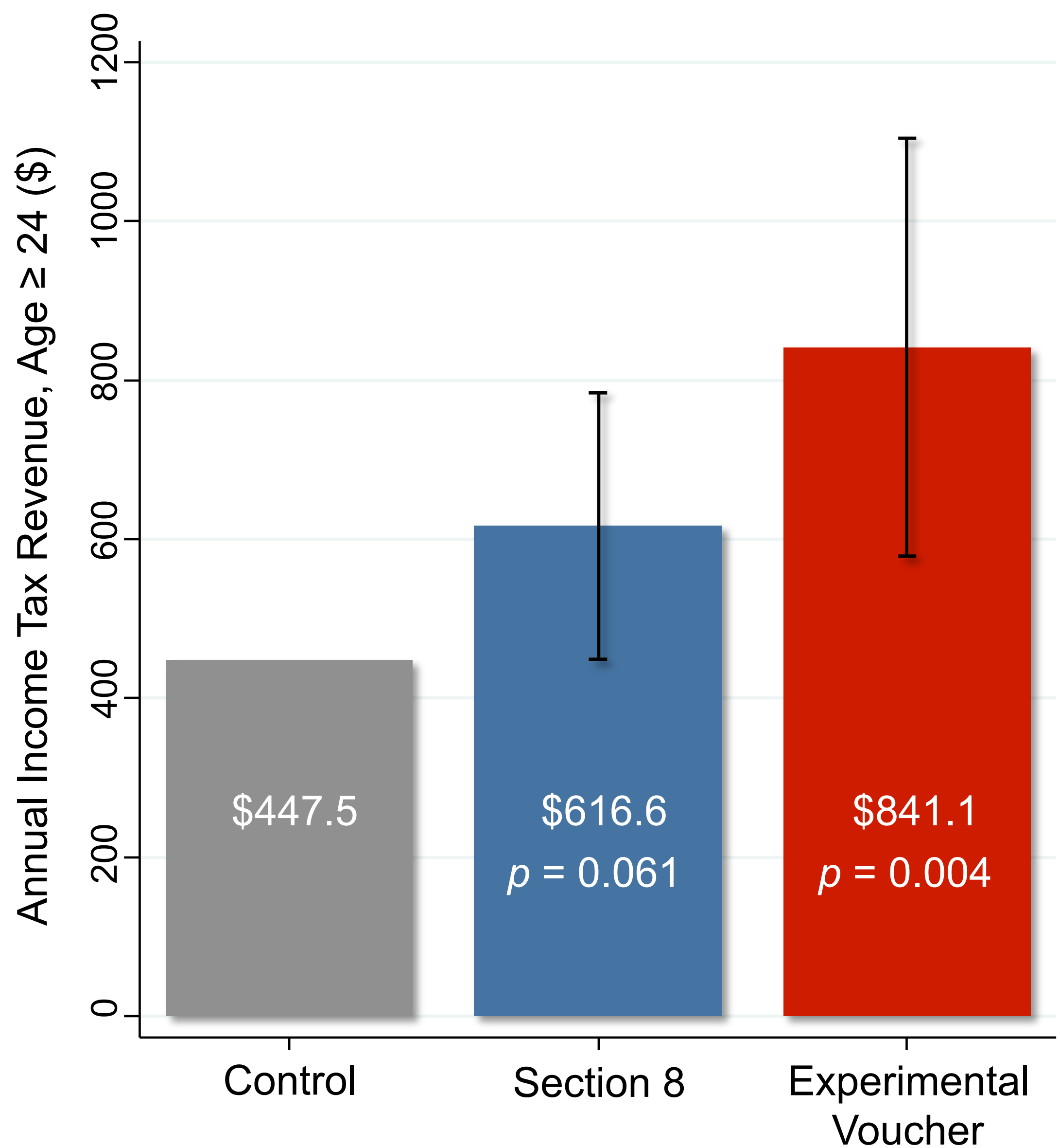
- MTO / Place-based policies
  - No impacts on adults (Kling et al. 2007, ECMA)
  - Strong impacts on young kids (Chetty, Hendren, and Katz 2015)

- Medicaid
  - Adult expansion increases utilization with minimal health impacts (Finkelstein et al. 2015)
  - Medicaid for children decreases long-run costs (Wherry et al 2015)

- Food Stamps / SNAP
  - Distortionary labor impacts on adults (Hoynes and Schanzenbach 2012, AEJ)
  - Positive impacts on children (Hoynes, Schanzenbach, and Almond 2015)

- Lesson: Becker's model was right – role of human capital formation

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



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

www.equality-of-opportunity.org/data

THE EQUALITY OF OPPORTUNITY PROJECT

HOME | EXECUTIVE SUMMARIES | PAPERS | SLIDES & VIDEOS | CITY RANKINGS | DOWNLOAD DATA | FAQ'S | RESEARCH TEAM | PREVIOUS RESEARCH | PRESS | CONTACT US

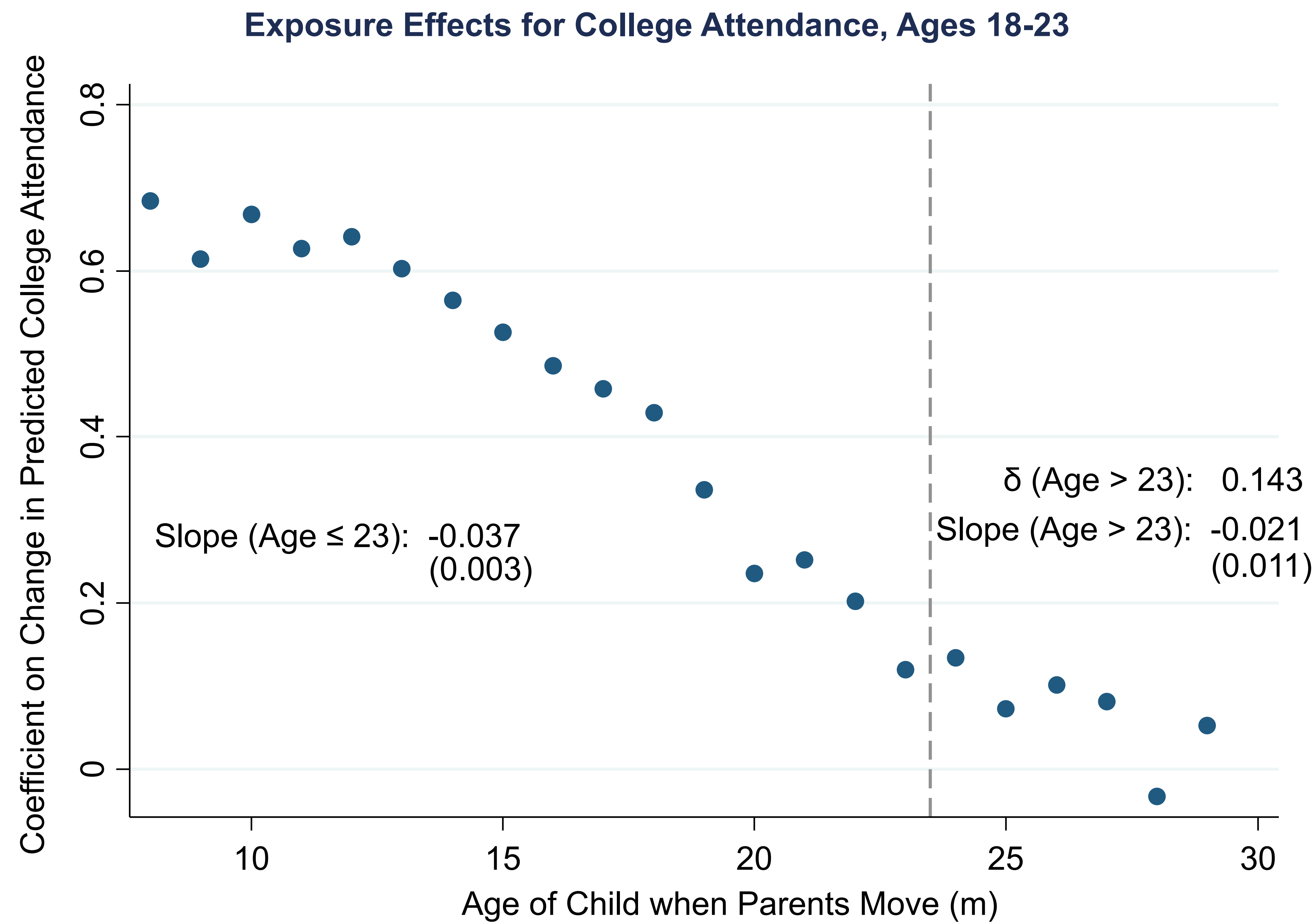
Downloadable Data

Data from Chetty and Hendren (2015): Causal Effects, Mobility Estimates and Covariates by County, CZ and Birth Cohort

Data Description			
Online Data Table 1: Preferred Estimates of Causal Place Effects by Commuting Zone	Stata file	Excel file	ReadMe
Online Data Table 2: Preferred Estimates of Causal Place Effects by County	Stata file	Excel file	ReadMe
Online Data Table 3: Complete CZ-Level Dataset: Causal Effects and Covariates	Stata file	Excel file	ReadMe
Online Data Table 4: Complete County-Level Dataset: Causal Effects and Covariates	Stata file	Excel file	ReadMe
Online Data Table 5: Pairwise Place Effects by Origin-Destination Pairs of Commuting Zones	Stata file	Excel file	ReadMe
Online Data Table 6: Parent Income Distribution by Child's Birth Cohort	Stata file	Excel file	ReadMe

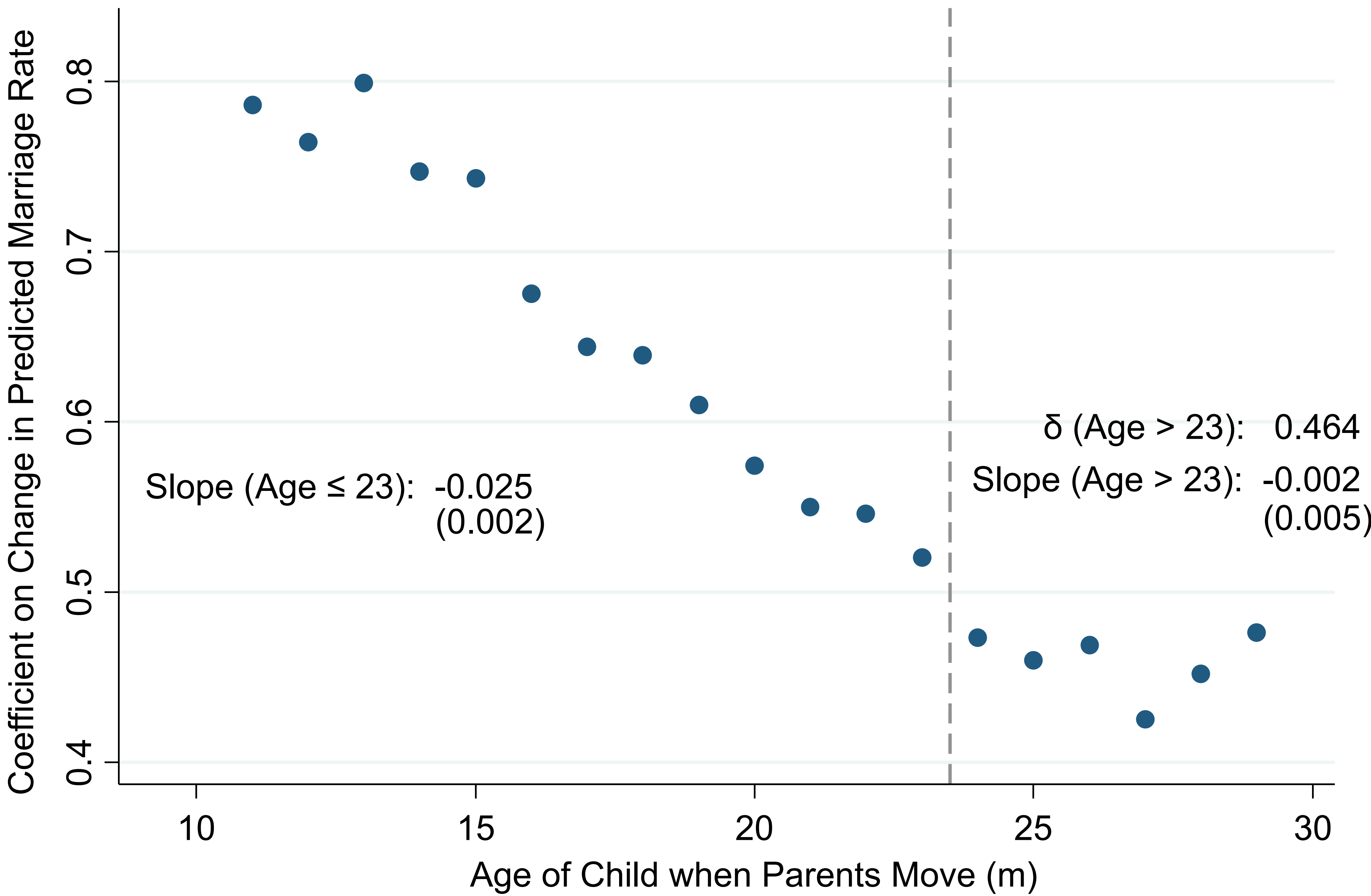
Neighborhood Effects on Other Outcomes

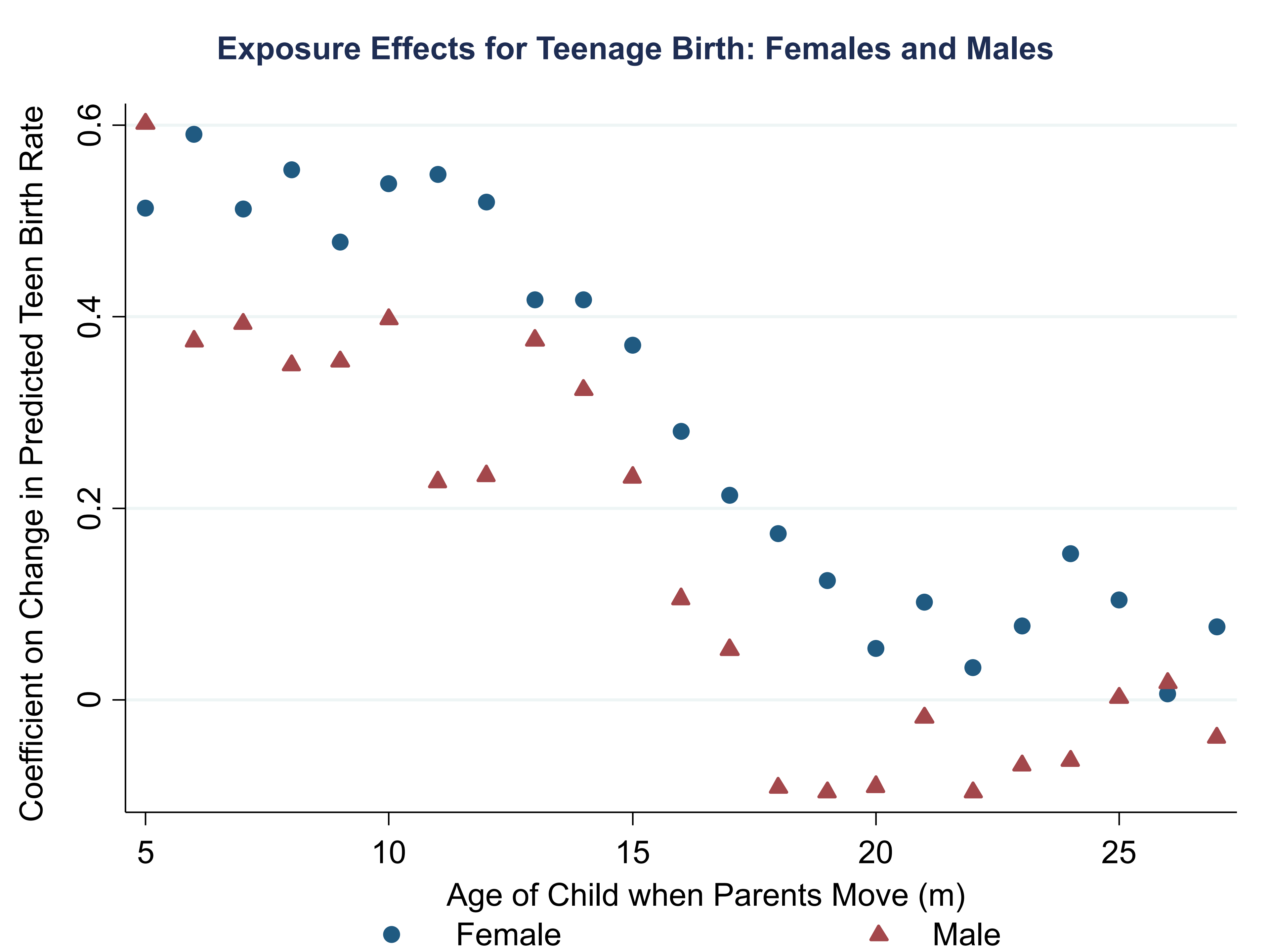
- We also find similar exposure effects for other outcomes:
  - College attendance (from 1098-T forms filed by colleges)
  - Teenage birth (from birth certificate data)
  - Teenage employment (from W-2 forms)
  - Marriage



Exposure Effects for College Attendance, Ages 18-23
Coefficient on Change in Predicted College Attendance
0
0.2
0.4
0.6
0.8
Age of Child when Parents Move (m)
10
15
20
25
30
Slope (Age ≤ 23): -0.037
(0.003)
δ (Age > 23): 0.143
Slope (Age > 23): -0.021
(0.011)

Exposure Effects for Marriage Rate, Age 26





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 (m)
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