The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates

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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 present new quasi-experimental estimates of the effects of neighborhoods on children using data on 5 million movers across U.S. counties
  - Also present a re-analysis of the Moving to Opportunity experiment using new data on children's long-term outcomes
- We find that neighborhoods have significant **childhood exposure effects**
  - Every year spent in a better environment improves long-term outcomes
  - Results help reconcile conflicting findings in prior work and shed light on the characteristics of good neighborhoods

Outline

- 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

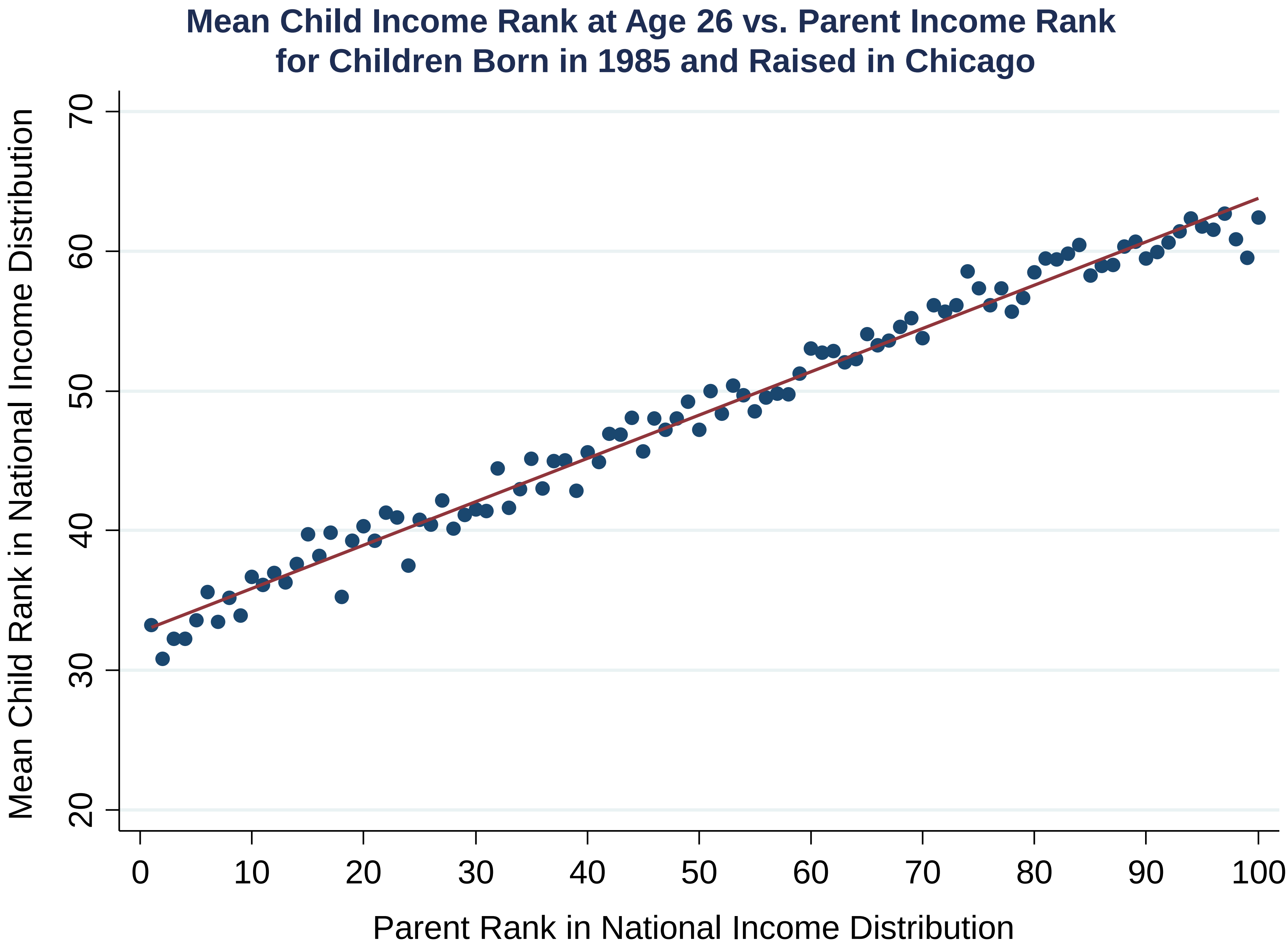
- Begin with a descriptive characterization of children's outcomes in each CZ

- Focus on "permanent residents" of CZs

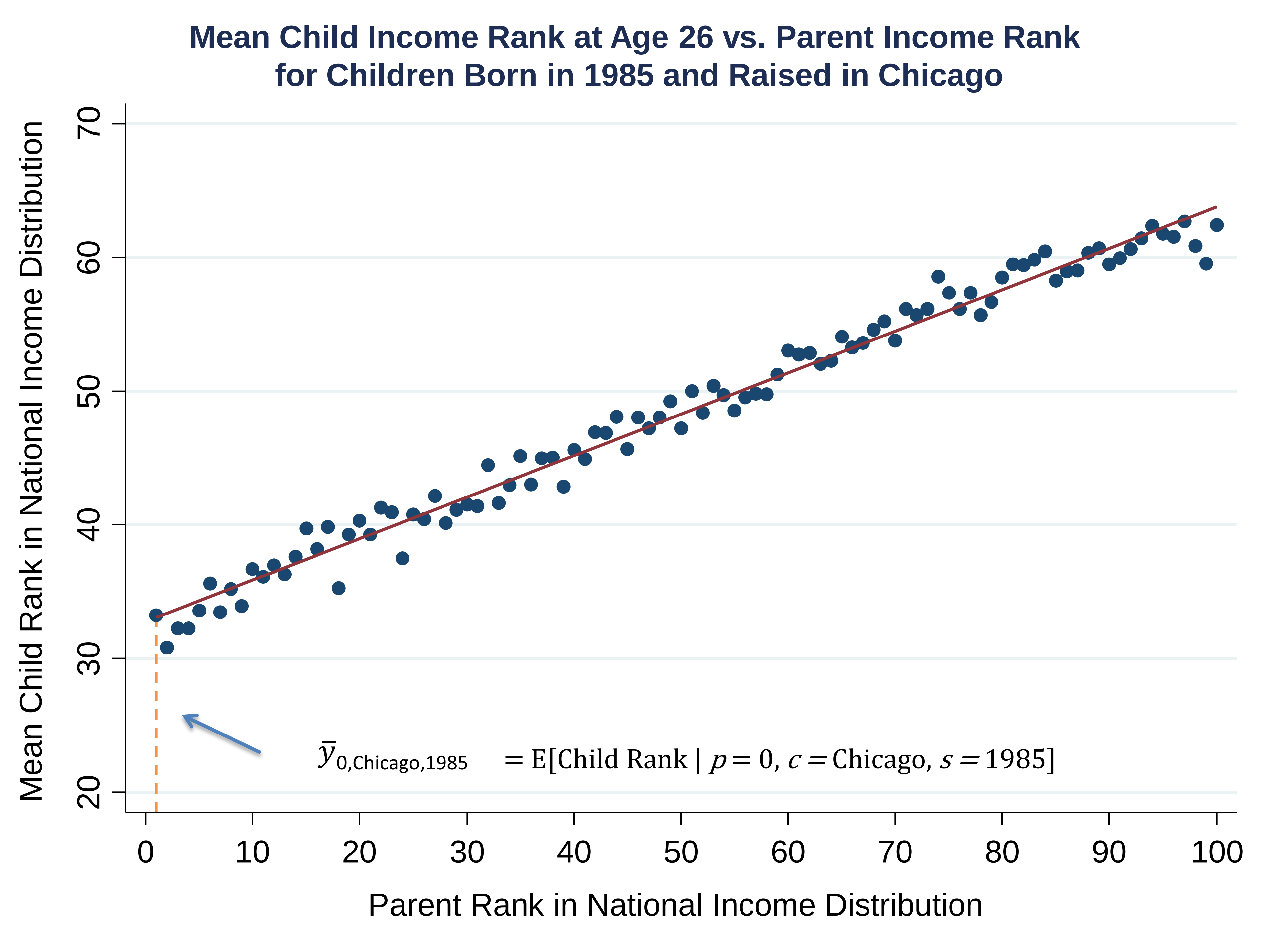
  - Permanent residents = parents who stay in CZ *c* between 1996-2012

  - Note that children who grow up in CZ *c* may move out as adults

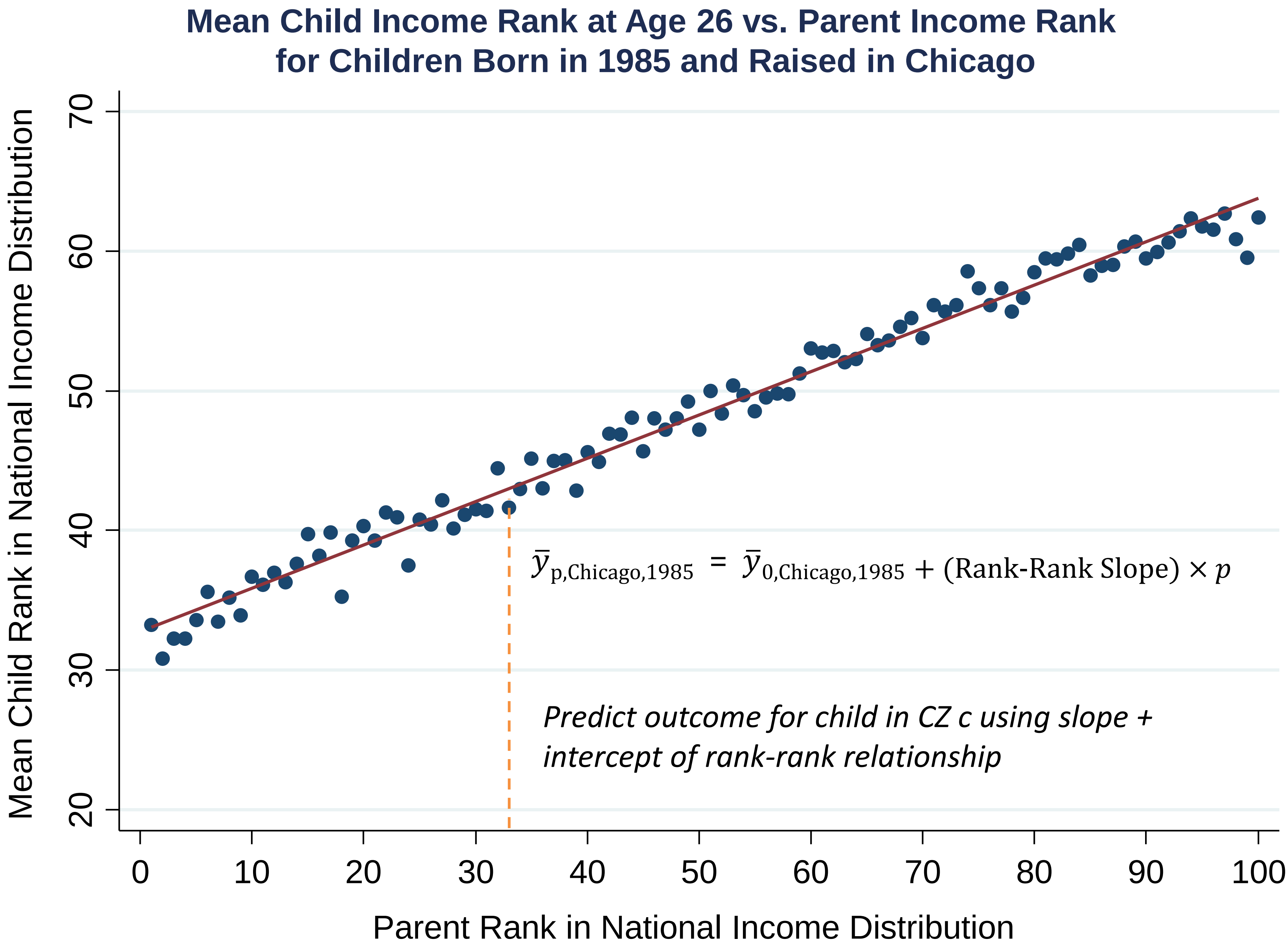
- Characterize relationship between child's income rank and parent's income rank *p* for each CZ *c* and birth cohort *s*



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



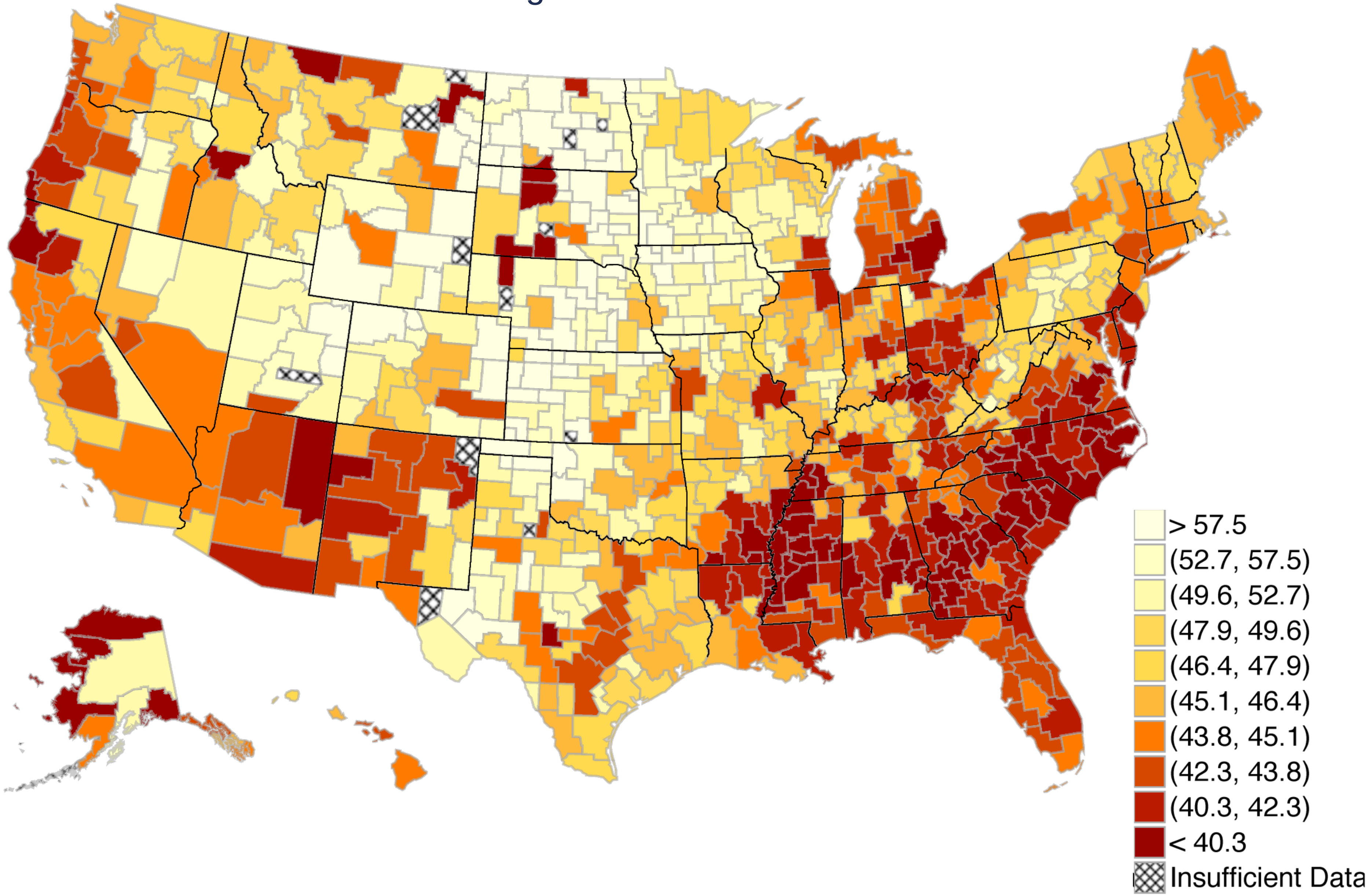
Mean Child Income Rank at Age 26 vs. Parent Income Rank
for Children Born in 1985 and Raised in Chicago
Mean Child Rank in National Income Distribution
20
30
40
50
60
70
0
10
20
30
40
50
60
70
80
90
100
Parent Rank in National Income Distribution
$\bar{y}_{0,\text{Chicago},1985} = \text{E}[\text{Child Rank} \mid p = 0, c = \text{Chicago}, s = 1985]$



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
$\bar{y}_{\text{p,Chicago,1985}} = \bar{y}_{0,\text{Chicago,1985}} + (\text{Rank-Rank Slope}) \times p$
Predict outcome for child in CZ c using slope +
intercept of rank-rank relationship

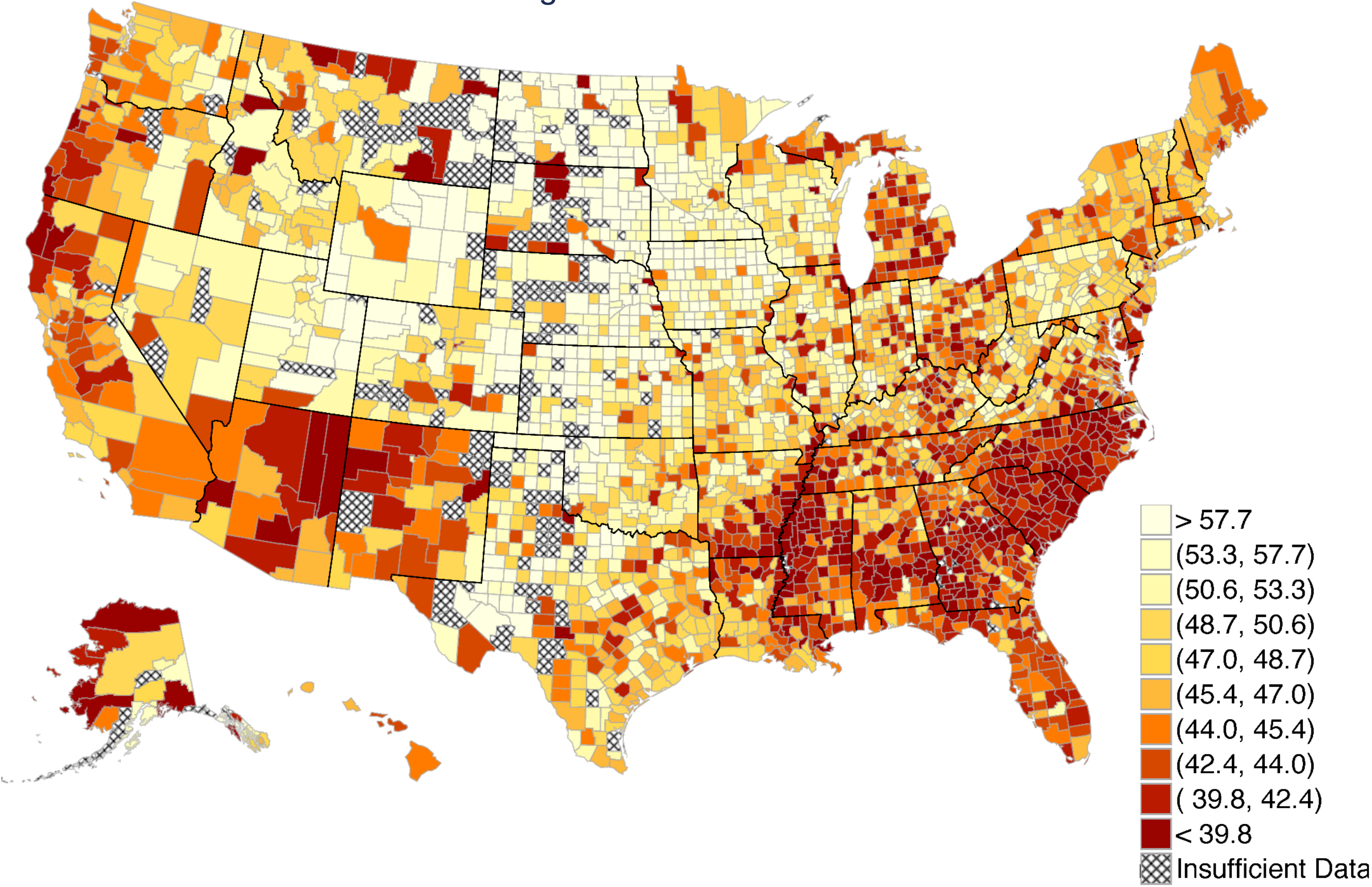
The Geography of Intergenerational Mobility in the United States

Predicted Income Rank at Age 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

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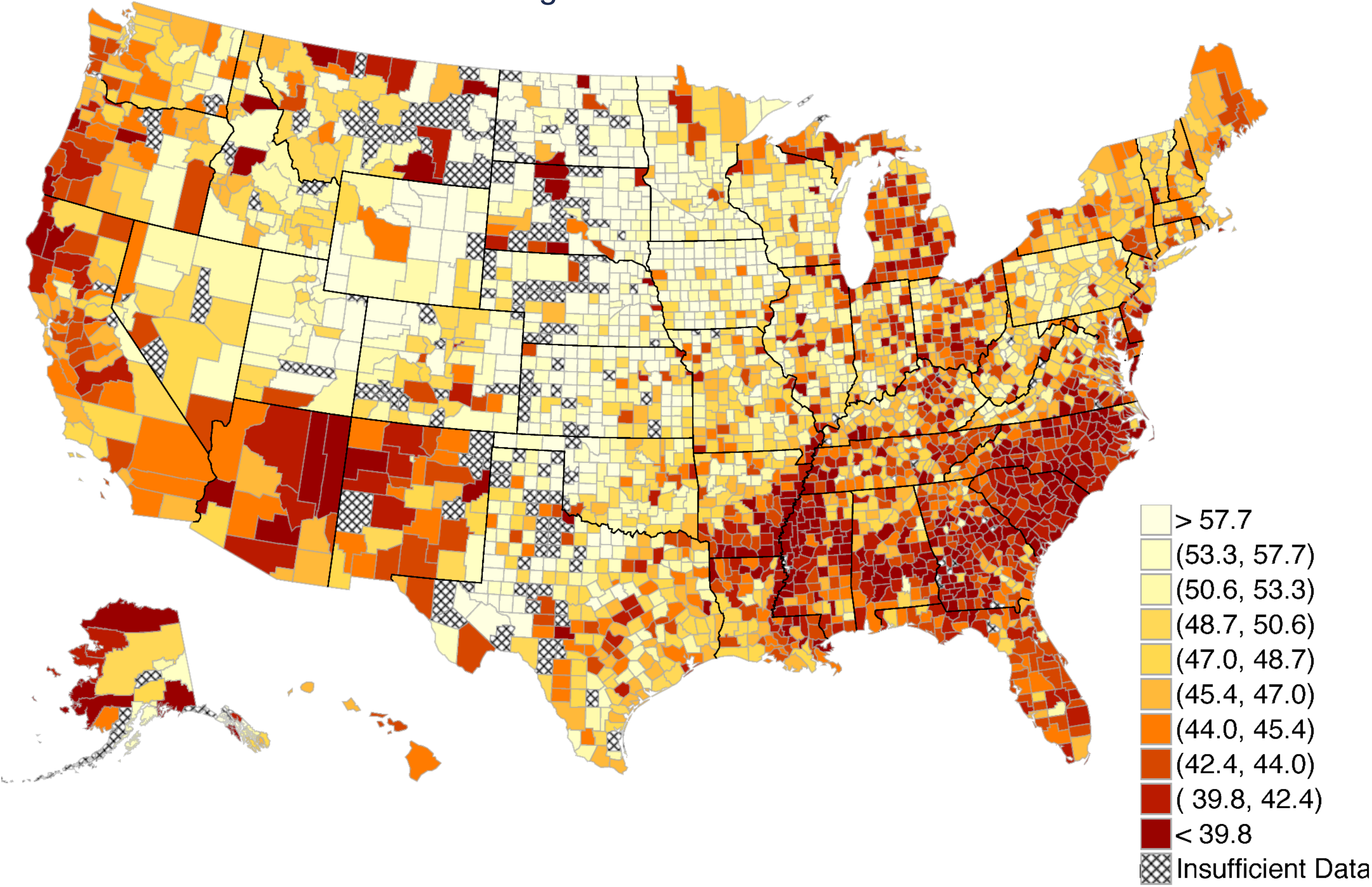
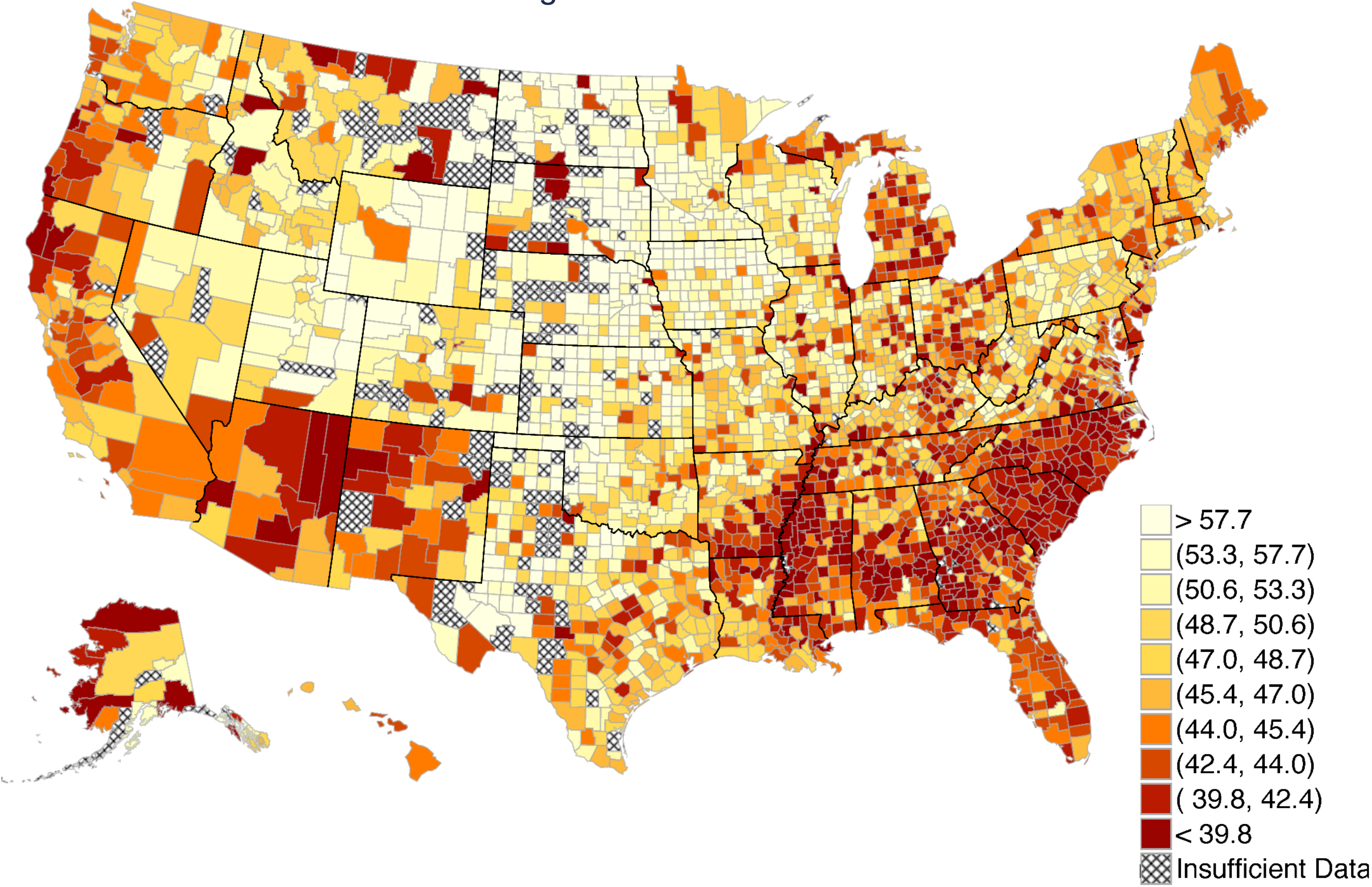


Part 1: What Fraction of Variance in this Map is Due to Causal Place Effects?

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 each 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

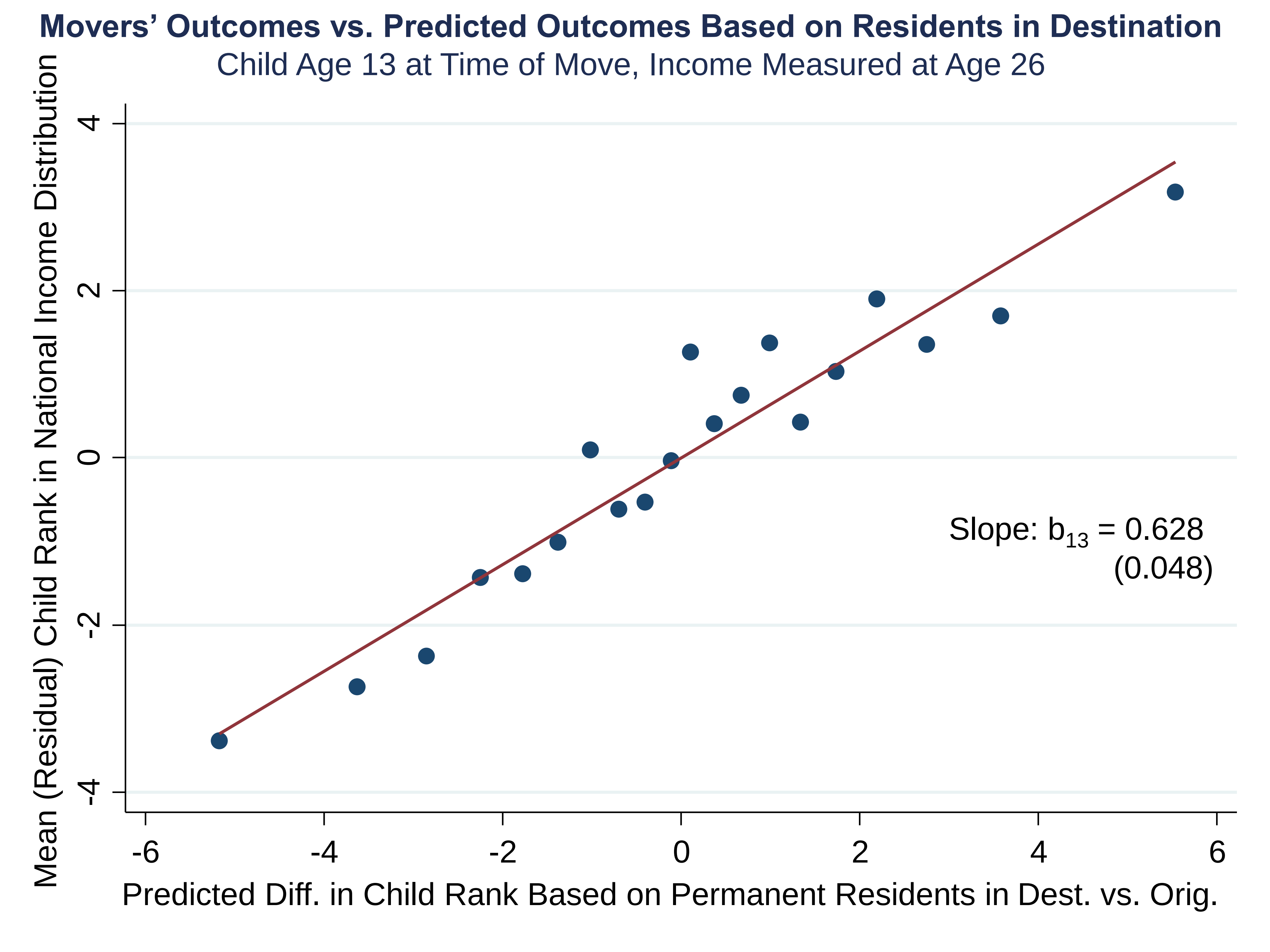
Estimating Exposure Effects in Observational Data

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

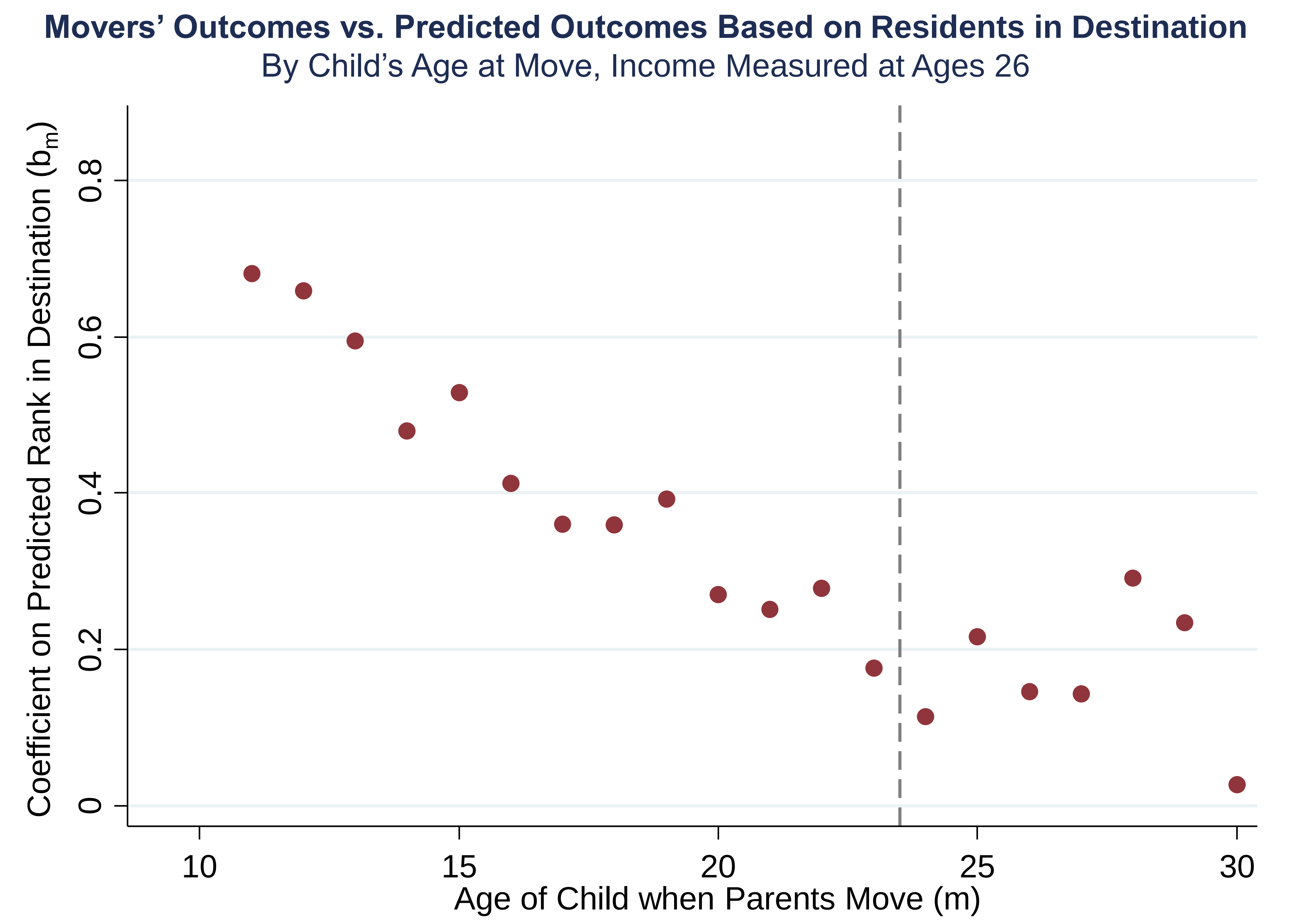
- Regress child's income rank at age 26 y_i on predicted outcome of permanent residents in destination:

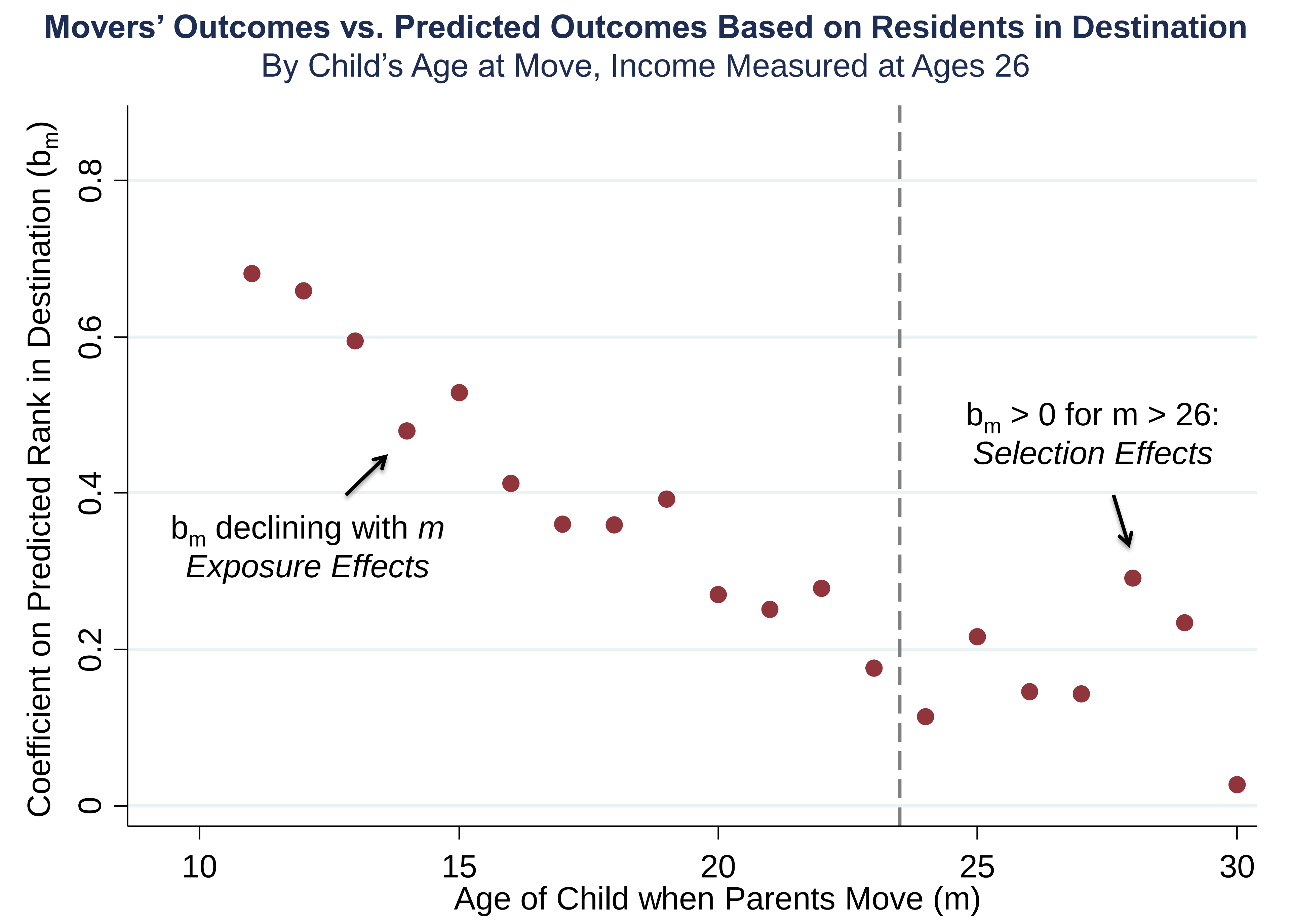
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

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



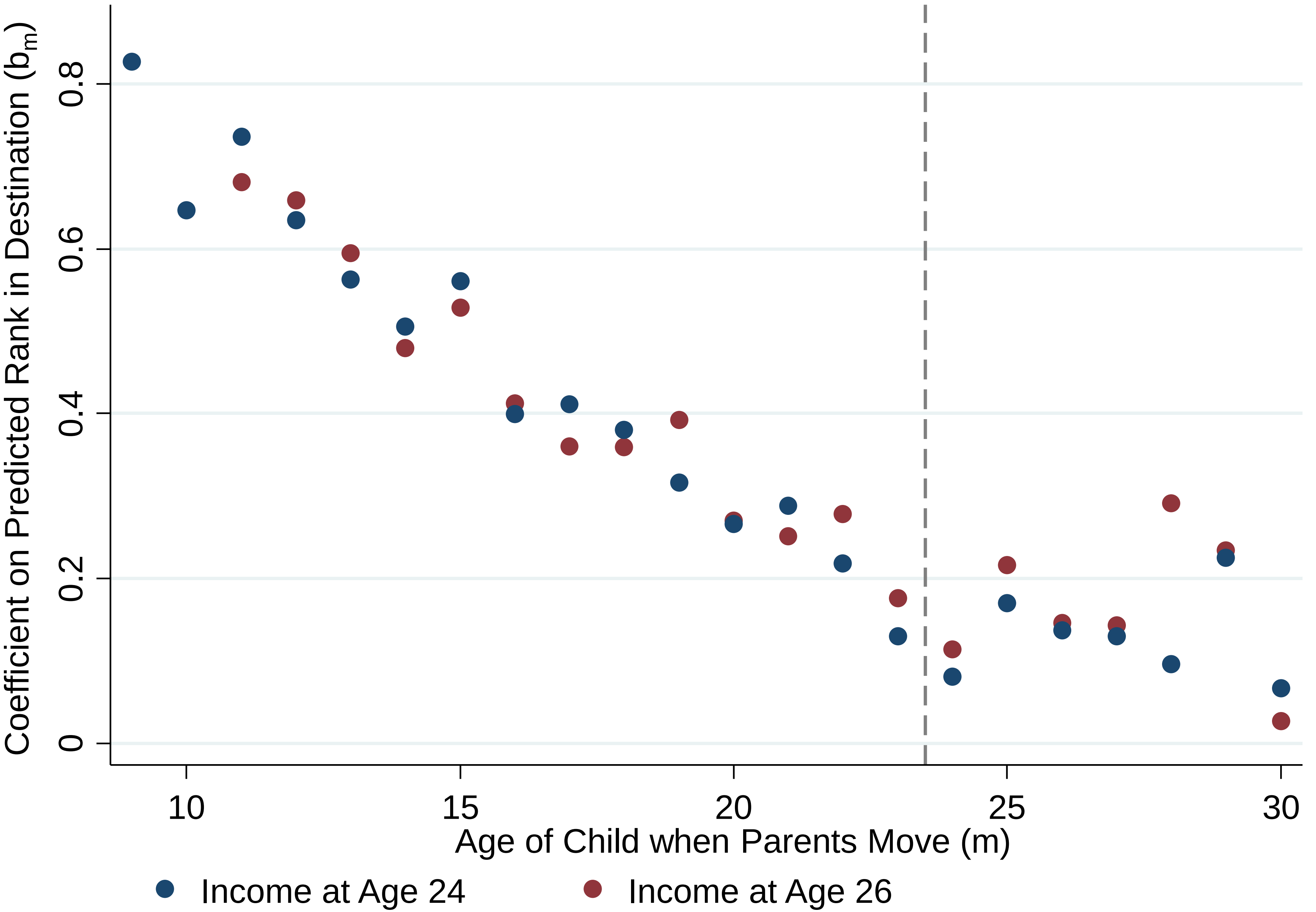
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
Child Age 13 at Time of Move, Income Measured at Age 26
Mean (Residual) Child Rank in National Income Distribution
4
2
0
-2
-4
Slope: b13 = 0.628
(0.048)
-6
-4
-2
0
2
4
6
Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.

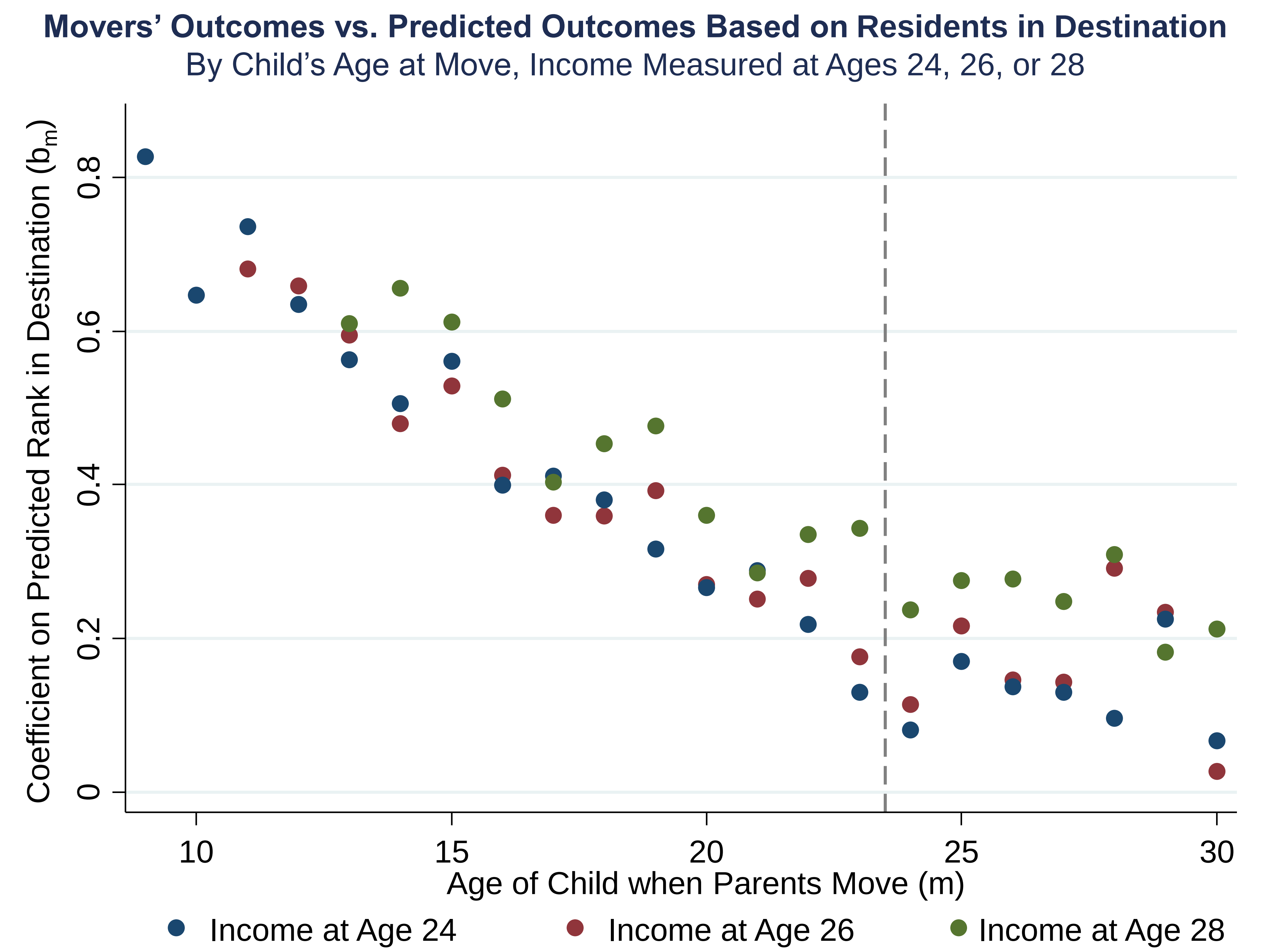

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 26
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)

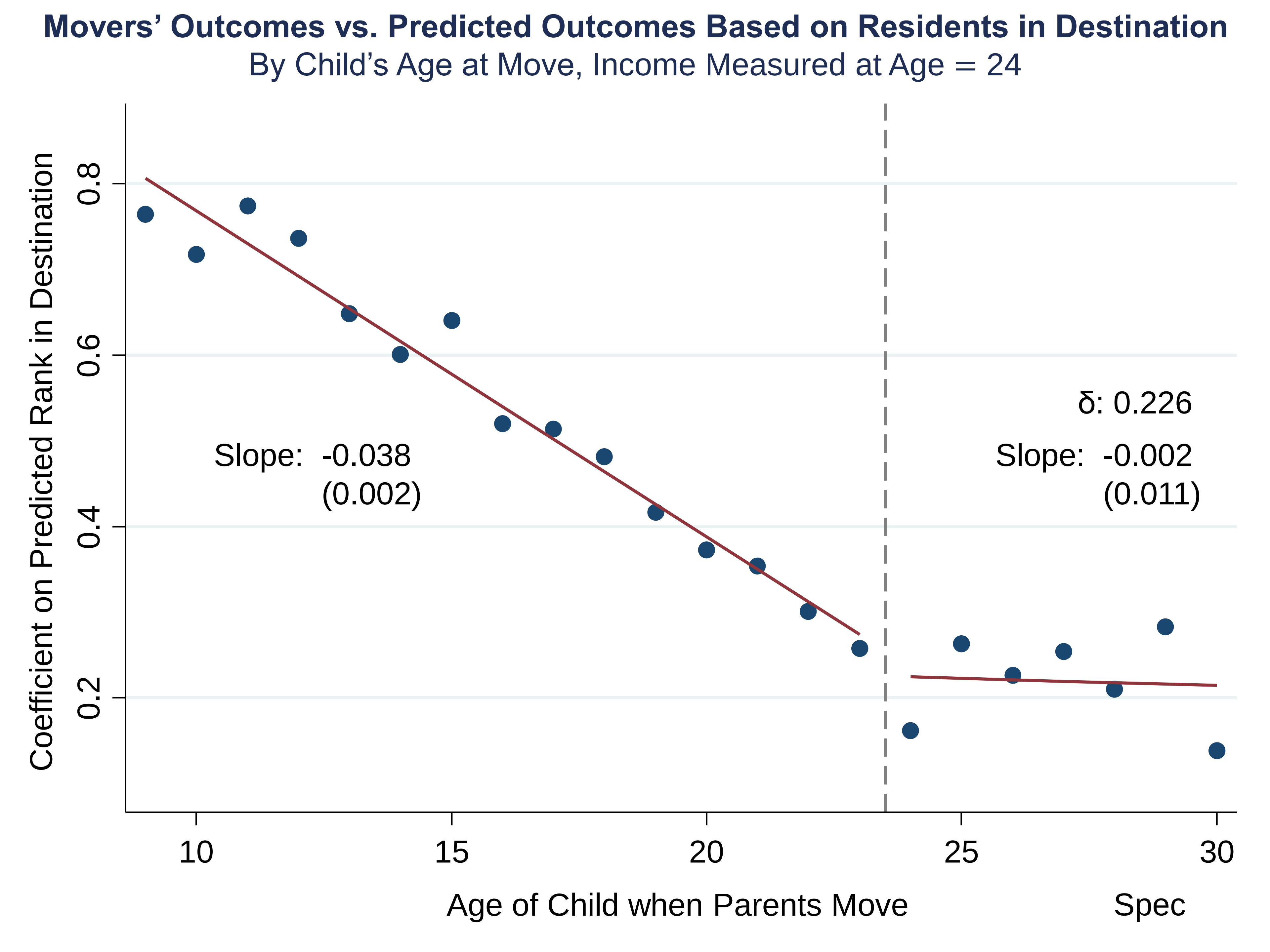

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 26
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)
b_m declining with *m*
Exposure Effects
b_m > 0 for m > 26: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

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

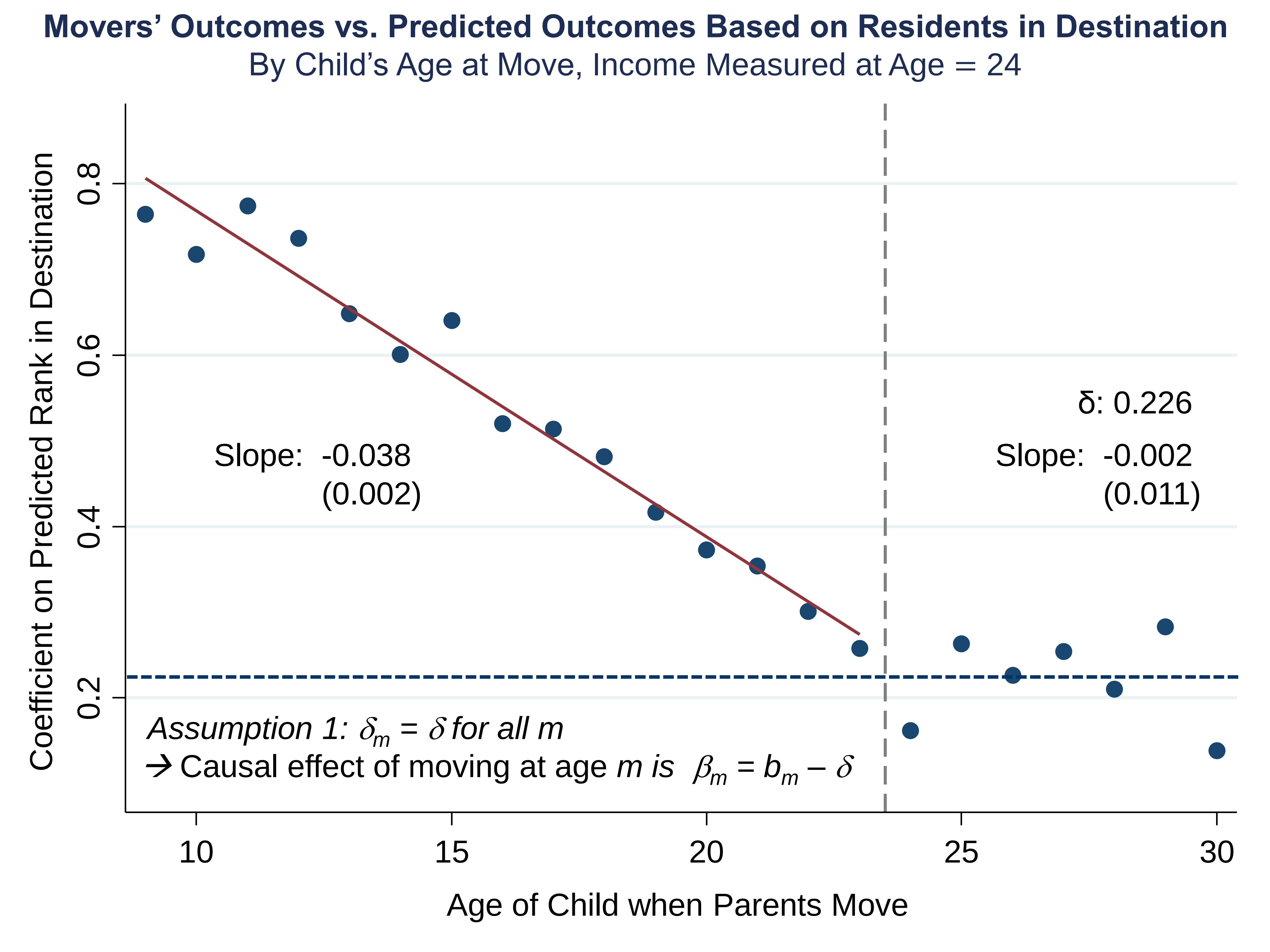
By Child's Age at Move, Income Measured at Ages 24, 26, or 28



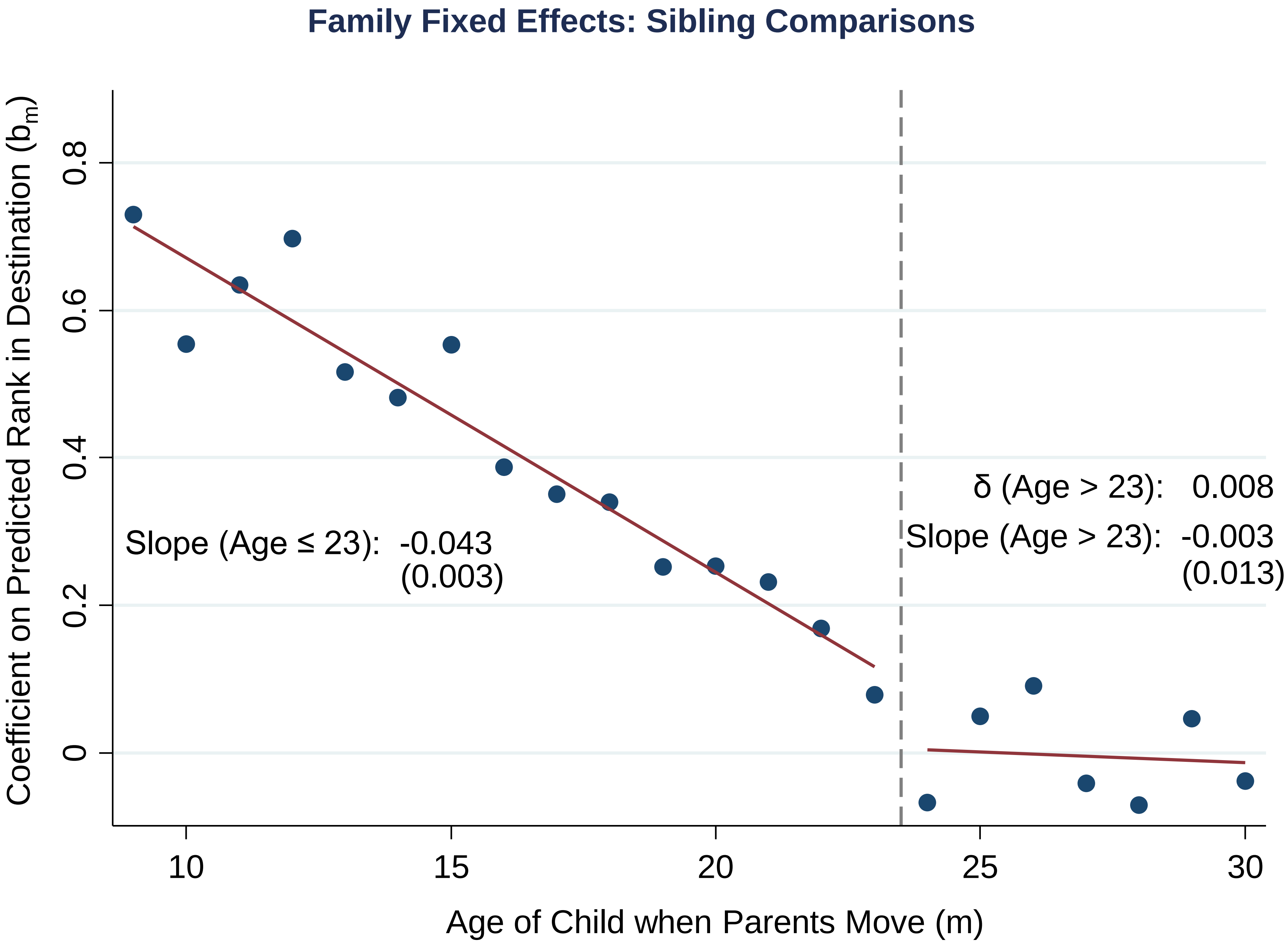

Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Ages 24, 26, or 28
Coefficient on Predicted Rank in Destination (b_m)
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move (m)
Income at Age 24
Income at Age 26
Income at Age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



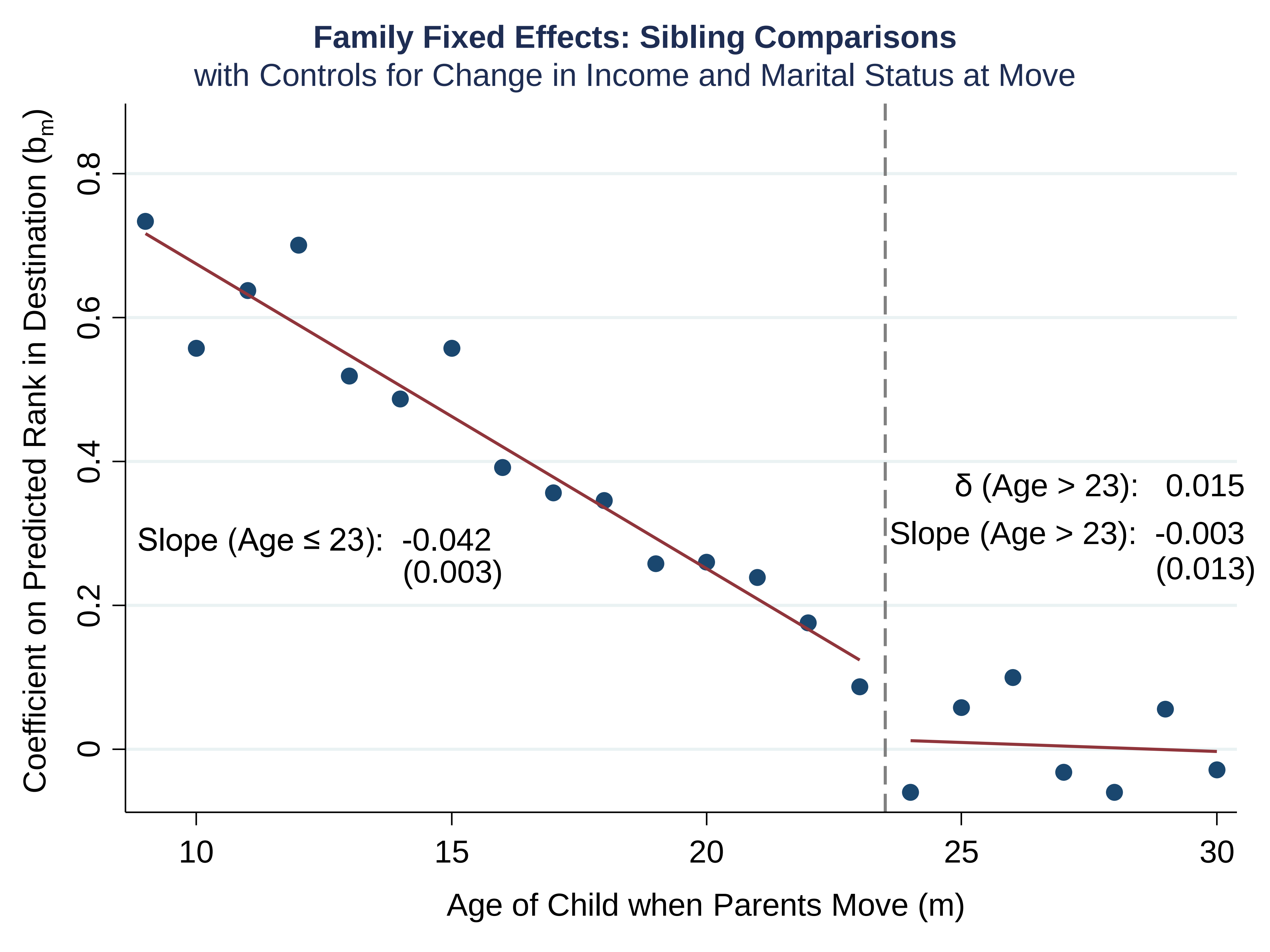
Movers' Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child's Age at Move, Income Measured at Age = 24
Coefficient on Predicted Rank in Destination
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Spec
Slope: -0.038
(0.002)
δ: 0.226
Slope: -0.002
(0.011)



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)



Family Fixed Effects: Sibling Comparisons
with Controls for Change in Income and Marital Status at Move
Coefficient on Predicted Rank in Destination (b_m)
0.8
0.6
0.4
0.2
0
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

- 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

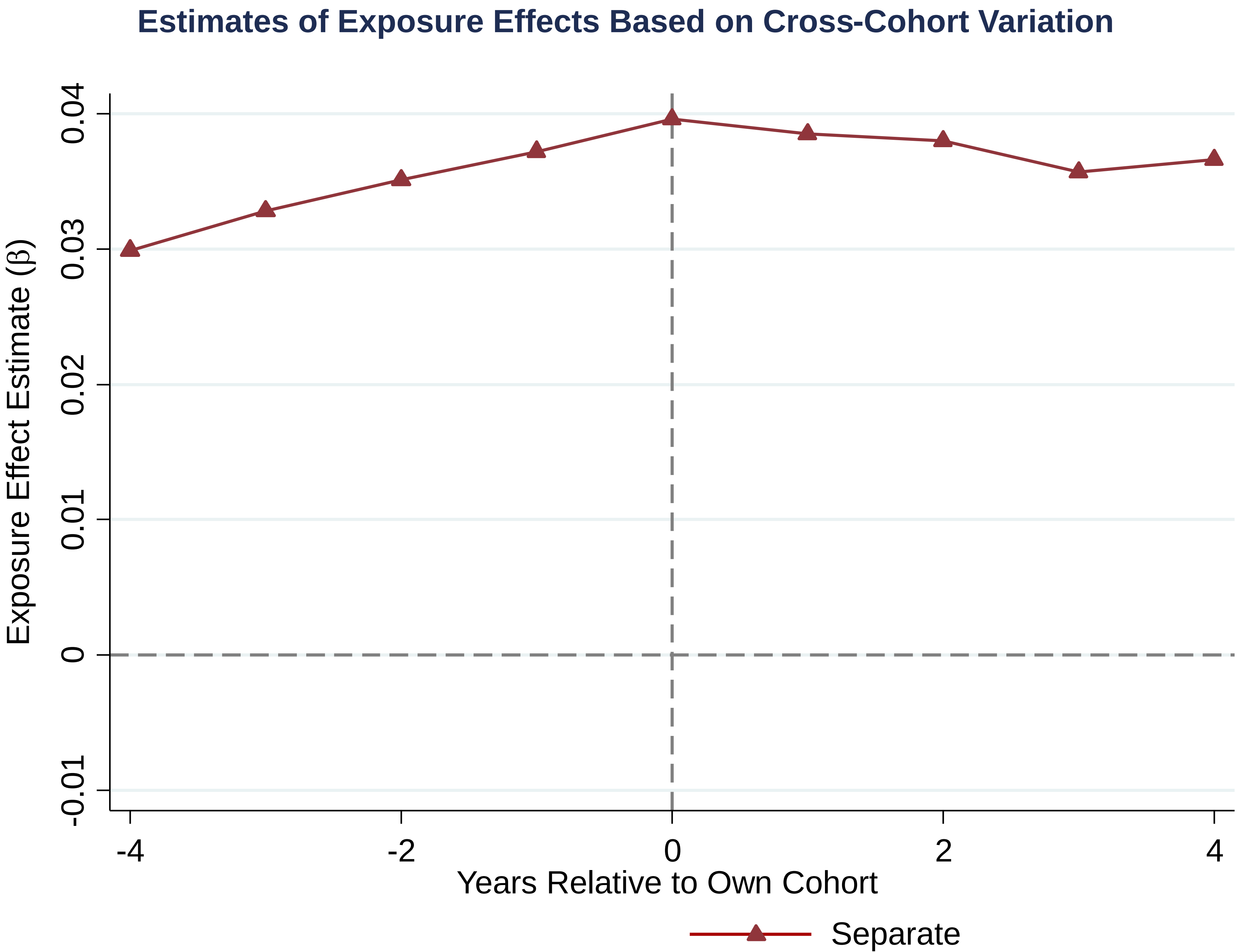
- Parents choose neighborhoods based on their preferences and information set at time of move

  - Difficult to predict high-frequency differences that are realized 15 years later → hard to sort on this dimension

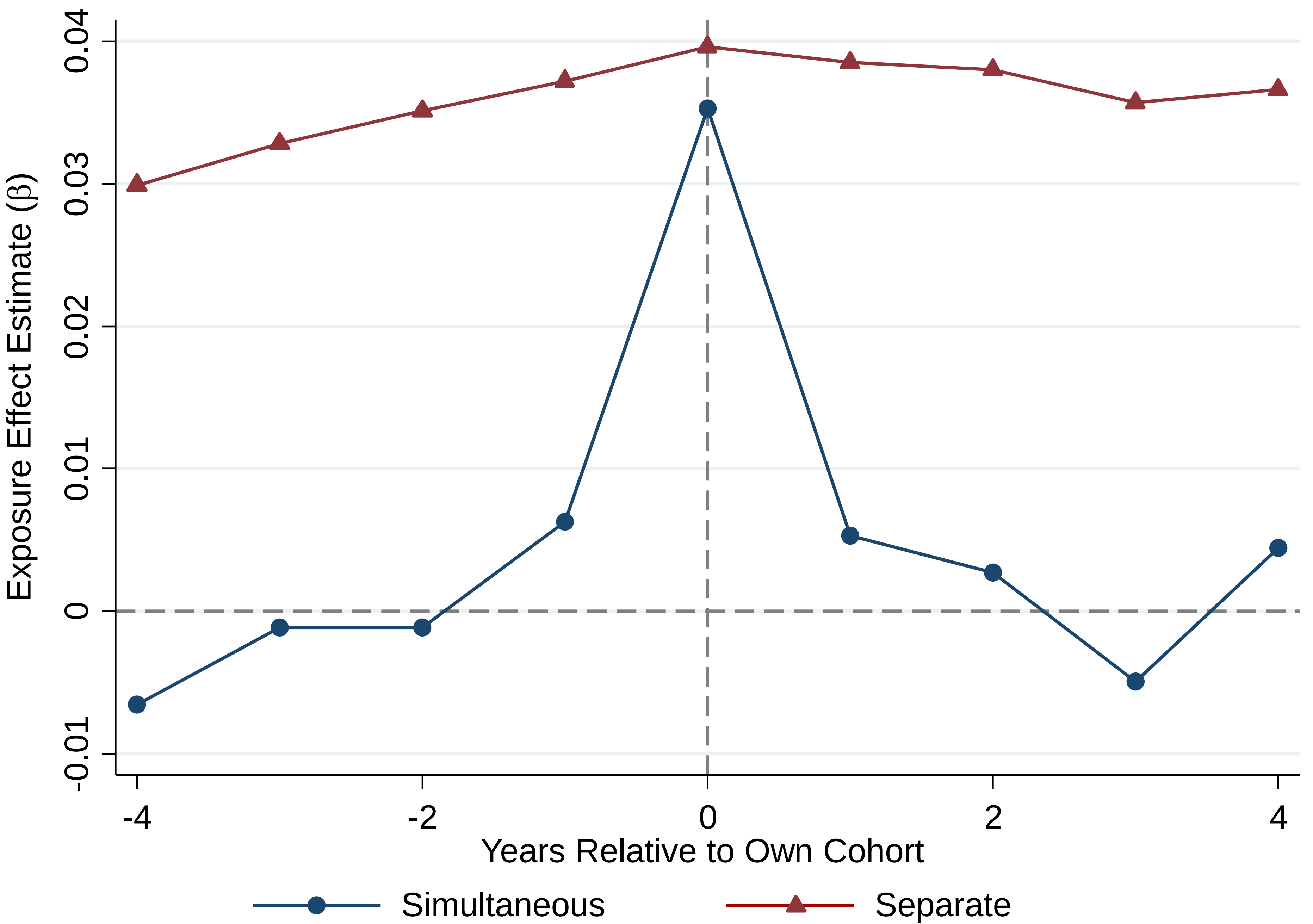
- Key assumption: if unobservables θ_i correlated with exposure effect for cohort *s*, then correlated with exposure effects for surrounding cohorts s′ as well

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

- 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



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 25^{th} percentile

  - Mean expected rank is 46^{th} 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 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 (Placebo)		0.022	0.004		0.021	0.000
		(0.002)	(0.003)		(0.002)	(0.003)

Gender Comparisons

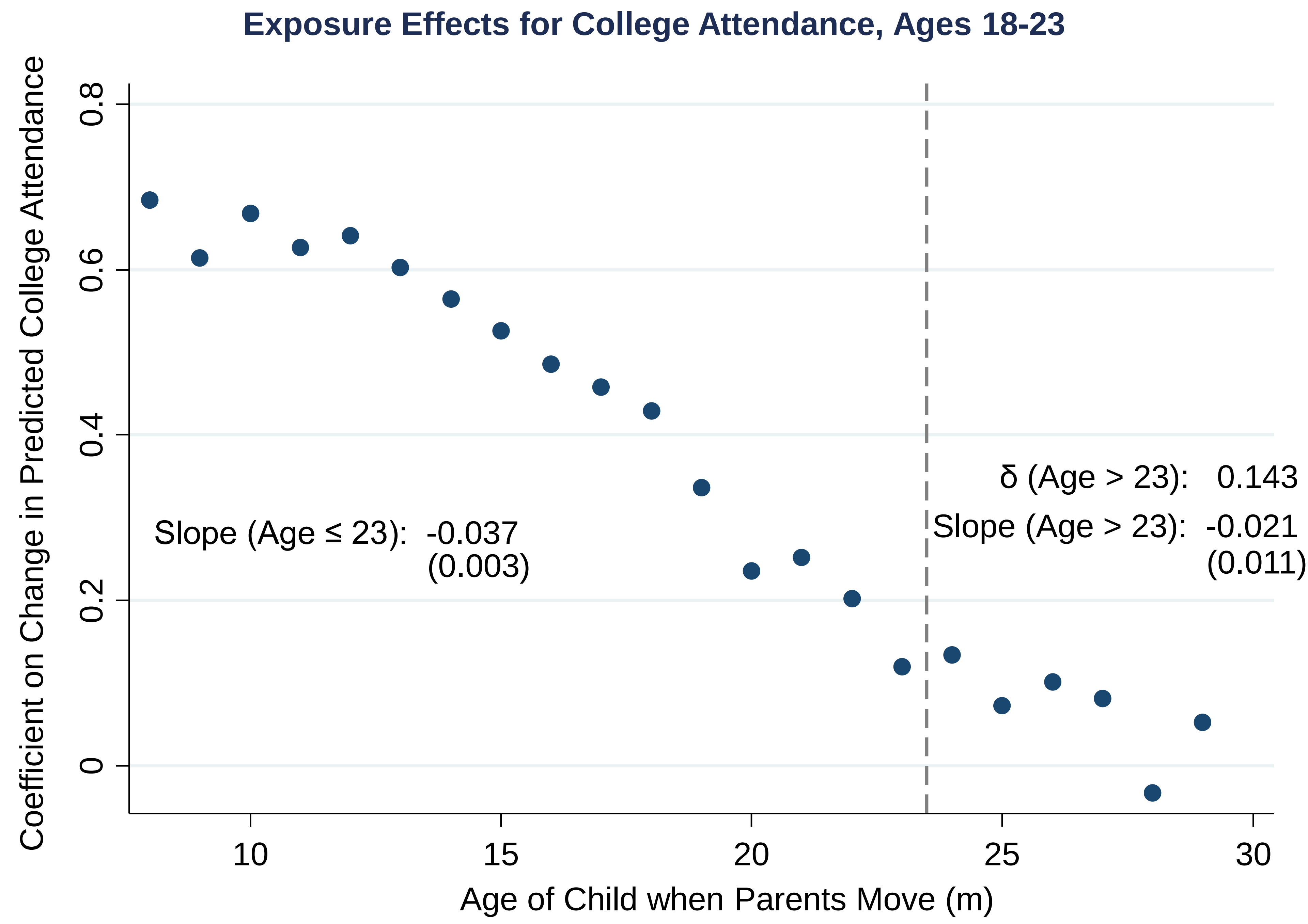
- Finally, exploit heterogeneity across genders
- Construct separate predictions of expected income rank conditional on parent income for girls and boys in each CZ
  - Correlation of male and female predictions across CZ’s is 0.90
- Low-income boys do worse than girls in areas with:
  1. More segregation (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

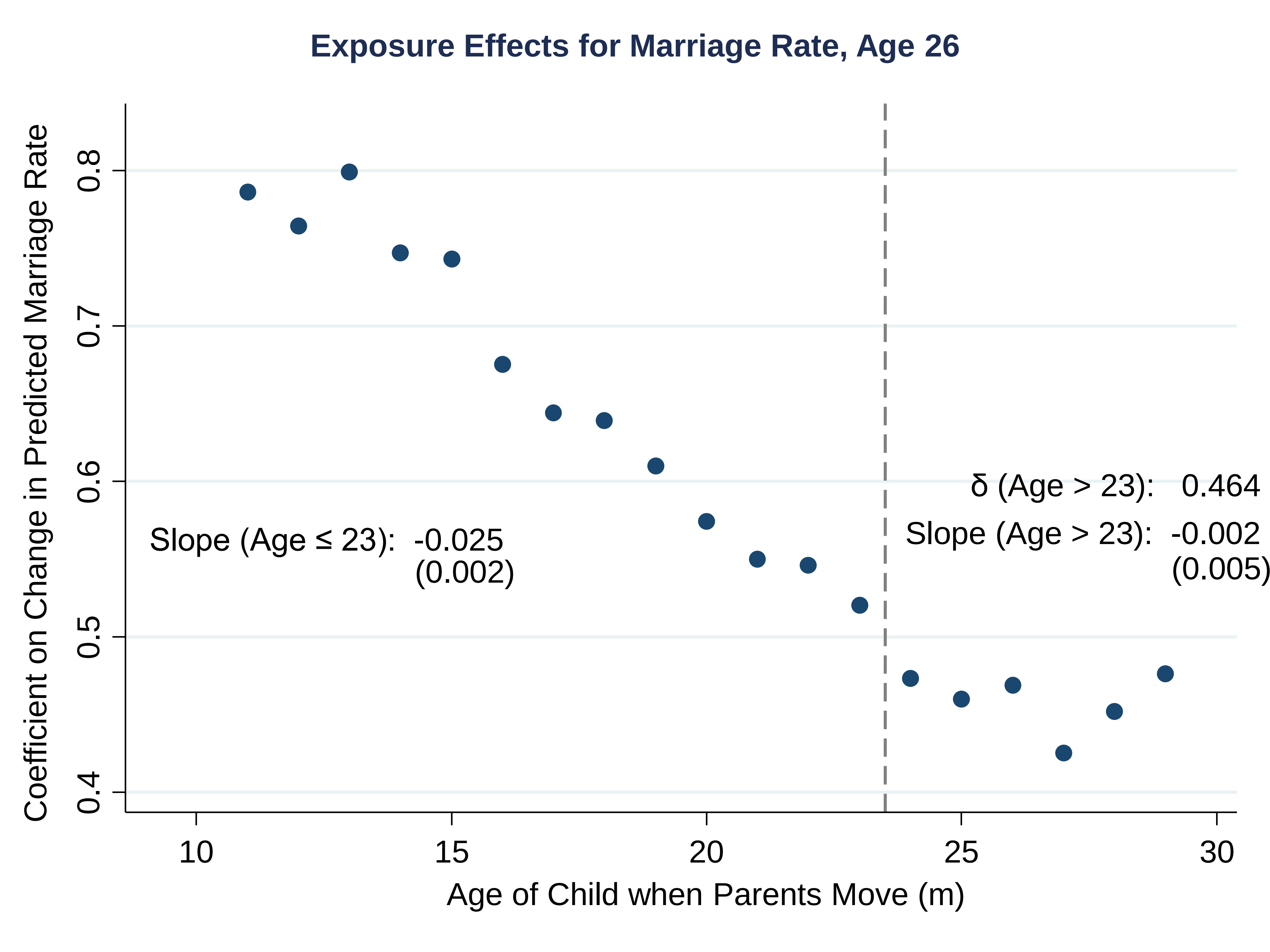
	No Family Fixed Effects			Family Fixed Effects
	(1)	(2)	(3)	(4)
Own Gender Prediction	0.038		0.031	**0.031**
	(0.002)		(0.003)	(0.007)
Other Gender Prediction (Placebo)		0.034	0.009	**0.012**
		(0.002)	(0.003)	(0.007)
Sample		Full Sample		2-Gender HH

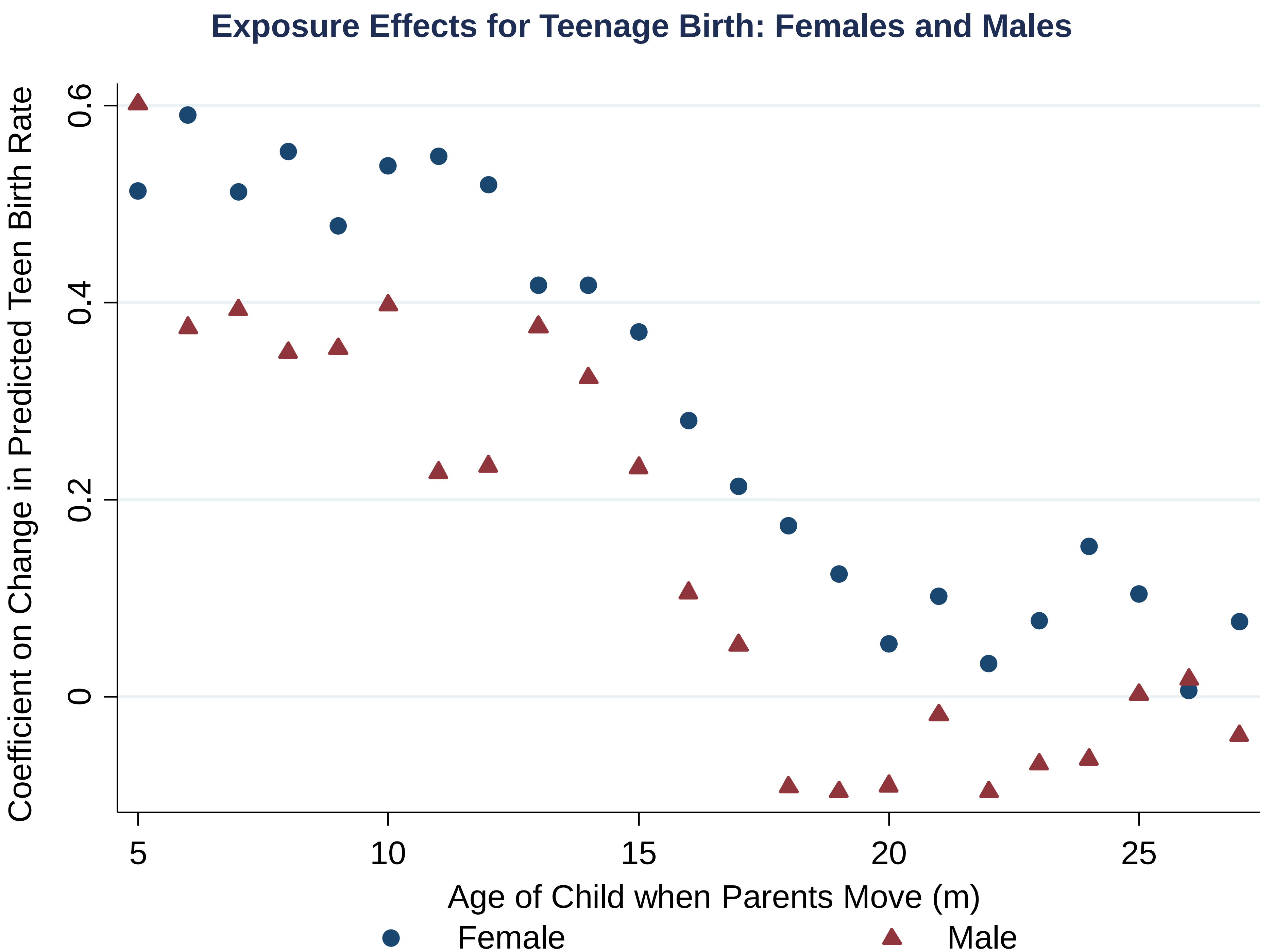
Neighborhood Effects on Other Outcomes

- 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
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 (m)
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
0.6
0.4
0.2
0
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

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

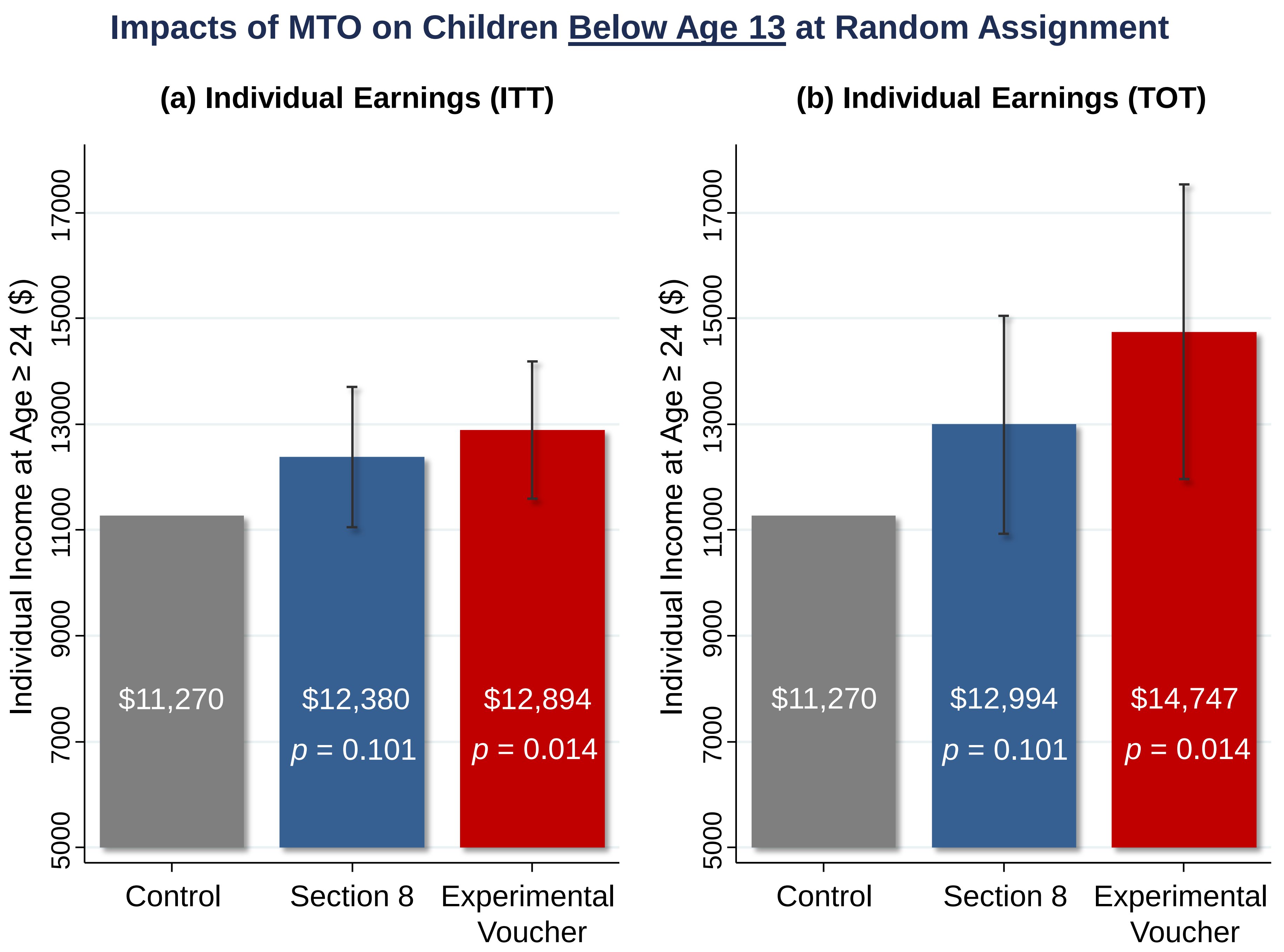
   - MTO identified from moves induced by vouchers

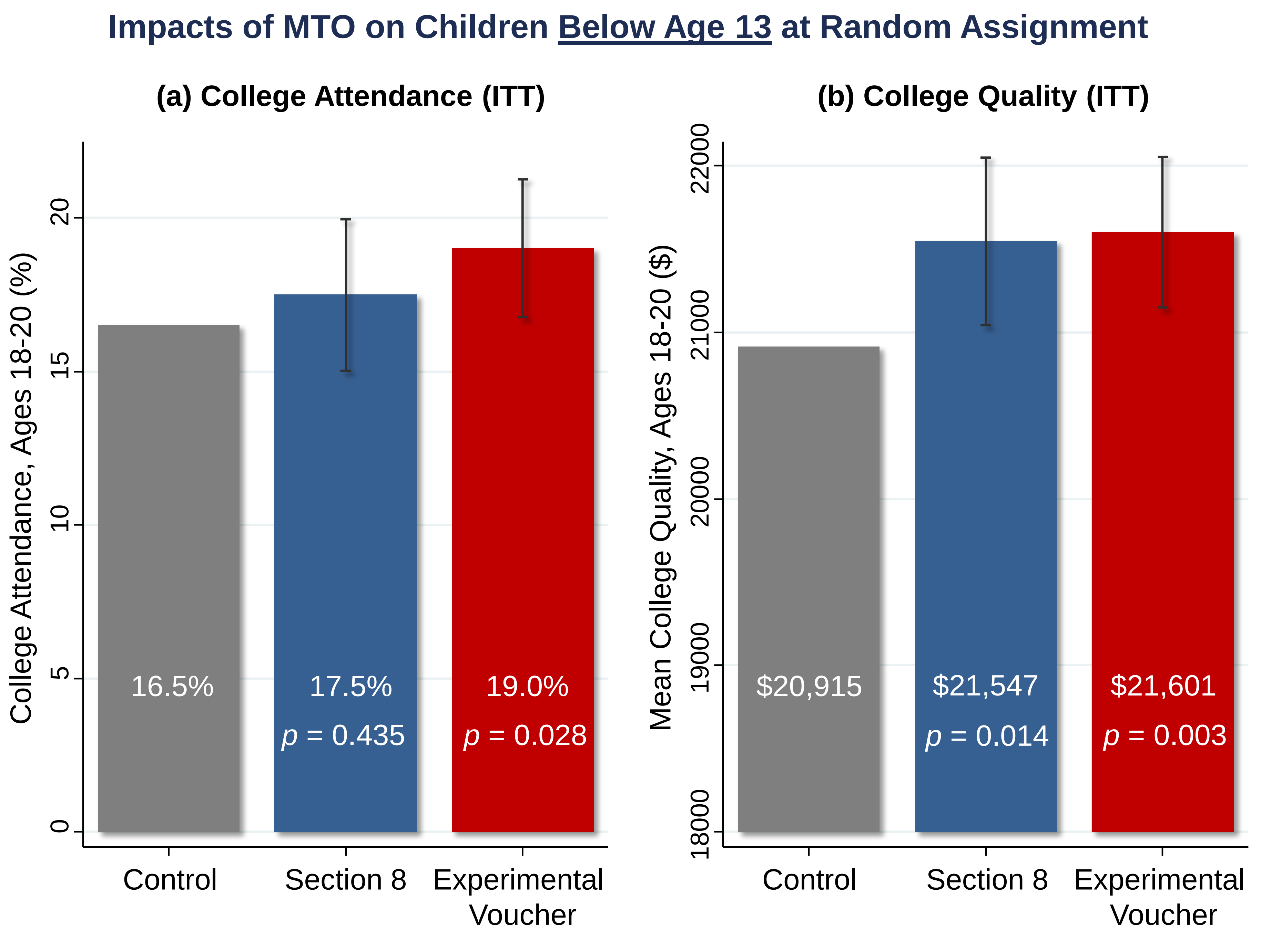
   - Quasi-experiment from moves that families chose in equilibrium

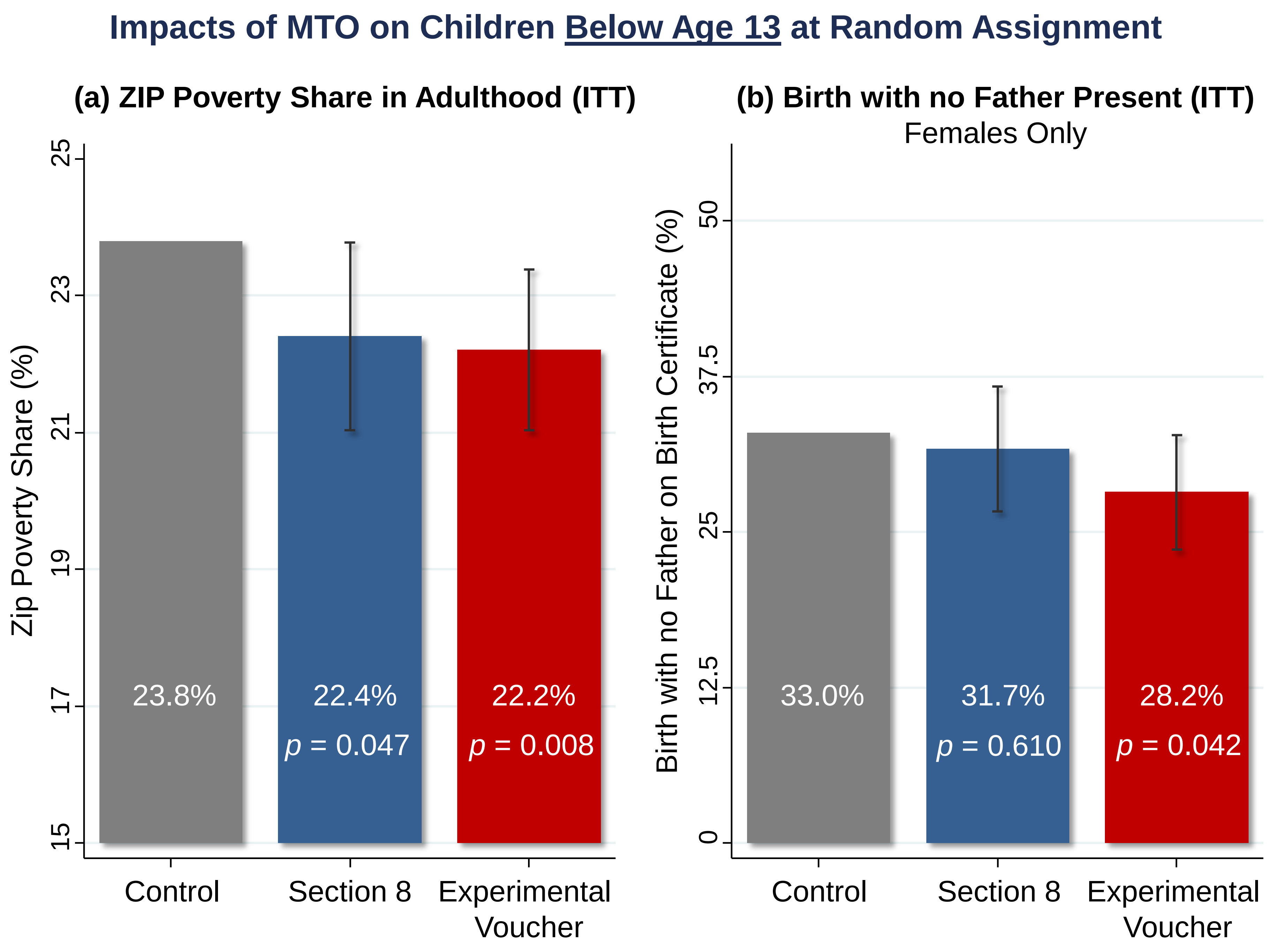
2. Inclusion of disruption effects from move

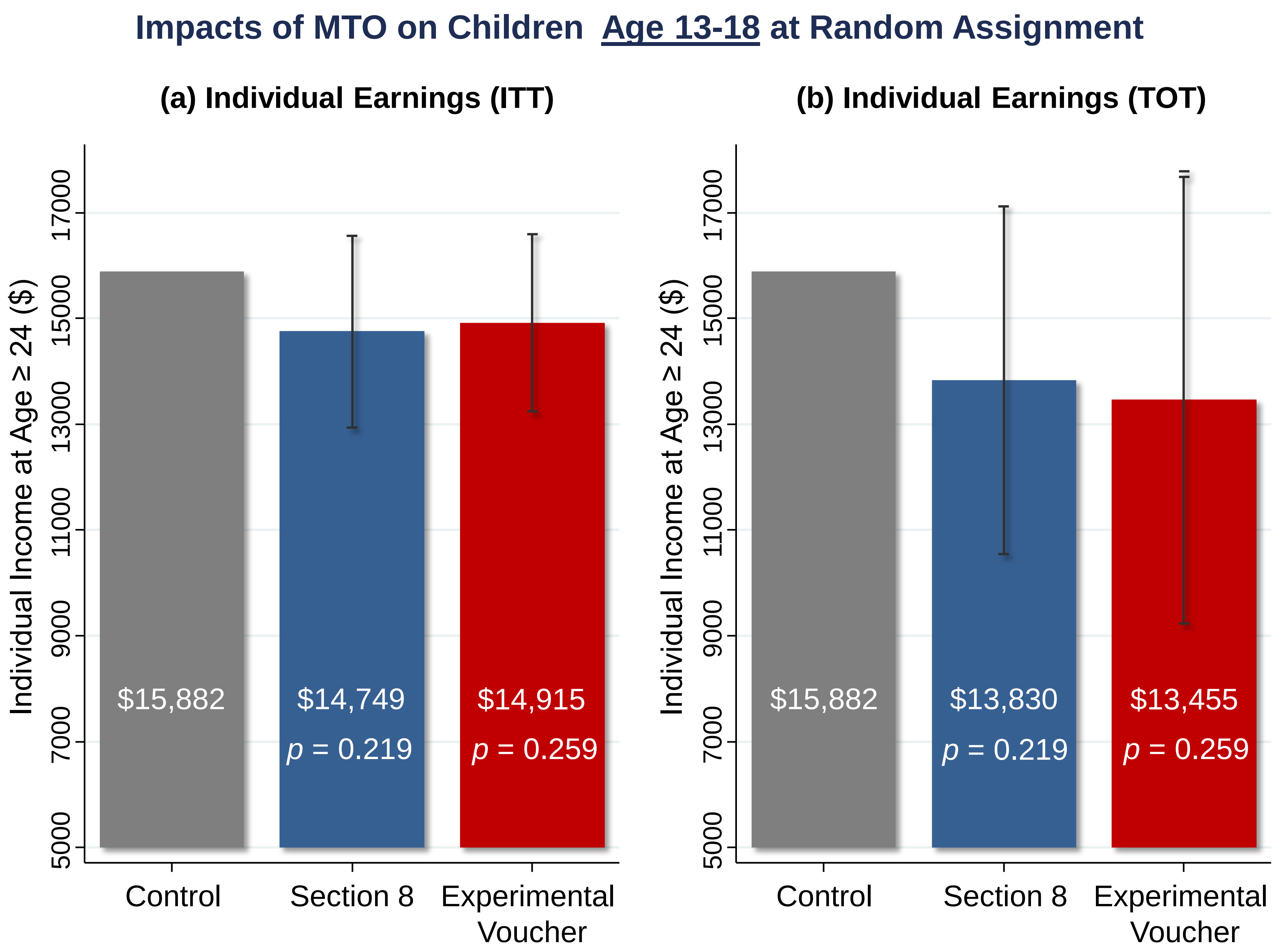
   - MTO compares movers to non-movers and therefore incorporates any disruption effect of move

   - Quasi-experimental design compares effect of moving to better vs. worse areas *conditional* on moving → fixed cost of move netted out

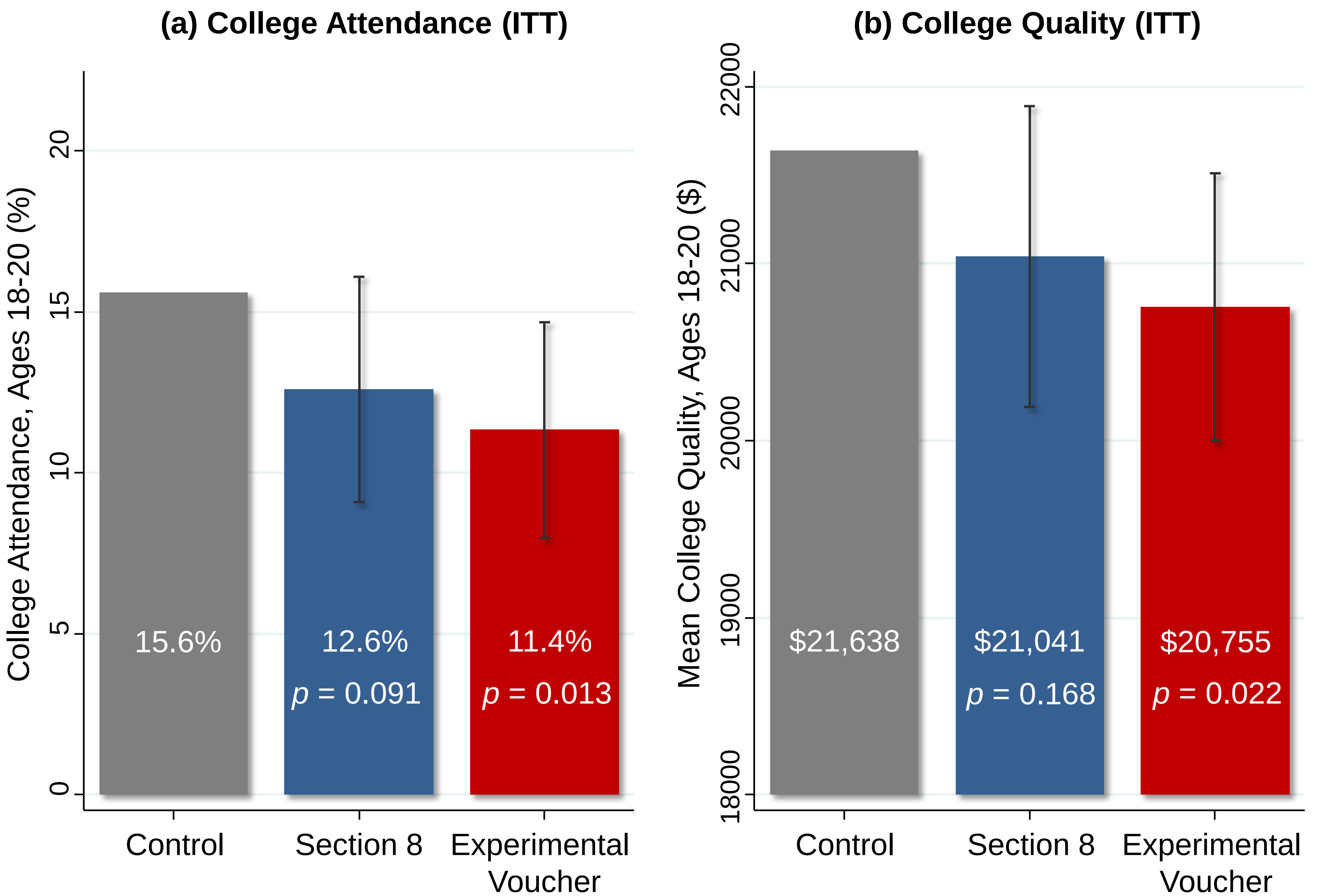

Impacts of MTO on Children Below Age 13 at Random Assignment
(a) Individual Earnings (ITT)
(b) Individual Earnings (TOT)
Individual Income at Age ≥ 24 ($)
5000
7000
9000
11000
13000
15000
17000
$11,270
$12,380
p = 0.101
$12,894
p = 0.014
$11,270
$12,994
p = 0.101
$14,747
p = 0.014
Control
Section 8
Experimental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

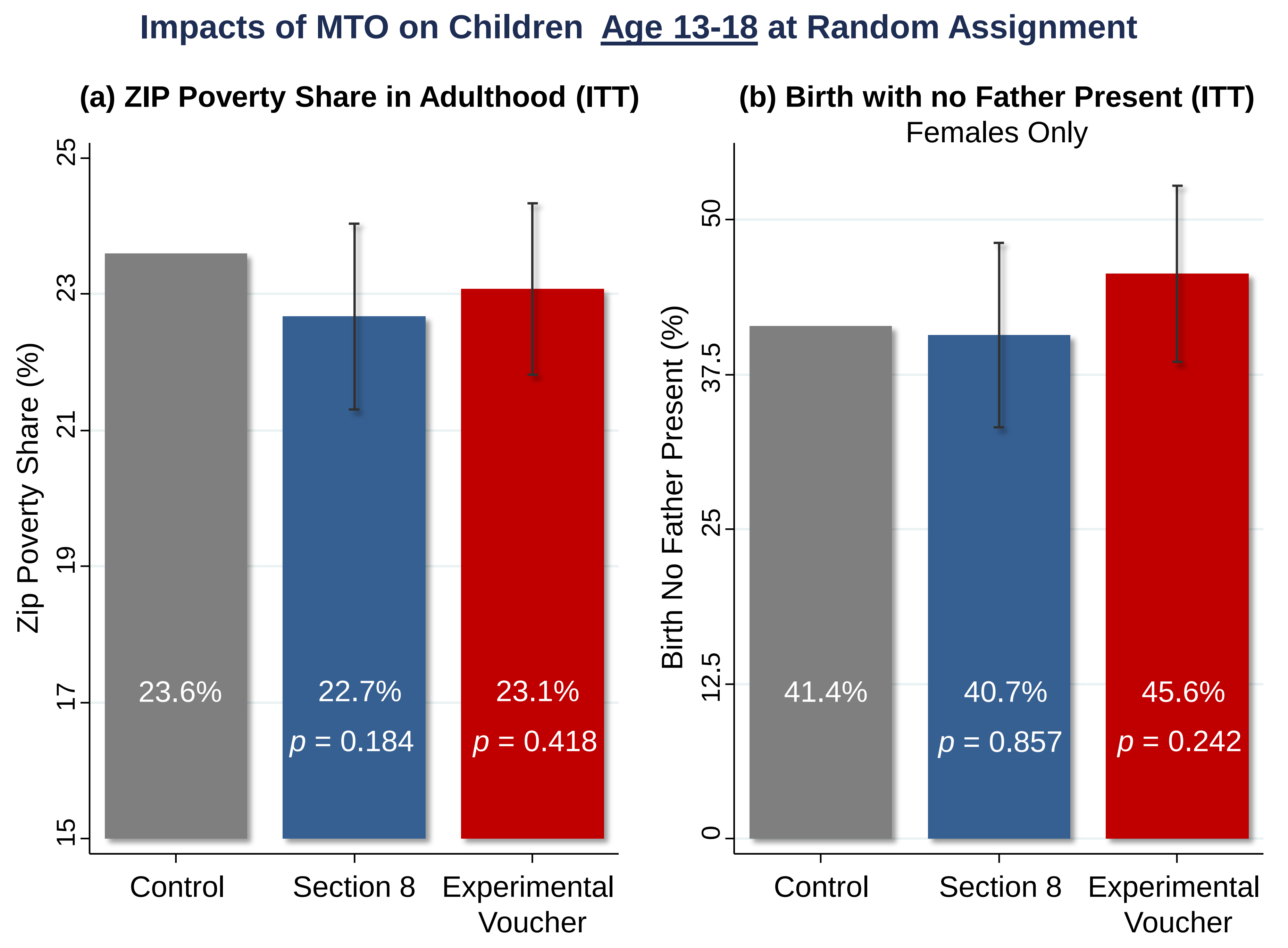

Impacts of MTO on Children Below Age 13 at Random Assignment
(a) College Attendance (ITT)
College Attendance, Ages 18-20 (%)
0
5
10
15
20
16.5%
17.5%
p = 0.435
19.0%
p = 0.028
Control
Section 8
Experimental Voucher
(b) College Quality (ITT)
Mean College Quality, Ages 18-20 ($)
18000
19000
20000
21000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

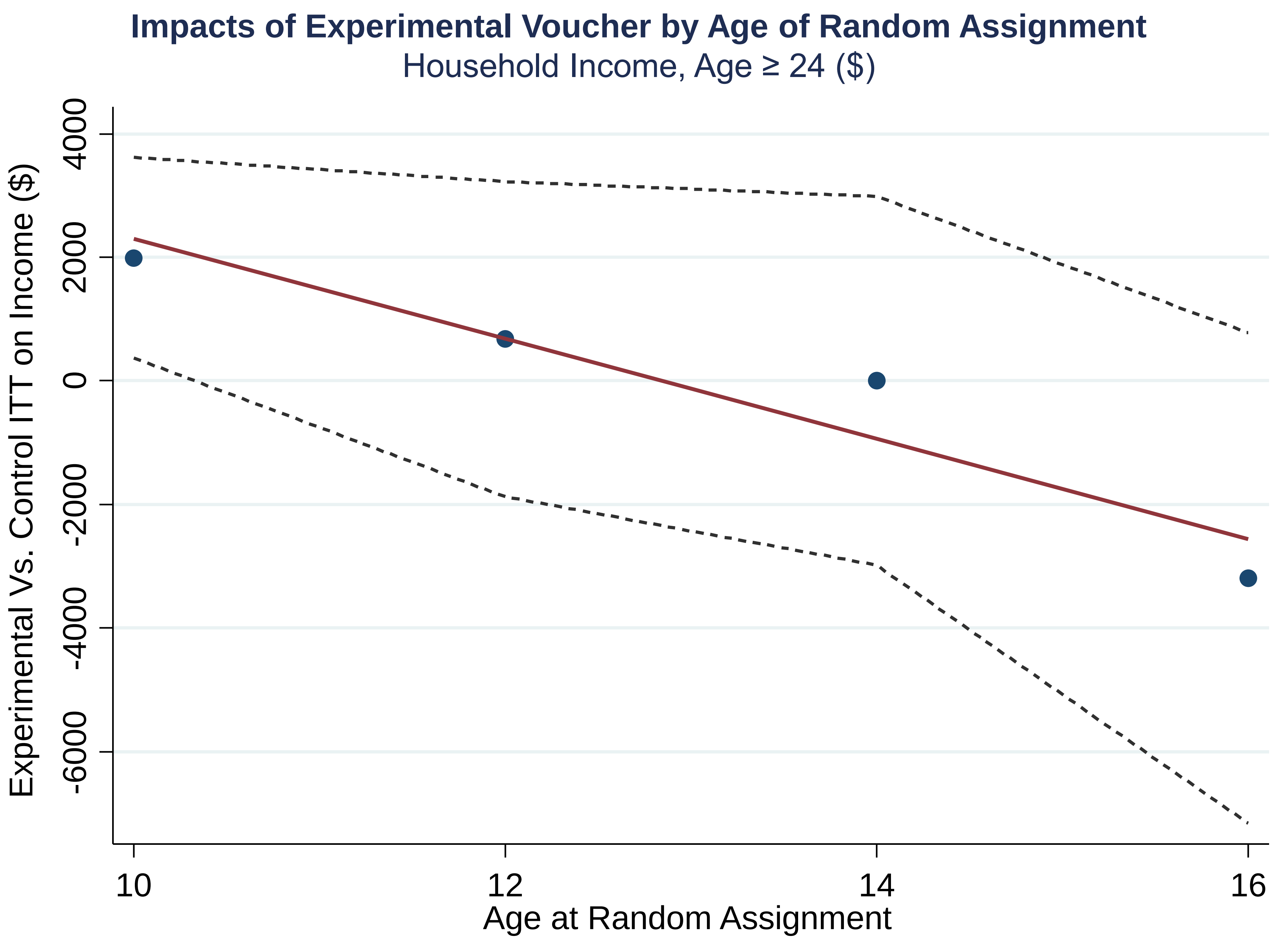

Impacts of MTO on Children Below Age 13 at Random Assignment
(a) ZIP Poverty Share in Adulthood (ITT)
Zip Poverty Share (%)
15
17
19
21
23
25
23.8%
22.4%
p = 0.047
22.2%
p = 0.008
Control
Section 8
Experimental Voucher
(b) Birth with no Father Present (ITT)
Females Only
Birth with no Father on Birth Certificate (%)
0
12.5
25
37.5
50
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
(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
$13,830
$13,455
Control
Section 8
Experimental Voucher

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




Impacts of MTO on Children Age 13-18 at Random Assignment
(a) ZIP Poverty Share in Adulthood (ITT)
Zip Poverty Share (%)
15
17
19
21
23
25
23.6%
22.7%
p = 0.184
23.1%
p = 0.418
Control
Section 8
Experimental Voucher
(b) Birth with no Father Present (ITT)
Females Only
Birth No Father Present (%)
0
12.5
25
37.5
50
41.4%
40.7%
p = 0.857
45.6%
p = 0.242
Control
Section 8
Experimental Voucher


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 each year of childhood exposure to a 1 percentile better CZ/county raises earnings by about 0.035 percentiles
  - Extrapolating over 20 years of childhood, implies that causal effects of place account for 70% of variance in intergen. mobility across areas
- This analysis shows 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:

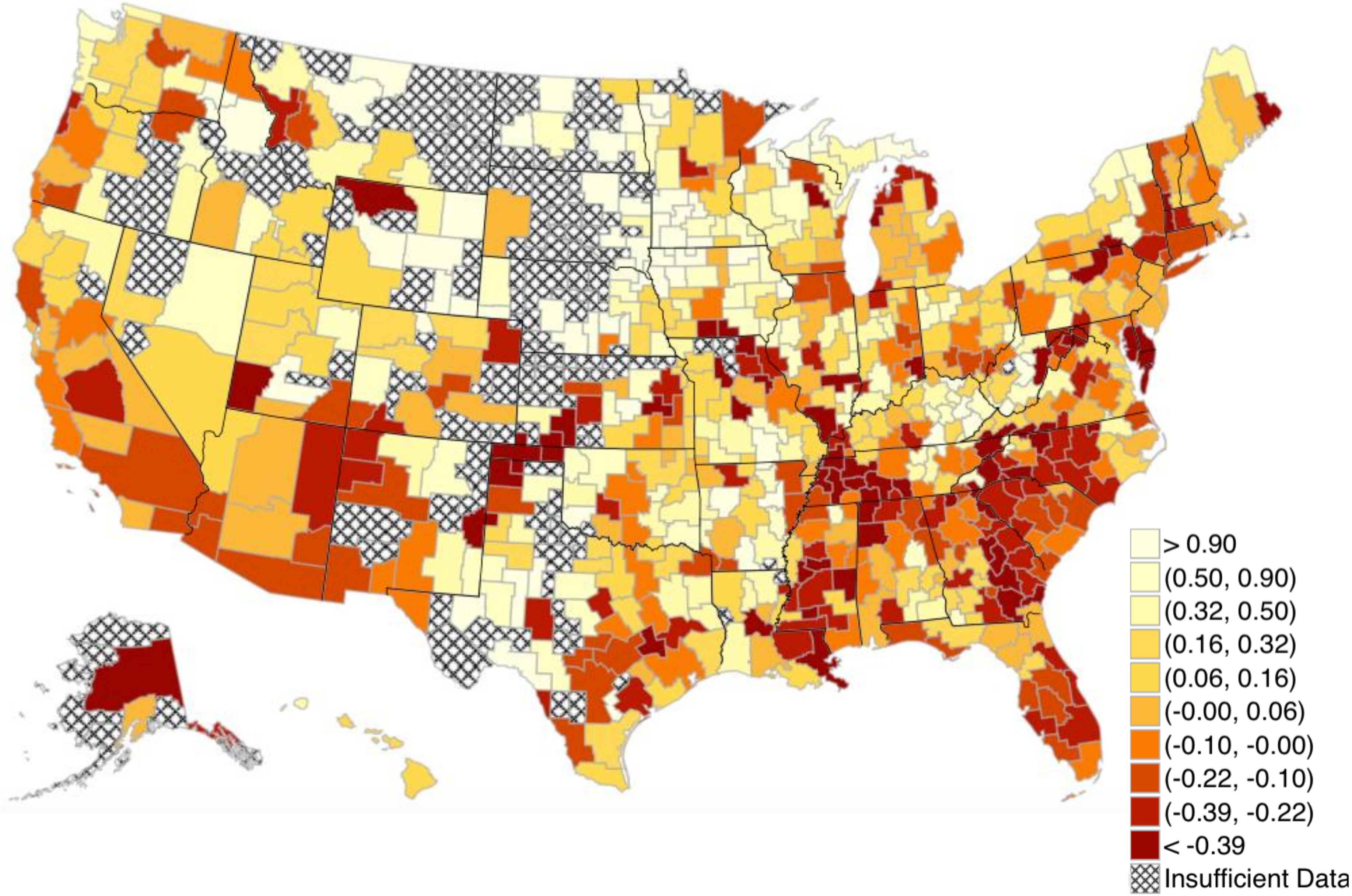
$$\mu_c = \mu_c^0 + \mu_c^P p$$

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

$$\alpha_{odps} = \left(\alpha_{od}^0 + \alpha_{od}^P p + \psi_{od}^0 s + \psi_{od}^1 s^2 + \psi_{od}^2 sp + \psi_{od}^3 s^2 p\right)$$

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
  - Signal SD of annual exposure effect is $\sigma_\mu = 0.13$ percentiles at CZ level and $\sigma_\mu = 0.17$ percentiles across counties for parents at 25th percentile

Translating Ranks to Dollars

- We use ranks instead of dollars because ranks have less noise
  - But for interpreting units, useful to think in terms of $ and % increases
- Regress mean child income on mean child rank at parent income rank *p* to obtain a scaling factor to translate ranks to dollars
  - At parent p=25: 1 percentile = $818 = 3.1% of mean income
  - At parent p=75: 1 percentile = $840 = 2.1% of mean income
- Note that we obtain very similar (but noisier) estimates if we estimate exposure effects on dollars directly

Estimation of Variance Components

- Signal SD of annual exposure effect is $\sigma_\mu = 0.17$ 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:

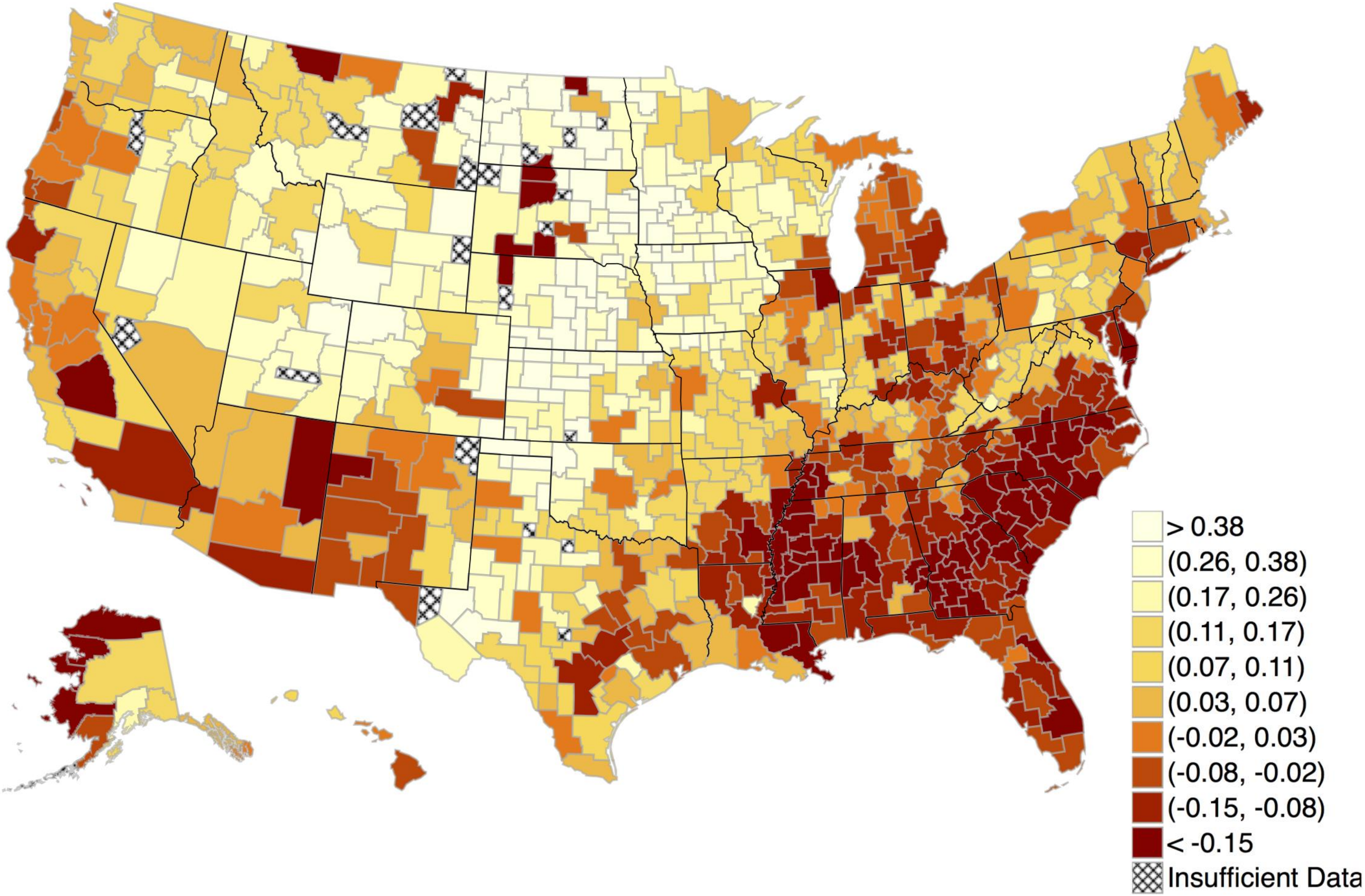
$$\rho_{1,pc} = \beta \frac{\sigma^2_{\varepsilon,pc}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}} \qquad \rho_{2,pc} = \frac{\sigma^2_{\nu,p}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}}$$

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 Rank at Age 26 by CZ

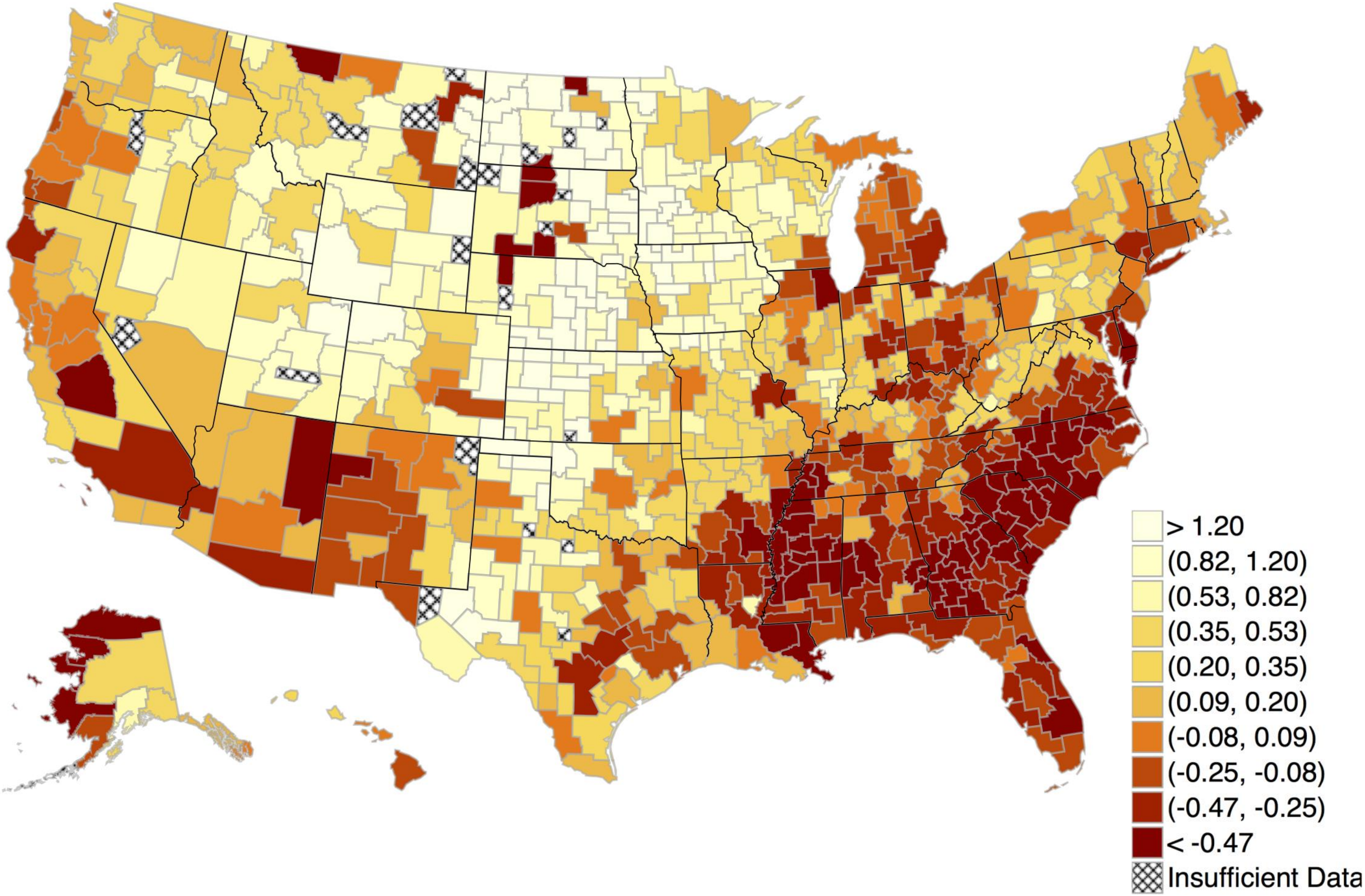
For Children with Parents at 25th Percentile of Income Distribution



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

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

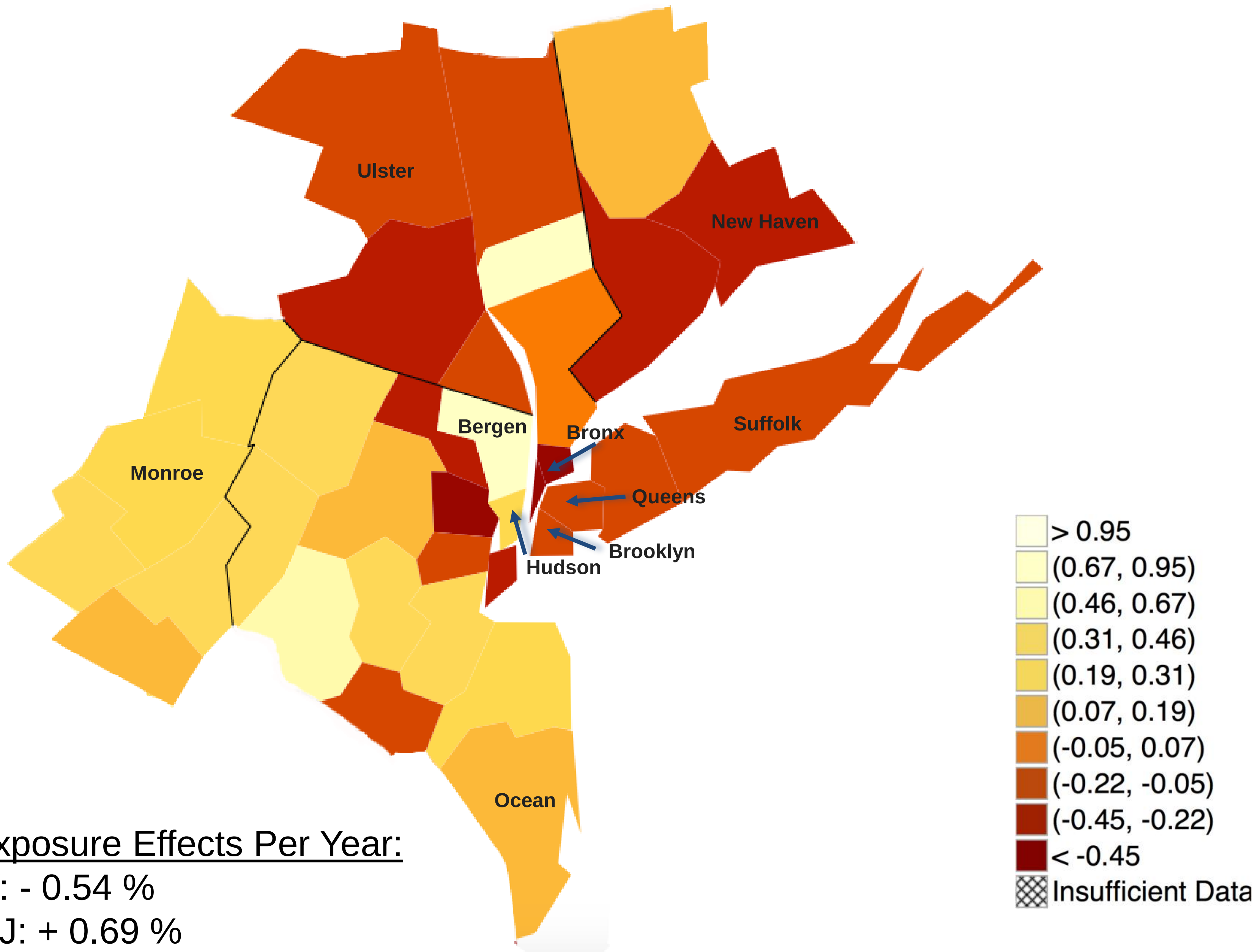
For Children with Parents at 25th Percentile of Income Distribution



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



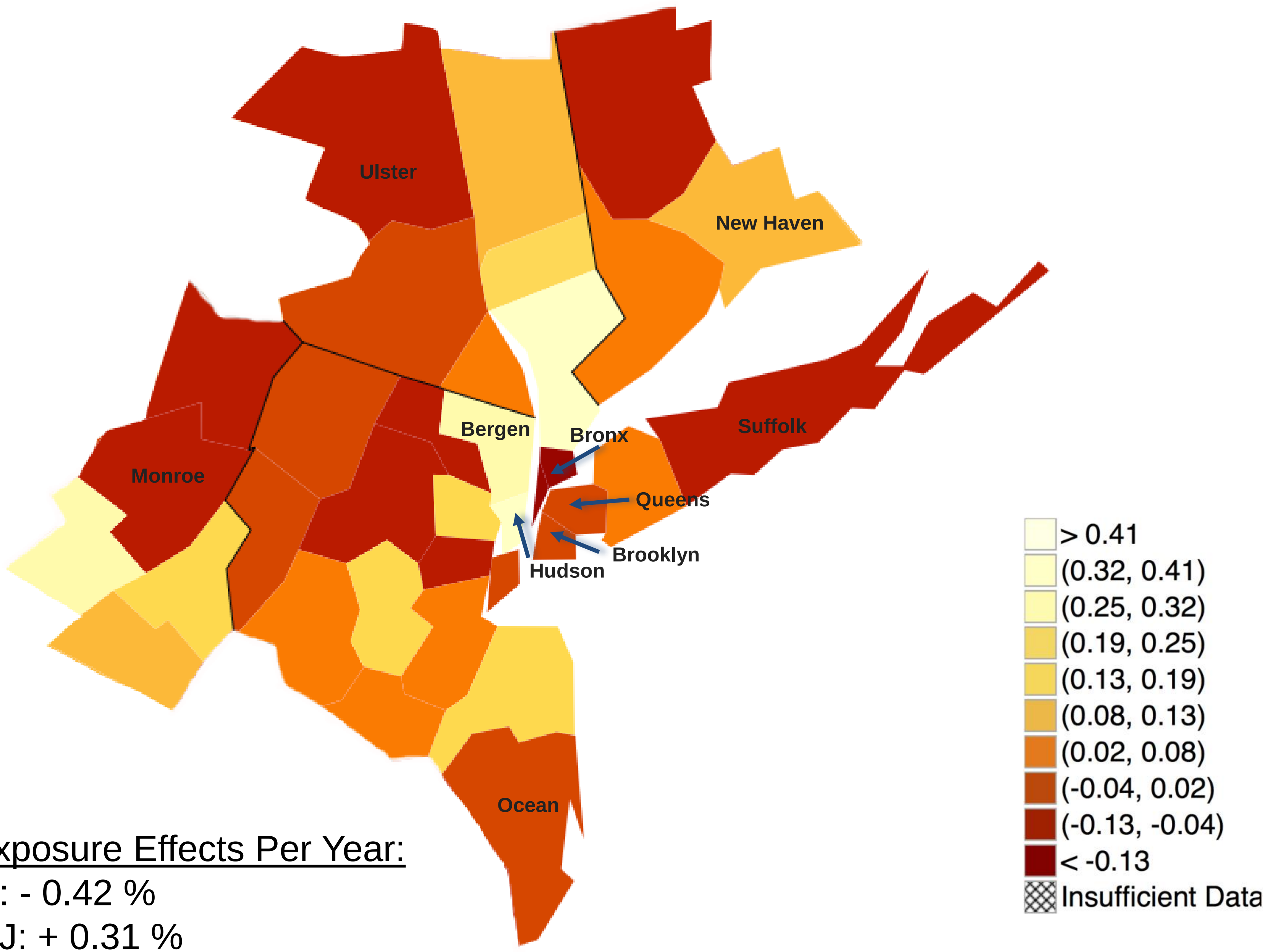
Causal Exposure Effects Per Year:

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



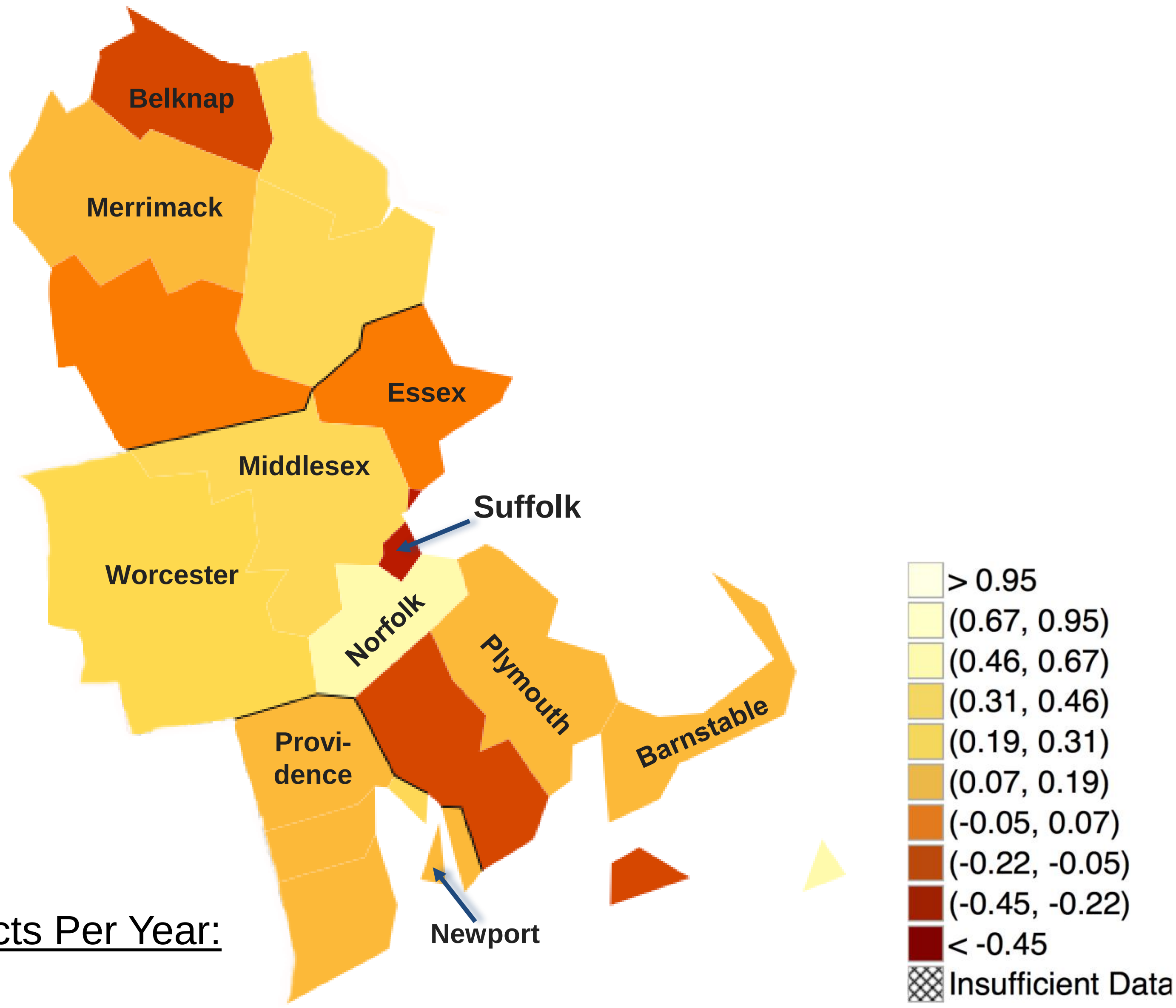
Causal Exposure Effects Per Year:

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



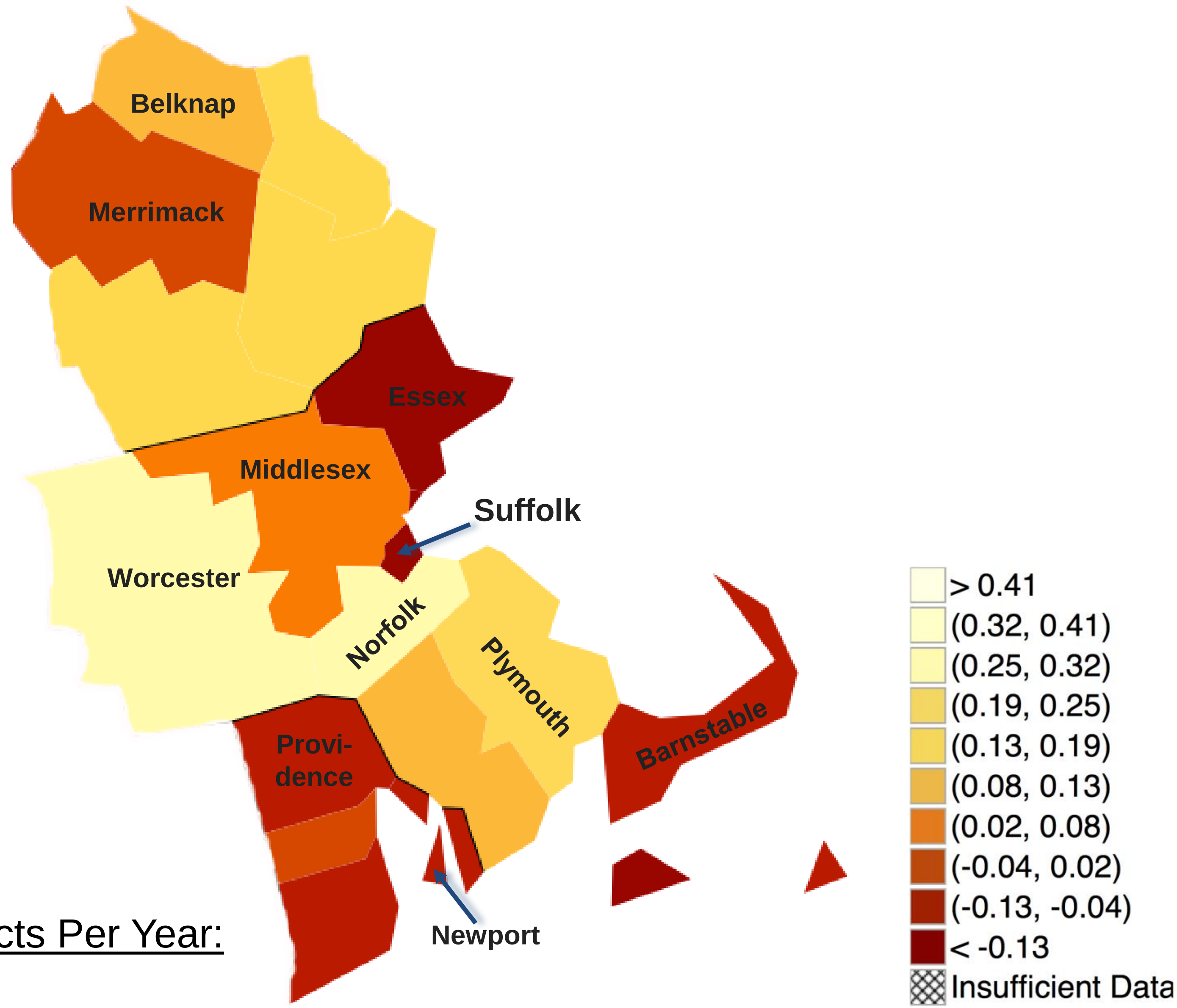
<u>Causal Exposure Effects Per Year:</u>

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

Rank	County	Annual Exposure Effect (%)
1	Dupage, IL	0.80
2	Fairfax, VA	0.75
3	Snohomish, WA	0.70
4	Bergen, NJ	0.69
5	Bucks, PA	0.62
6	Norfolk, MA	0.57
7	Montgomery, PA	0.49
8	Montgomery, MD	0.47
9	King, WA	0.47
10	Middlesex, NJ	0.46

Bottom 10 Counties

Rank	County	Annual Exposure Effect (%)
91	Wayne, MI	-0.57
92	Orange, FL	-0.61
93	Cook, IL	-0.64
94	Palm Beach, FL	-0.65
95	Marion, IN	-0.65
96	Shelby, TN	-0.66
97	Fresno, CA	-0.67
98	Hillsborough, FL	-0.69
99	Baltimore City, MD	-0.70
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

Annual Exposure Effects on Income for Children in Low-Income Families (p25)

Gender Average vs. Pooled Specification

Top 10 Counties				Bottom 10 Counties			
Rank	County	Gender Avg (%)	Pooled (%)	Rank	County	Gender Avg (%)	Pooled (%)
1	Dupage, IL	0.76	0.80	91	Pima, AZ	-0.61	-0.45
2	Snohomish, WA	0.72	0.70	92	Bronx, NY	-0.62	-0.54
3	Bergen, NJ	0.71	0.69	93	Milwaukee, WI	-0.62	-0.50
4	Bucks, PA	0.66	0.62	94	Wayne, MI	-0.63	-0.57
5	Contra Costa, CA	0.61	0.44	95	Fresno, CA	-0.65	-0.67
6	Fairfax, VA	0.60	0.75	96	Cook, IL	-0.67	-0.64
7	King, WA	0.57	0.47	97	Orange, FL	-0.67	-0.60
8	Norfolk, MA	0.54	0.57	98	Hillsborough, FL	-0.67	-0.69
9	Montgomery, MD	0.52	0.47	99	Mecklenburg, NC	-0.69	-0.72
10	Middlesex, NJ	0.43	0.46	100	Baltimore City, MD	-0.86	-0.70

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]

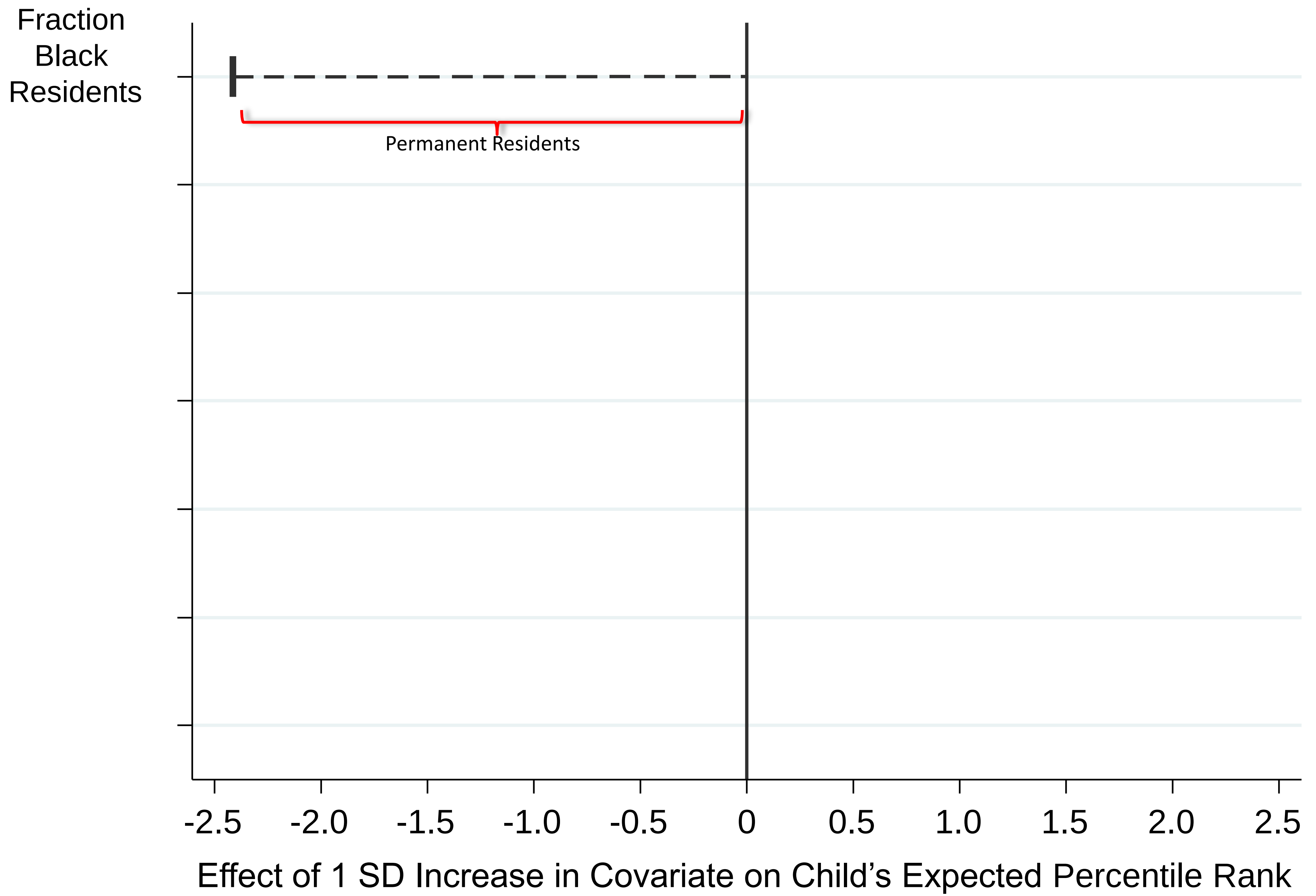
  - Segregation, Inequality, School Quality, Social Capital, Family Structure

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

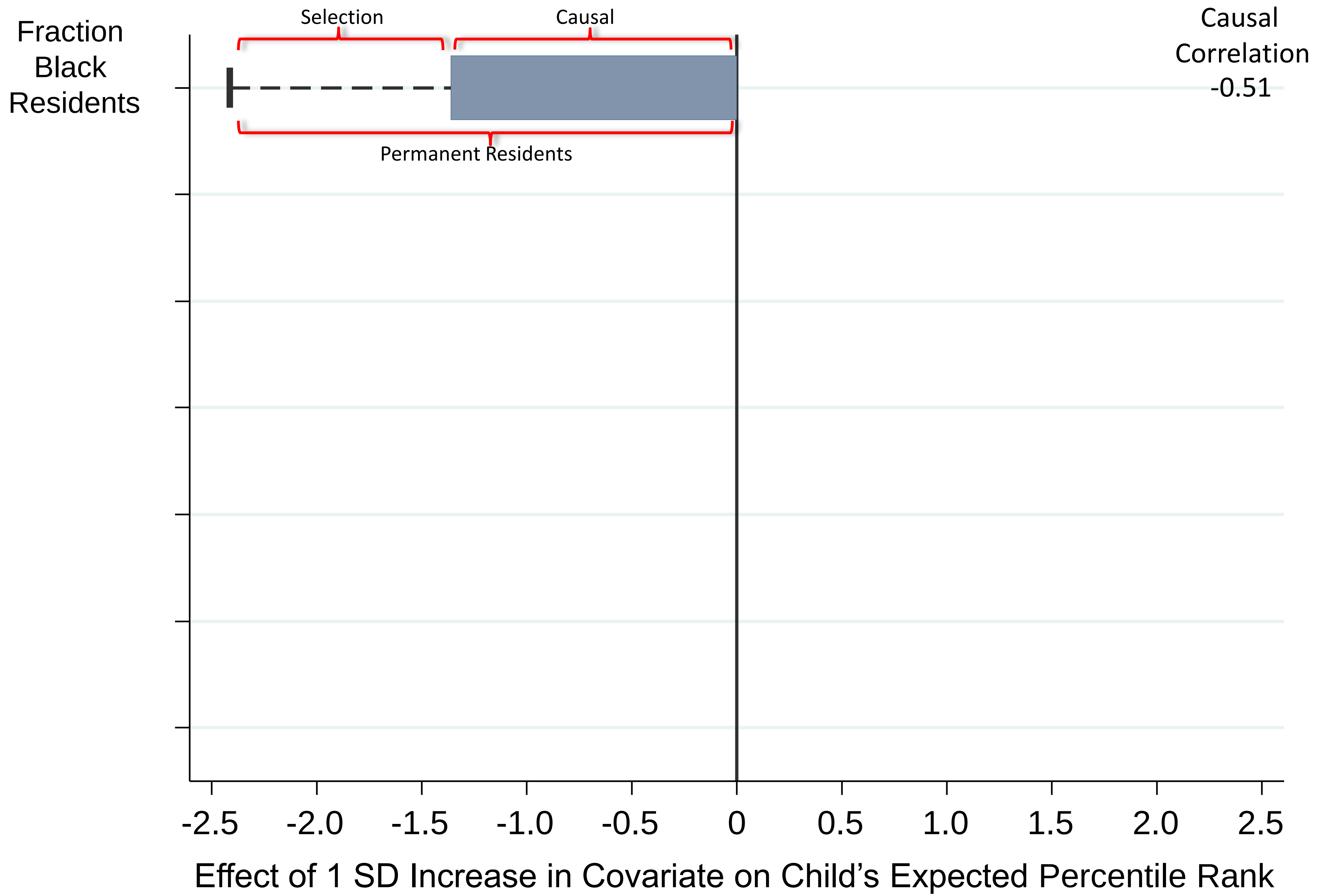
Step 4: Characteristics of Good Areas

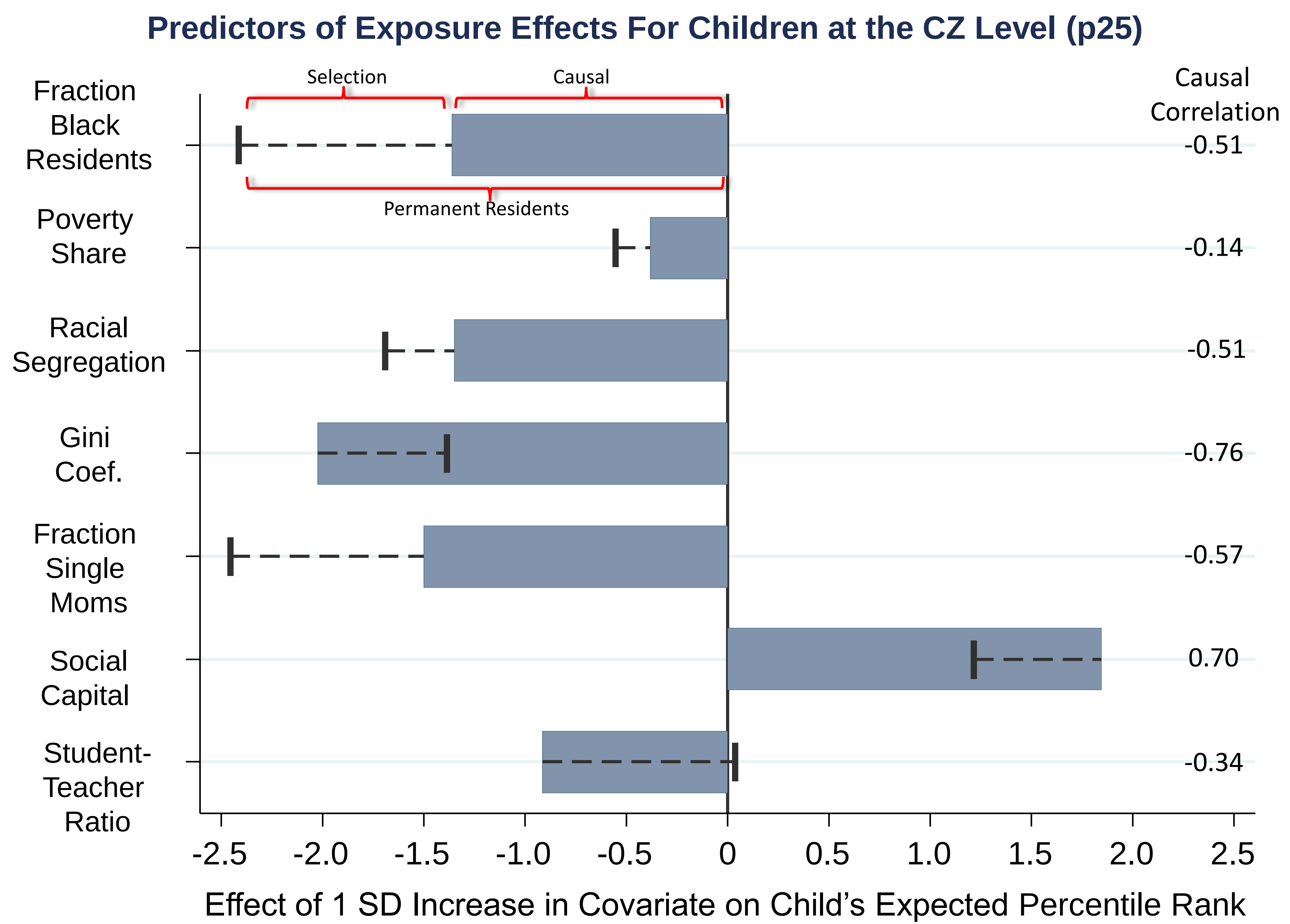
- Decompose observed rank for stayers (y_{pc}) into causal and sorting components by multiplying annual exposure effect μ_{pc} by 20:
  - Causal component = $20\mu_{pc}$
  - Sorting component = $y_{pc} – 20\mu_{pc}$
- Regress y_{pc}, causal, and sorting components on covariates
  - Standardize covariates 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)

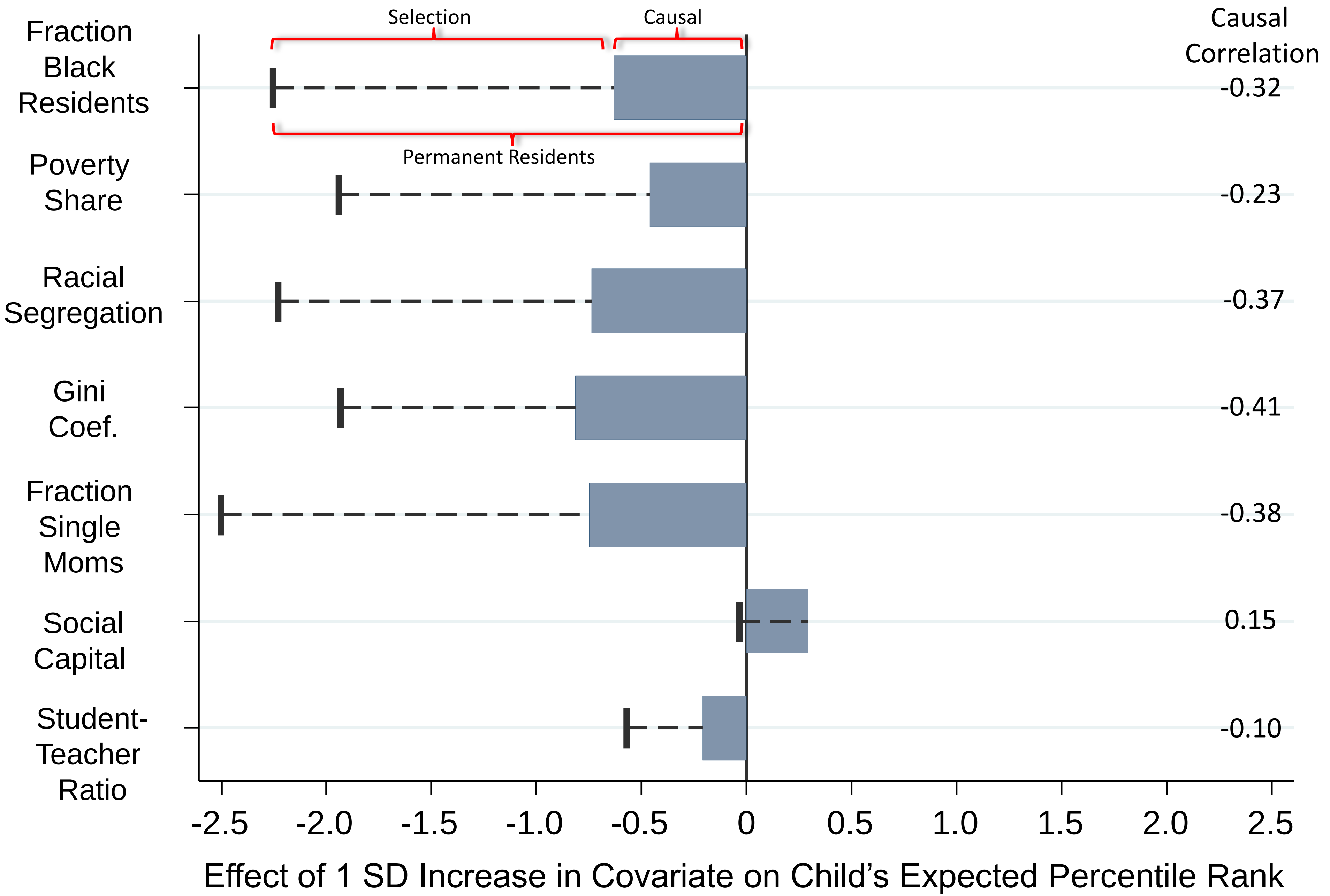


Predictors of Exposure Effects For Children at the CZ Level (p25)

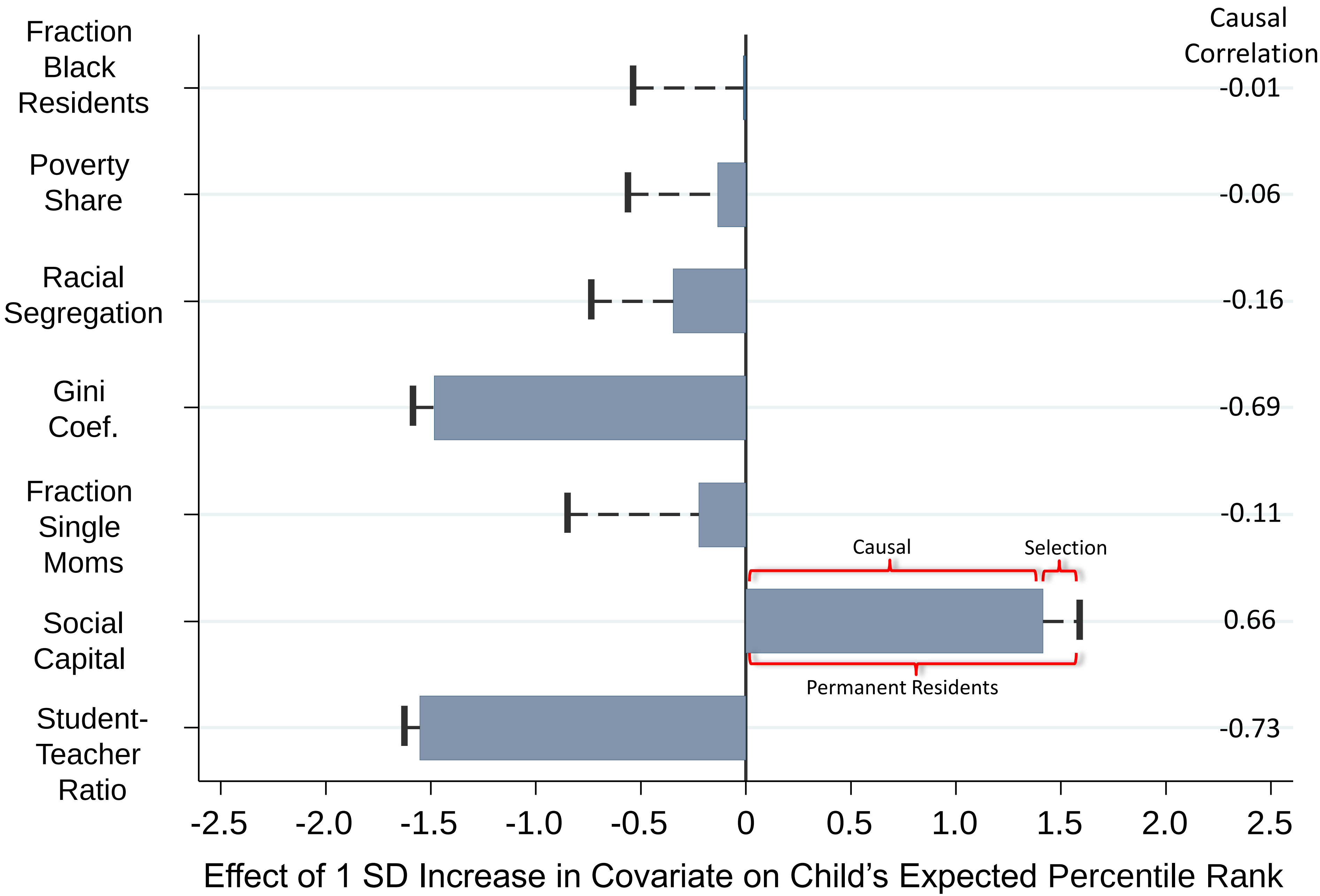


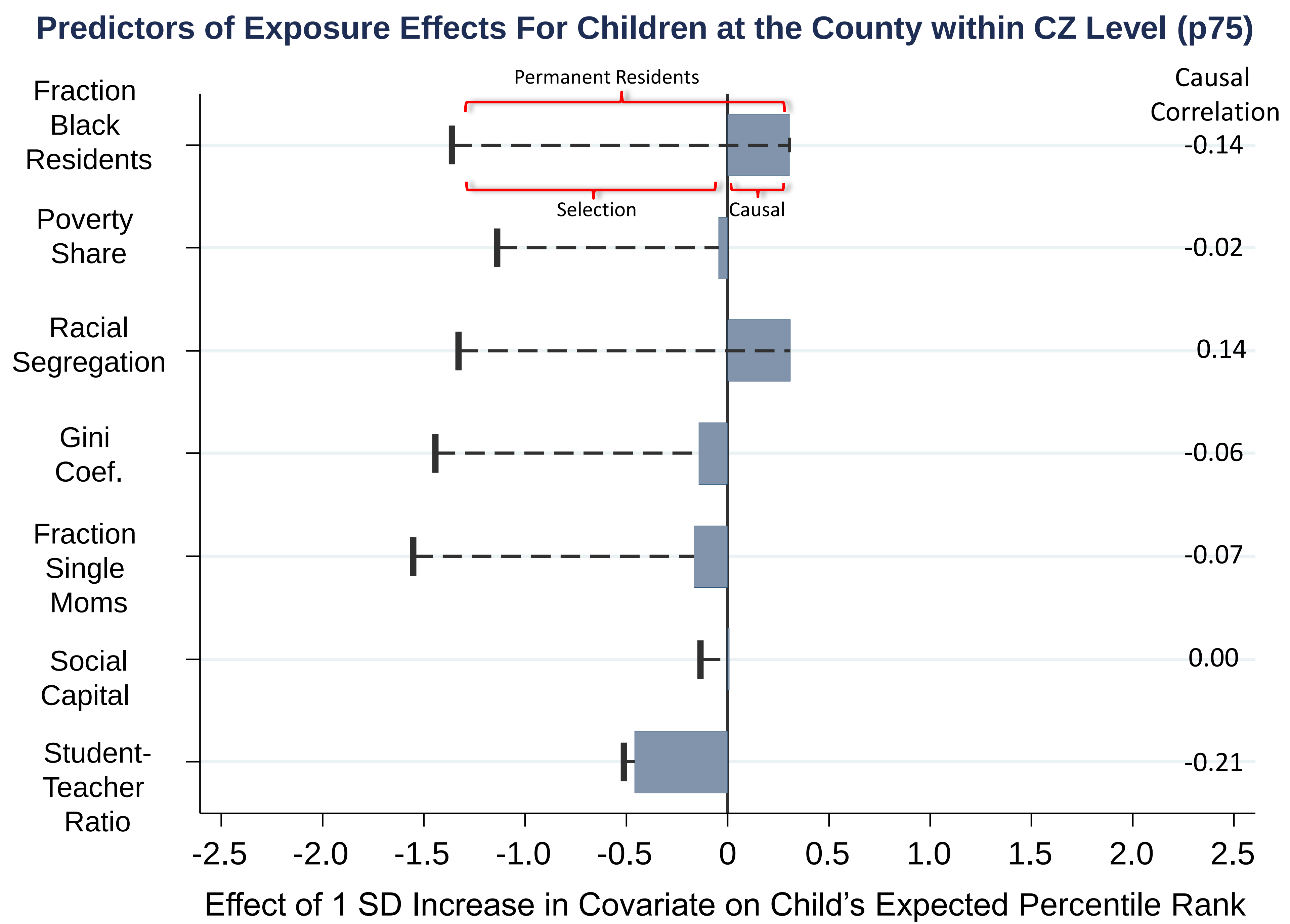

Predictors of Exposure Effects For Children at the CZ Level (p25)
Selection
Causal
Permanent Residents
Causal Correlation
Fraction Black Residents
-0.51
Poverty Share
-0.14
Racial Segregation
-0.51
Gini Coef.
-0.76
Fraction Single Moms
-0.57
Social Capital
0.70
Student-Teacher Ratio
-0.34
-2.5
-2.0
-1.5
-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)
Permanent Residents
Selection
Causal
Causal Correlation
Fraction Black Residents
-0.14
Poverty Share
-0.02
Racial Segregation
0.14
Gini Coef.
-0.06
Fraction Single Moms
-0.07
Social Capital
0.00
Student-Teacher Ratio
-0.21
-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

House Prices

- Does it cost more to live in a county that improves children's outcomes?

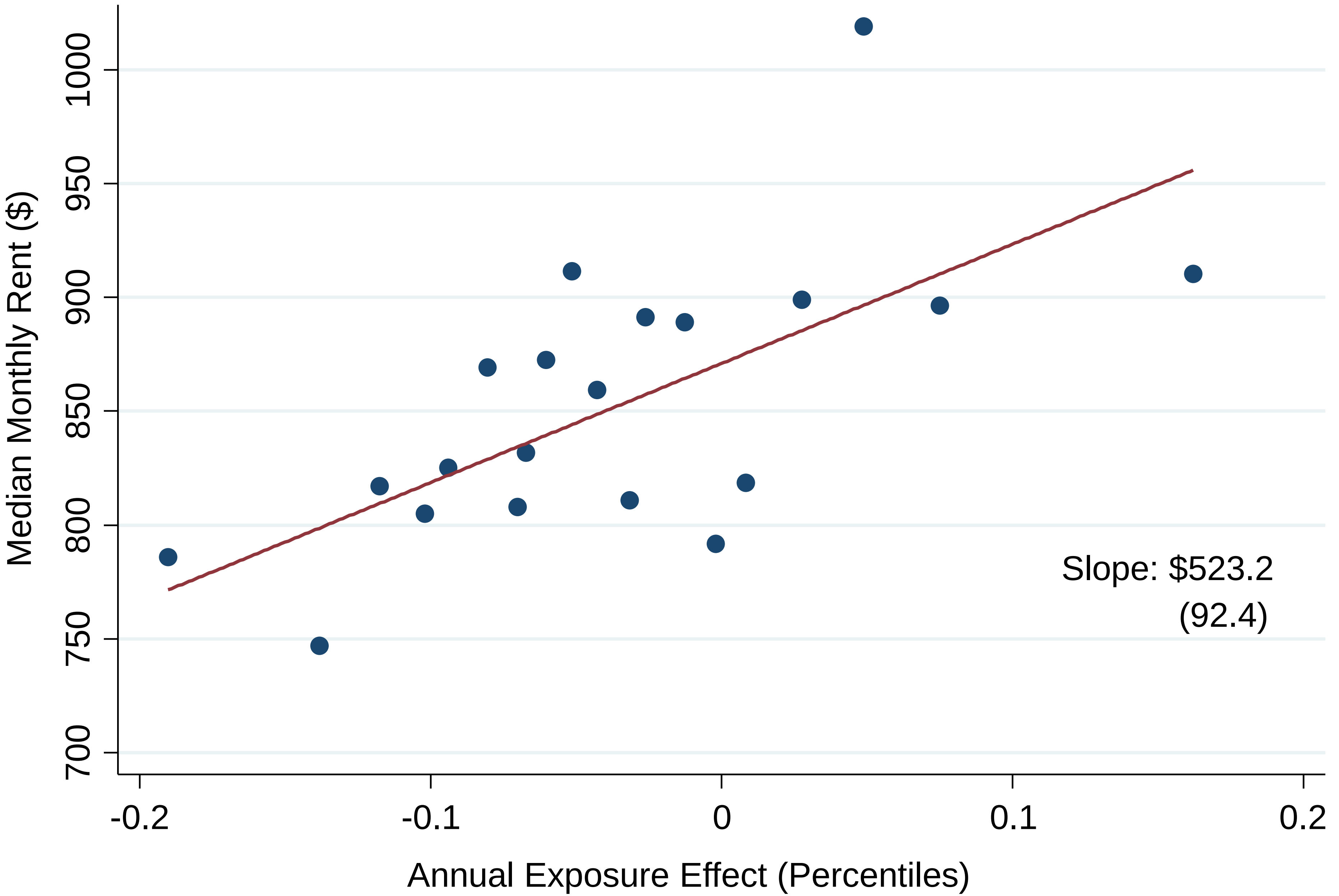
- Correlation between causal exposure effect and median rent is *negative* (-0.3) across CZs
  - Rural areas produce better outcomes

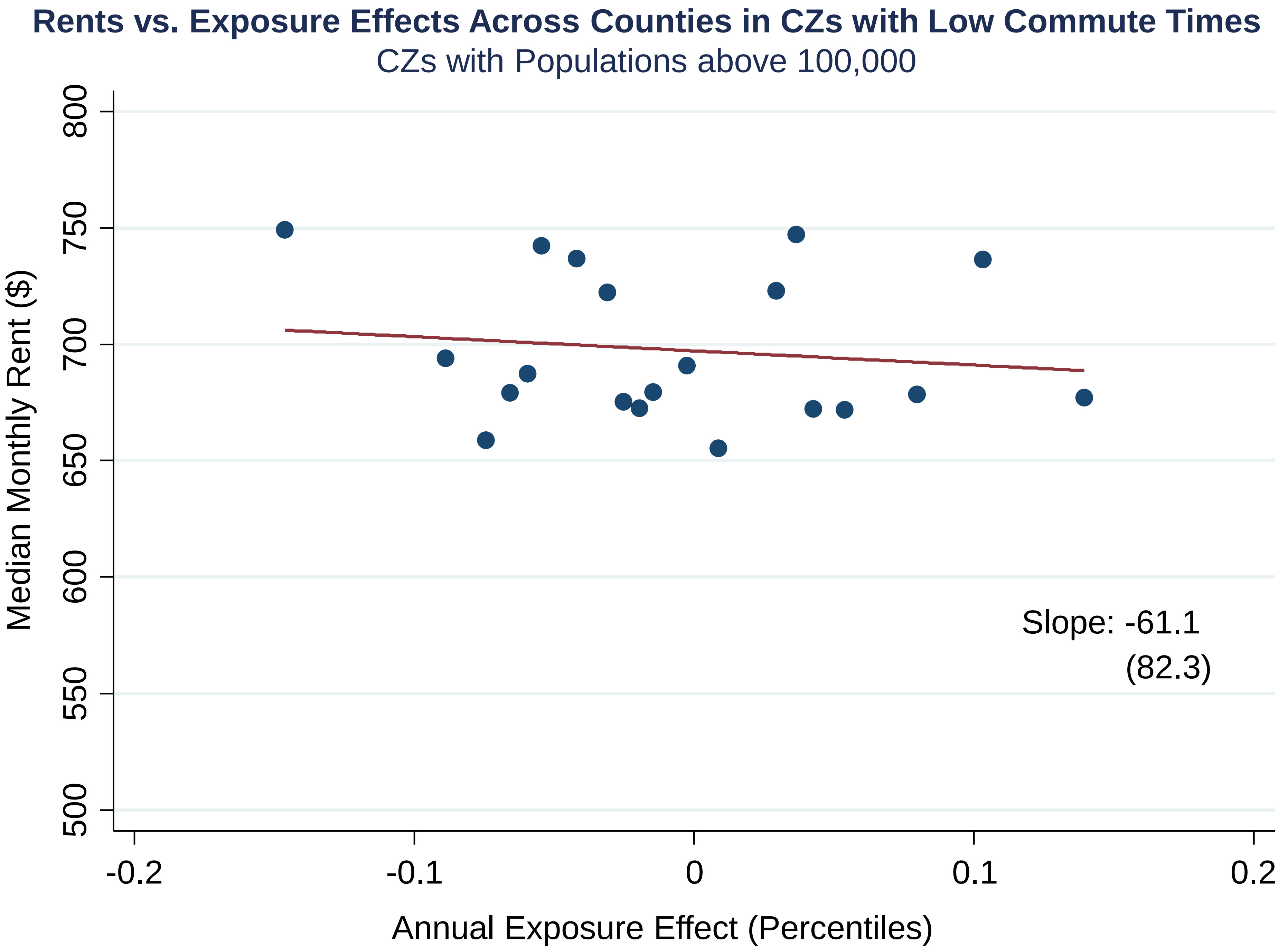
- Across counties within CZ's, correlation is +0.07 overall

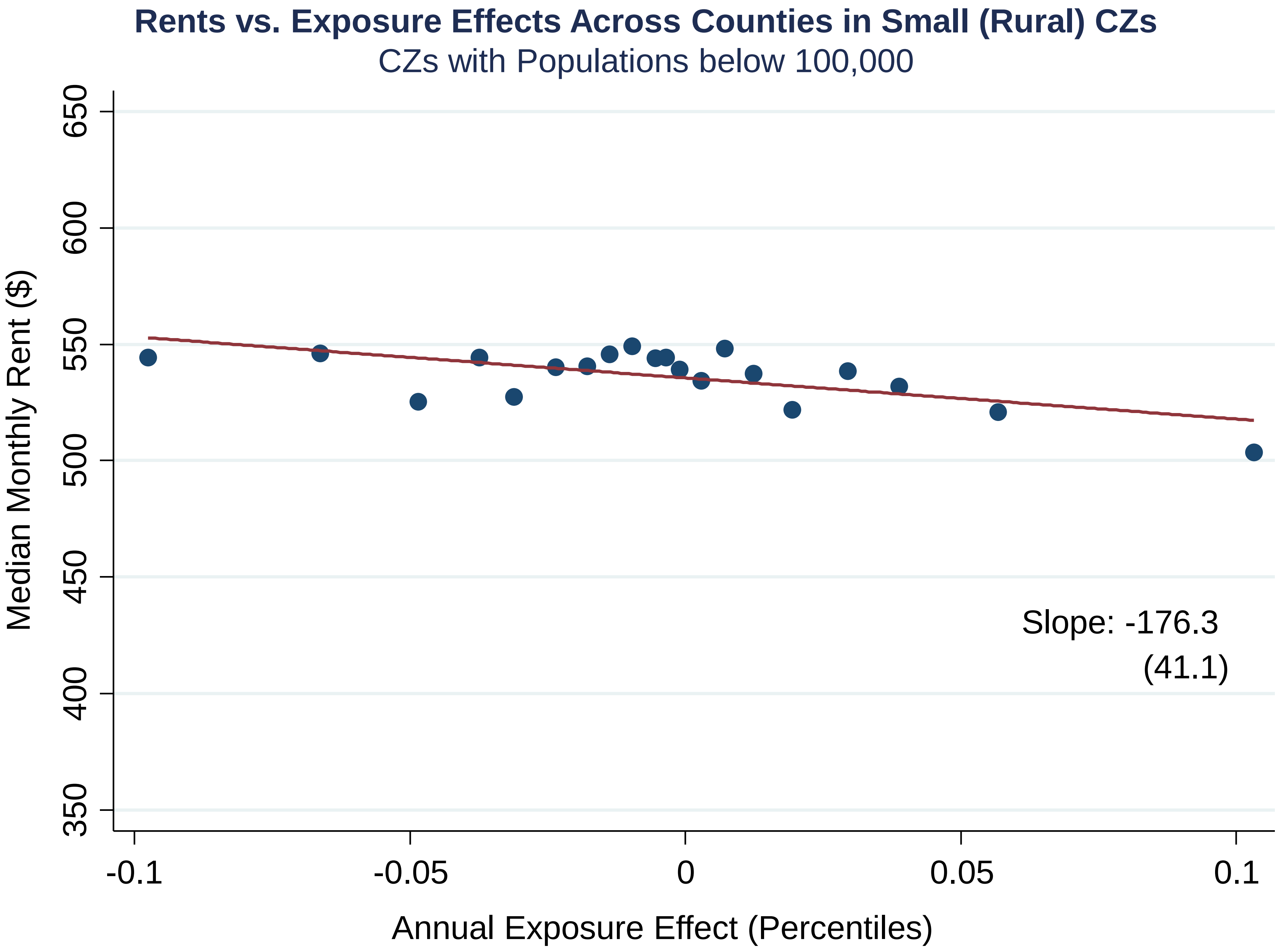
- But significant heterogeneity across CZ's with low vs. high levels of segregation/sprawl
  - Split sample into CZs based on average commute times

Rents vs. Exposure Effects Across Counties in CZs with High Commute Times

CZs with Populations above 100,000



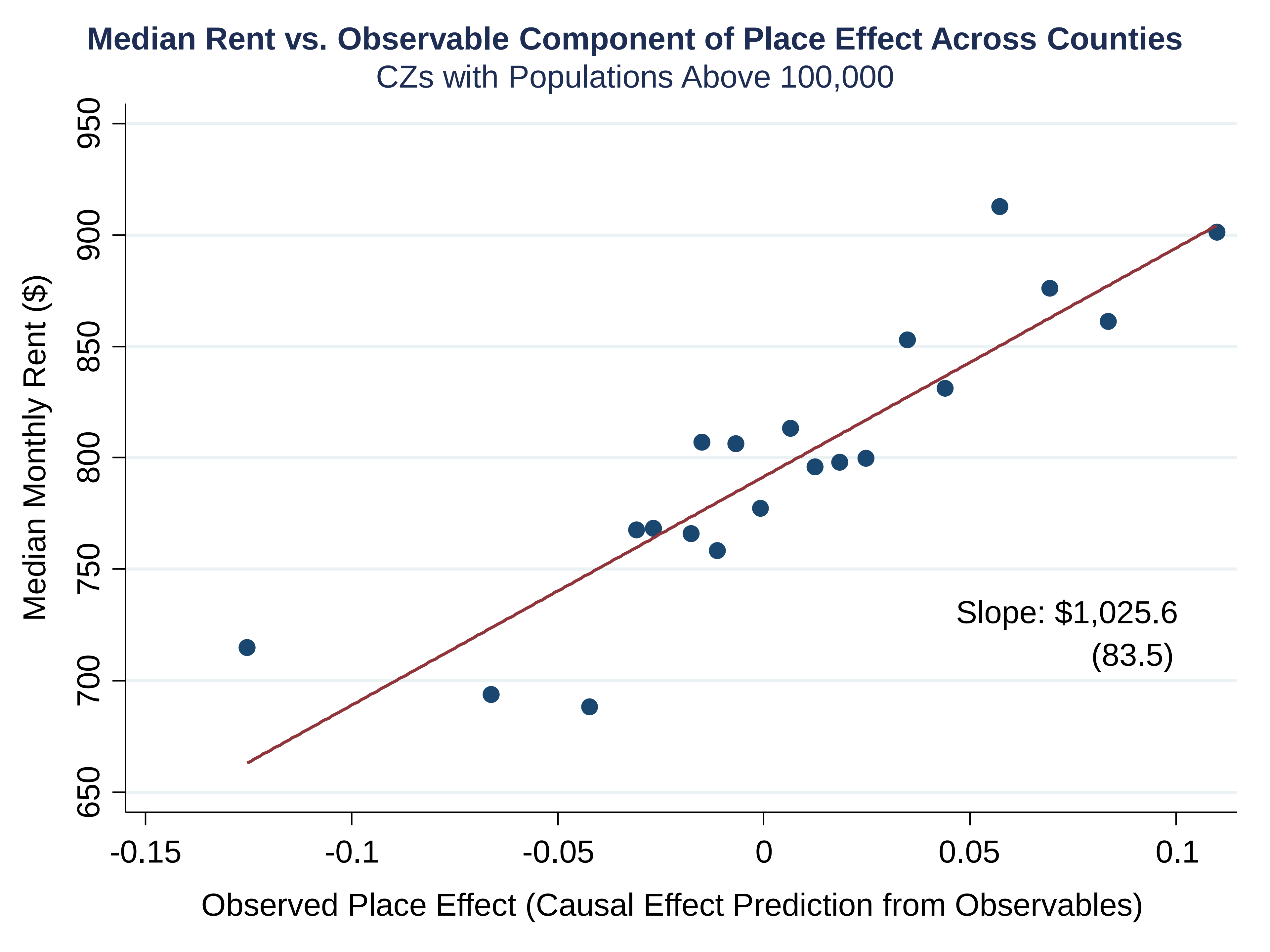

Rents vs. Exposure Effects Across Counties in CZs with Low Commute Times
CZs with Populations above 100,000
Median Monthly Rent ($)
800
750
700
650
600
550
500
-0.2
-0.1
0
0.1
0.2
Annual Exposure Effect (Percentiles)
Slope: -61.1
(82.3)



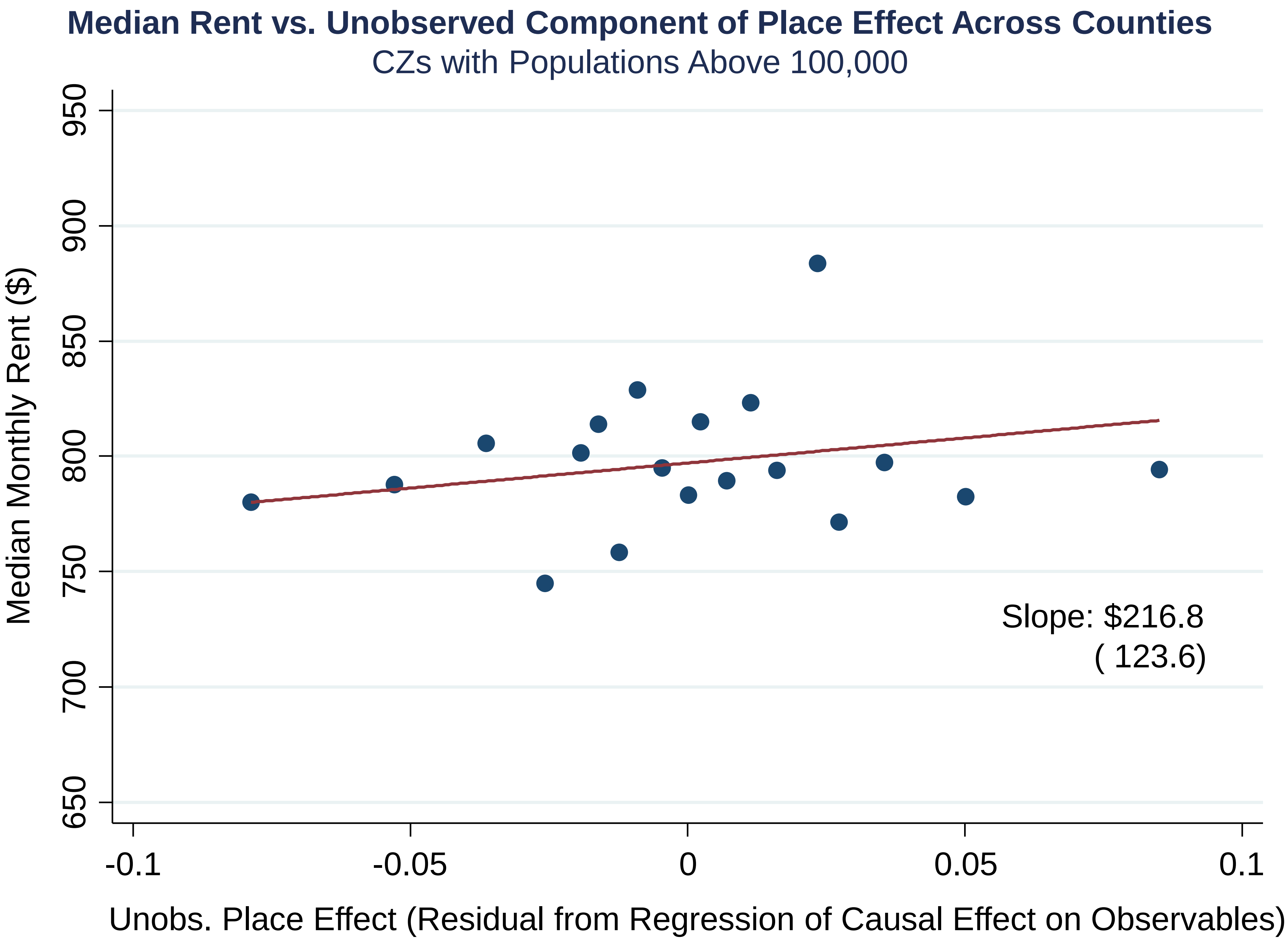
Rents vs. Exposure Effects Across Counties in Small (Rural) CZs
CZs with Populations below 100,000
Median Monthly Rent ($)
650
600
550
500
450
400
350
-0.1
-0.05
0
0.05
0.1
Annual Exposure Effect (Percentiles)
Slope: -176.3
(41.1)

House Prices

- Why are causal effects on children not fully capitalized in house prices?
  - One explanation: causal effects not fully observed
- Test by splitting place effects into "observable" and "unobservable" components
- Define observable component as projection of place effect onto observables: poverty rate, commute time, single parent share, test scores, and Gini
- Define unobservable component as residual from this regression, shrunk to adjust for measurement error
- Regress median rent on observable and unobservable components
  - Roughly one-third of the variance is "observable" and two-thirds is not



Median Rent vs. Observable Component of Place Effect Across Counties
CZs with Populations Above 100,000
Median Monthly Rent ($)
950
900
850
800
750
700
650
-0.15
-0.1
-0.05
0
0.05
0.1
Observed Place Effect (Causal Effect Prediction from Observables)
Slope: $1,025.6
(83.5)


Median Rent vs. Unobserved Component of Place Effect Across Counties
CZs with Populations Above 100,000
Median Monthly Rent ($)
950
900
850
800
750
700
650
-0.1
-0.05
0
0.05
0.1
Unobs. Place Effect (Residual from Regression of Causal Effect on Observables)
Slope: $216.8
(123.6)

House Prices

- Main lesson: substantial scope to move to areas that generate greater upward mobility for children without paying much more
  - Especially true in cities with low levels of segregation
- In segregated cities, places that generate good outcomes without having typical characteristics (better schools, lower poverty rates) provide bargains
  - Ex: Hudson County, NJ vs. Bronx in New York metro area
- Encouraging for housing-voucher policies that seek to help low-income families move to better areas

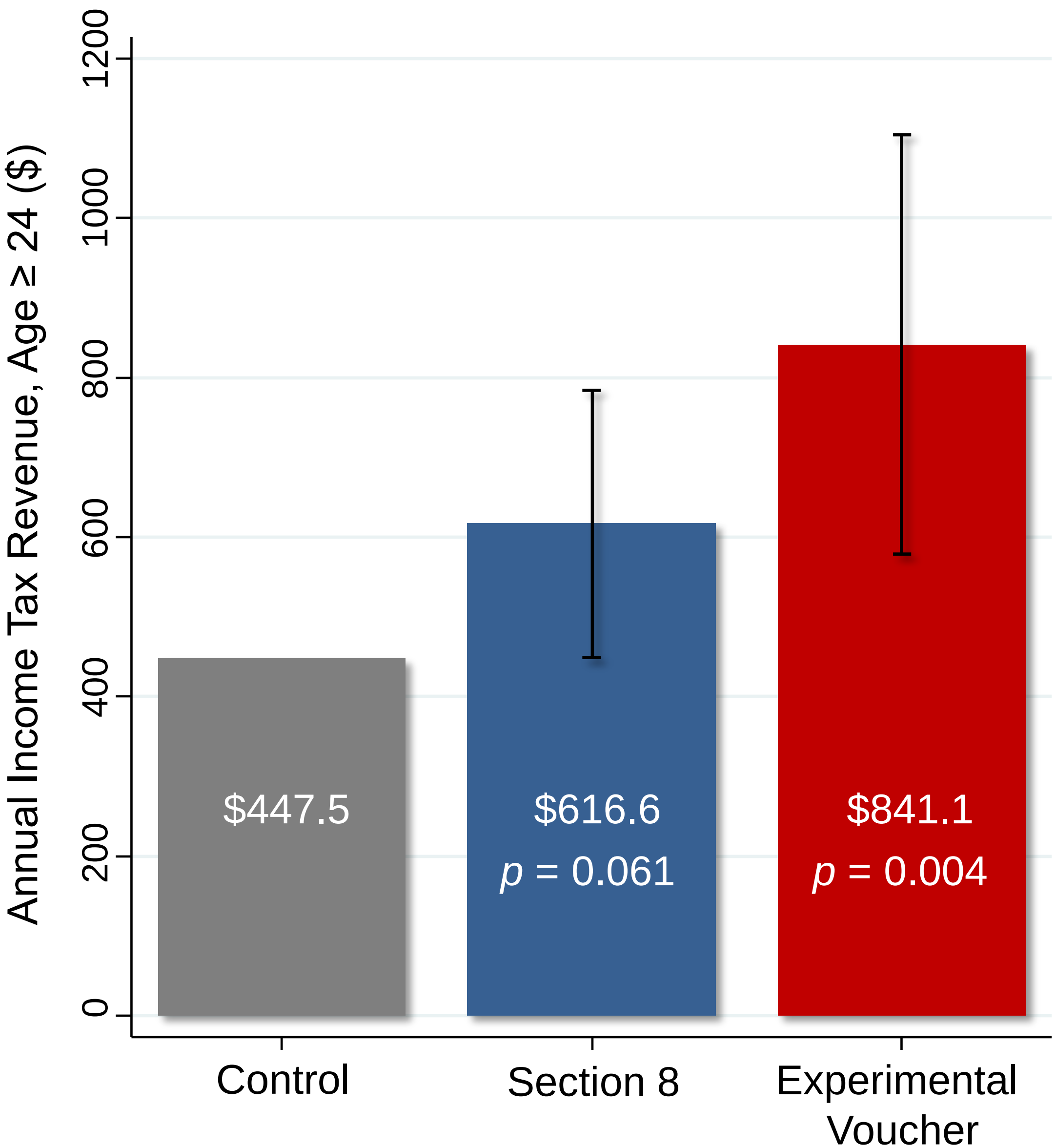
Conclusion: Policy Lessons

- 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)



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

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

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

www.equality-of-opportunity.org/data

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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