# SSSI 2017

# Neighborhoods, Intergenerational Mobility, and Opportunity in the United States

Nathaniel Hendren

Harvard University

Summer, 2017

# Impact of Neighborhoods

- Large literature, esp. in Sociology, documents wide variation in outcomes for both children and adults across areas
  - Wilson (1987), Massey and Denton (1993), Cutler and Glaeser (1997). Wodtke et al. (1999)
- Does this reflect a causal role of place?
- Key issue: separating **causality** vs. **sorting**
  - [Sorting] Do different types of people live in different places?
  - [Causal] Or, do places have causal effects?
- This lecture: Focus on place's impact on children

# This Lecture

- **Part A:** Does place matter for kids' outcomes in adulthood?
  - Chetty and Hendren (2016): Variation in intergenerational mobility in the U.S. reflects the causal effect of exposure during childhood
  - Separate sorting versus causal story using cross-area movers
- **Part B:** What are the implications for policies?
  - [Place-based] Improve places
    - E.g. Harlem Children's Zone (Dobbie and Fryer, 2011)
  - [Choice-based] Relax constraints faced by families choosing where to raise their children
    - E.g. Moving to Opportunity experiment (Chetty, Hendren, and Katz, 2016)

# Part A: Chetty and Hendren (2016) Data

- Begin by documenting variation in intergenerational mobility in the US
- 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"

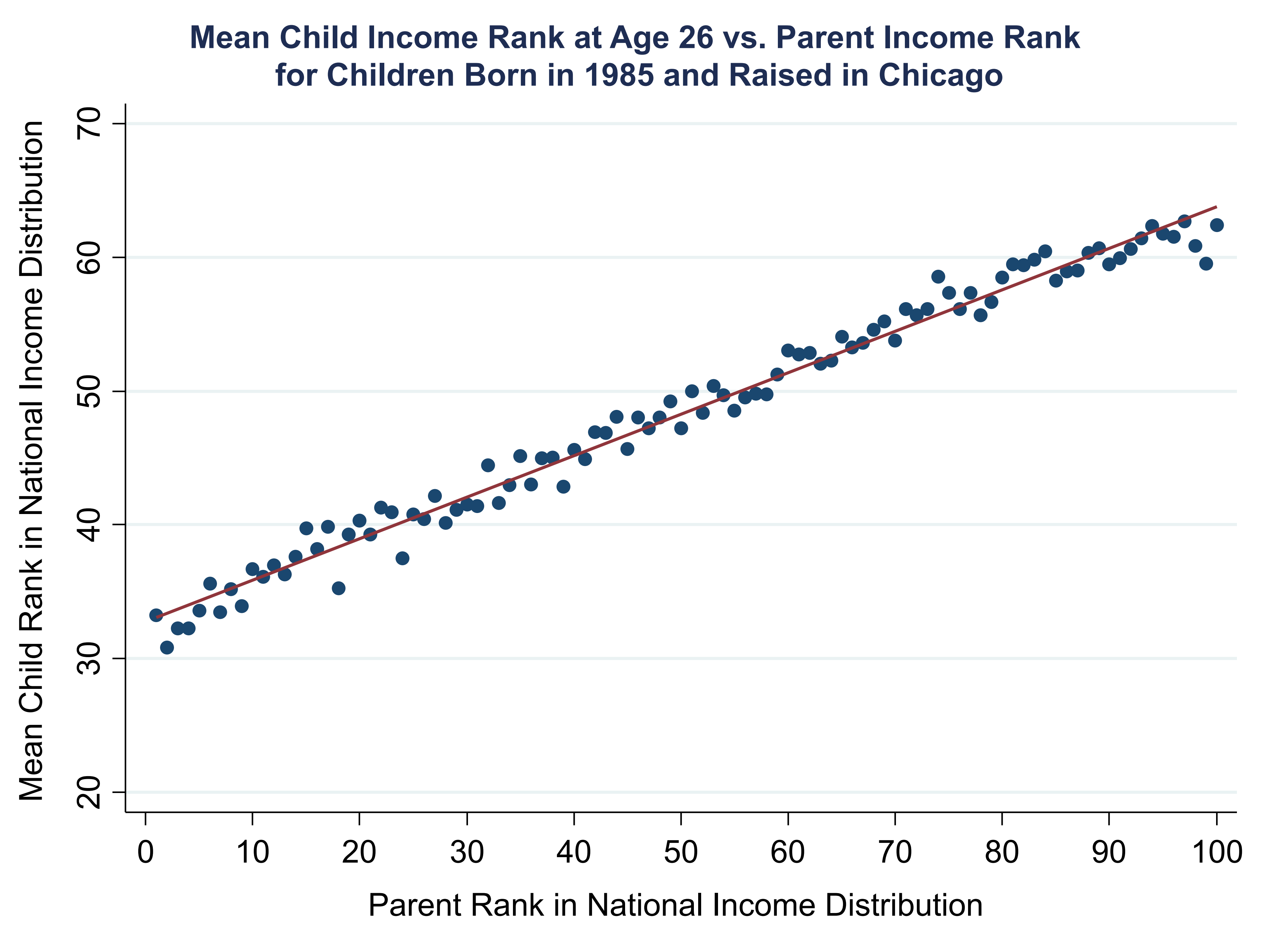
- Conceptualize neighborhood effects as the sum of effects at different geographies (hierarchical model)

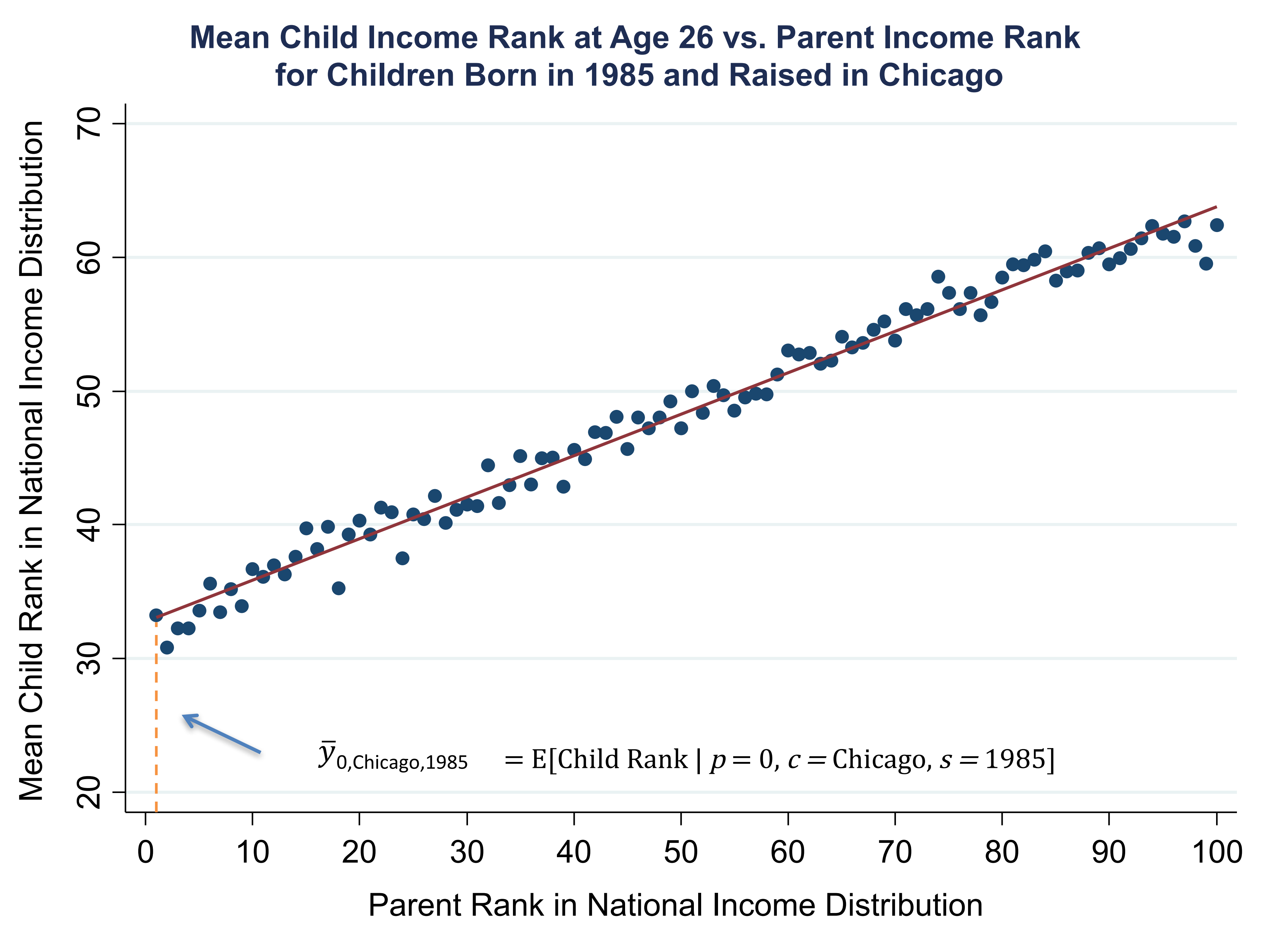
$$\mu_{nbhd} = \mu_{CZ} + \mu_{County} + \mu_{Zip} + \mu_{Block}$$

- 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

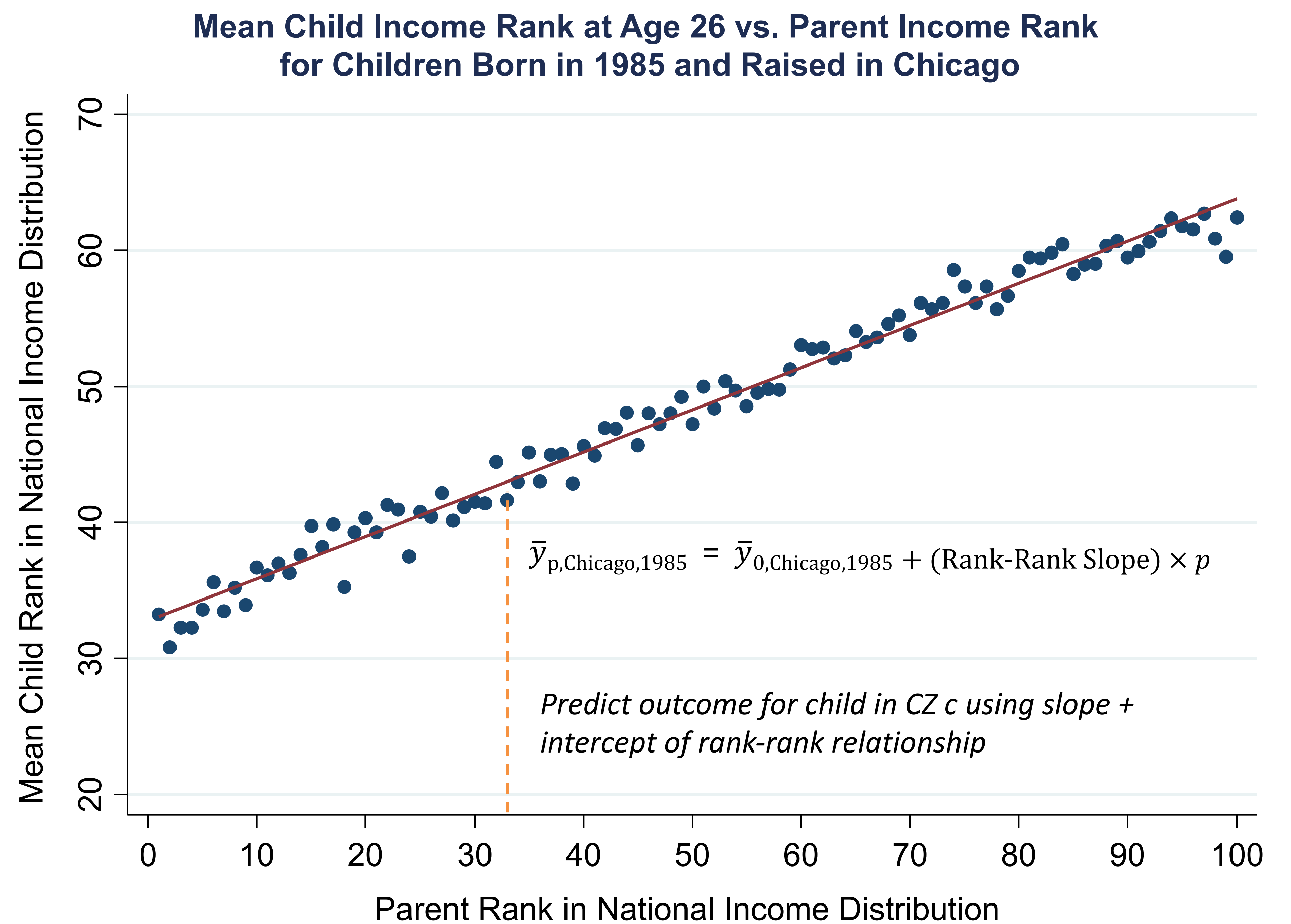
# Intergenerational Mobility by CZ

- Begin with a descriptive characterization of children's outcomes in each CZ
  - CZ's are aggregations of counties analogous to MSAs
    [Tolbert and Sizer 1996; Autor and Dorn 2013]
- 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
Parent Rank in National Income Distribution
20
30
40
50
60
70
0
10
20
30
40
50
60
70
80
90
100



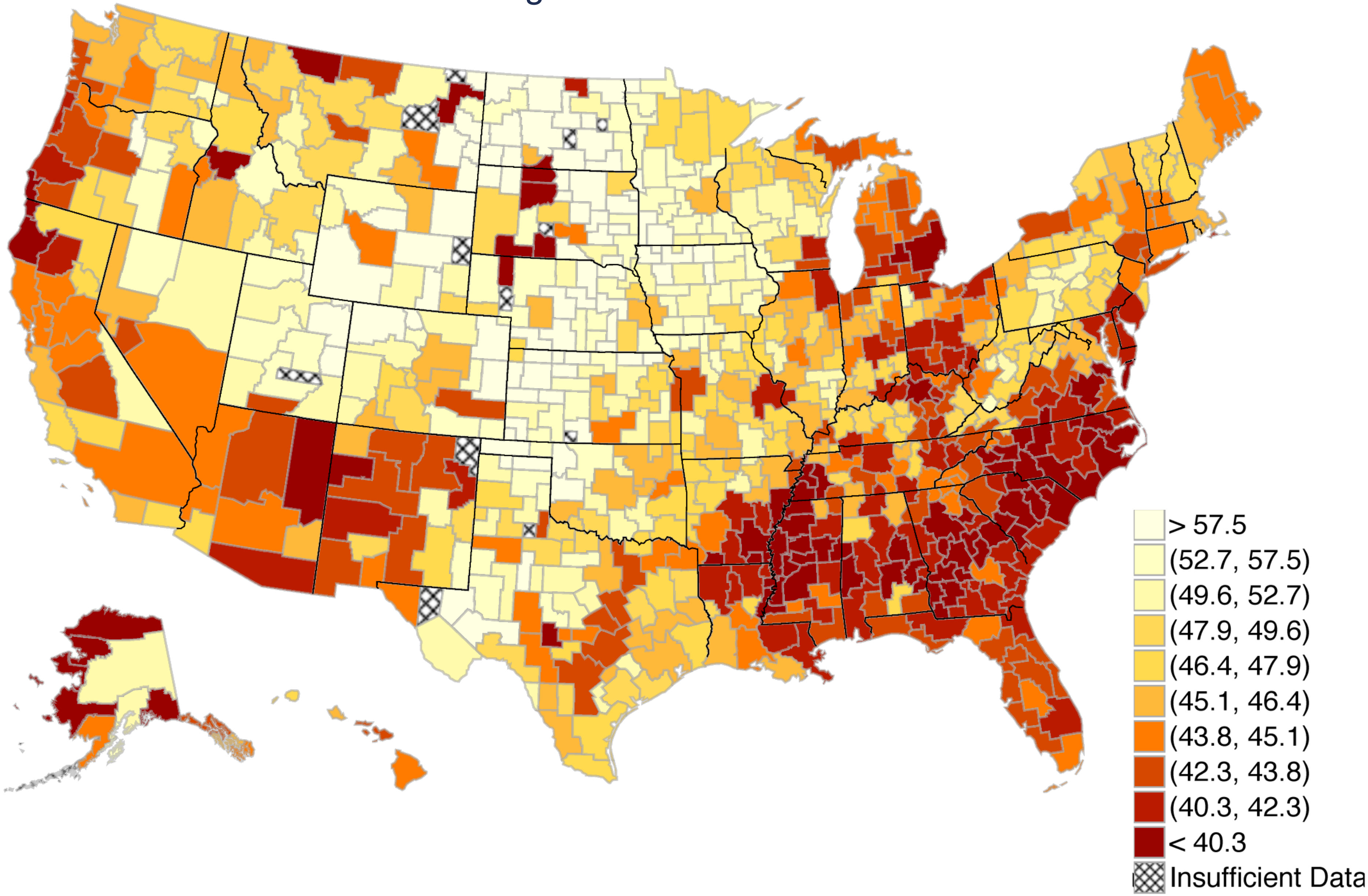
Mean Child Income Rank at Age 26 vs. Parent Income Rank
for Children Born in 1985 and Raised in Chicago
Mean Child Rank in National Income Distribution
20
30
40
50
60
70
0
10
20
30
40
50
60
70
80
90
100
Parent Rank in National Income Distribution
$\bar{y}_{0,\text{Chicago},1985} = \text{E}[\text{Child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



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
Parent Rank in National Income Distribution
20
30
40
50
60
70
0
10
20
30
40
50
60
70
80
90
100
$\bar{y}_{p,\text{Chicago},1985} = \bar{y}_{0,\text{Chicago},1985} + (\text{Rank-Rank Slope}) \times p$
Predict outcome for child in CZ c using slope +
intercept of rank-rank relationship

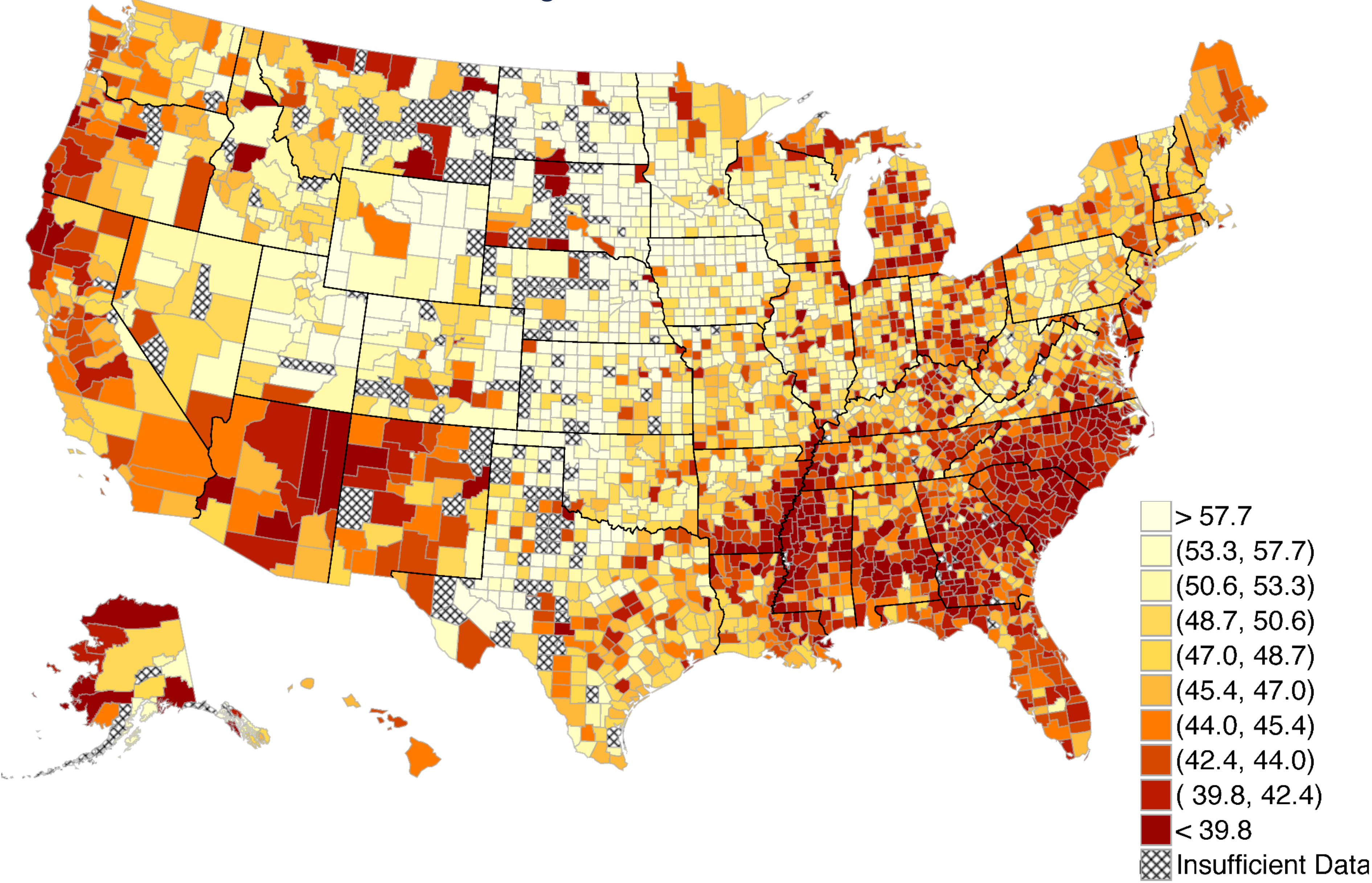
# The Geography of Intergenerational Mobility in the United States

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



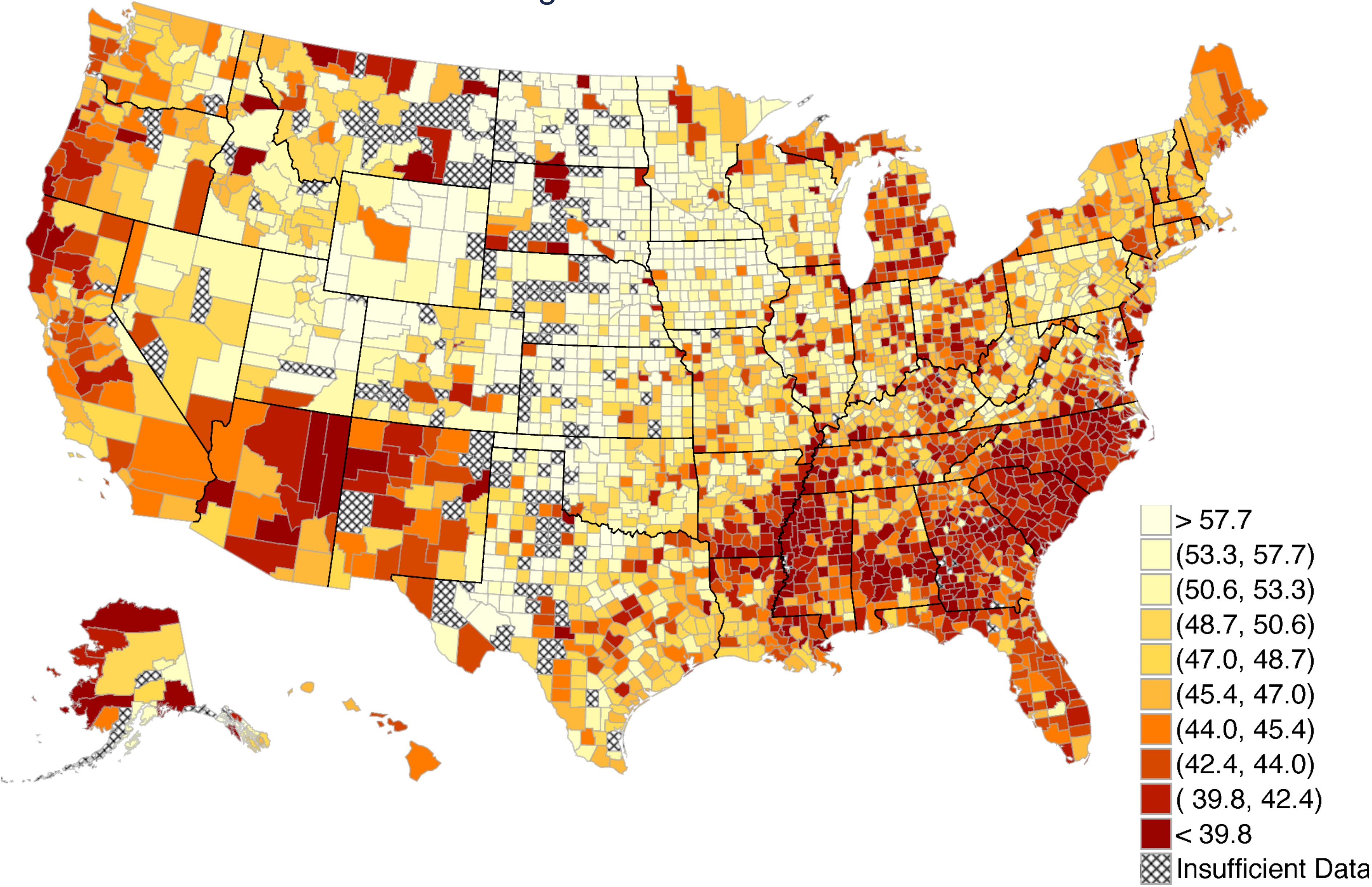
# The Geography of Intergenerational Mobility in the United States

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



# The Geography of Intergenerational Mobility in the United States

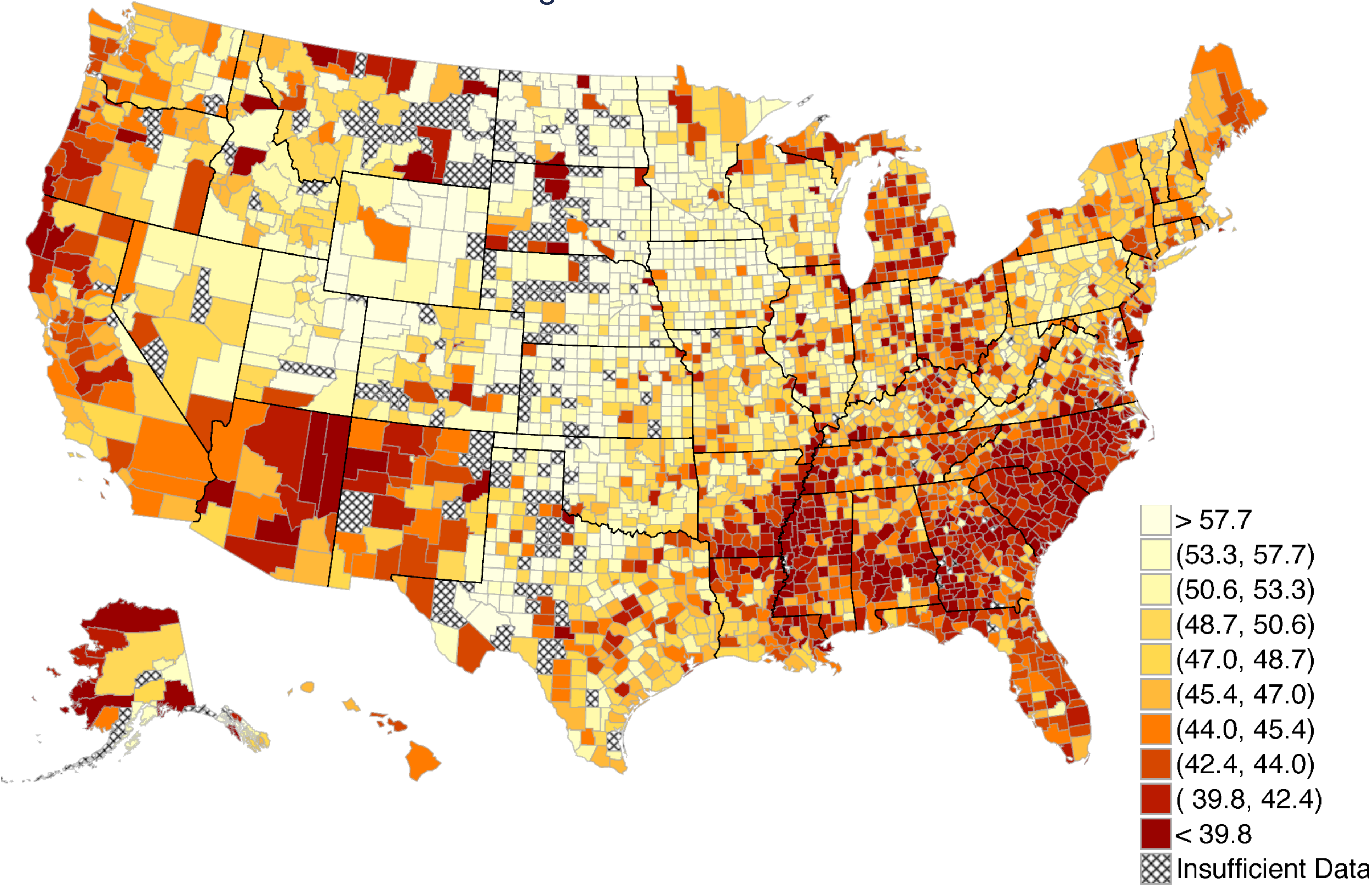
Predicted Income Rank at Age 26 for Children with Parents at 25th Percentile




**Question 1: What happens if you move to a lighter-shade county?**

# The Geography of Intergenerational Mobility in the United States

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




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

# Question 1: Neighborhood Exposure Effects

- Analyze 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

- Chetty and Hendren (2016) estimate exposure effects by studying families that move across CZ's with children at different ages in observational data

- Key problem: 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 ($\theta_i$) 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 (vs. worse) 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

  - Will evaluate this assumption in detail after baseline results

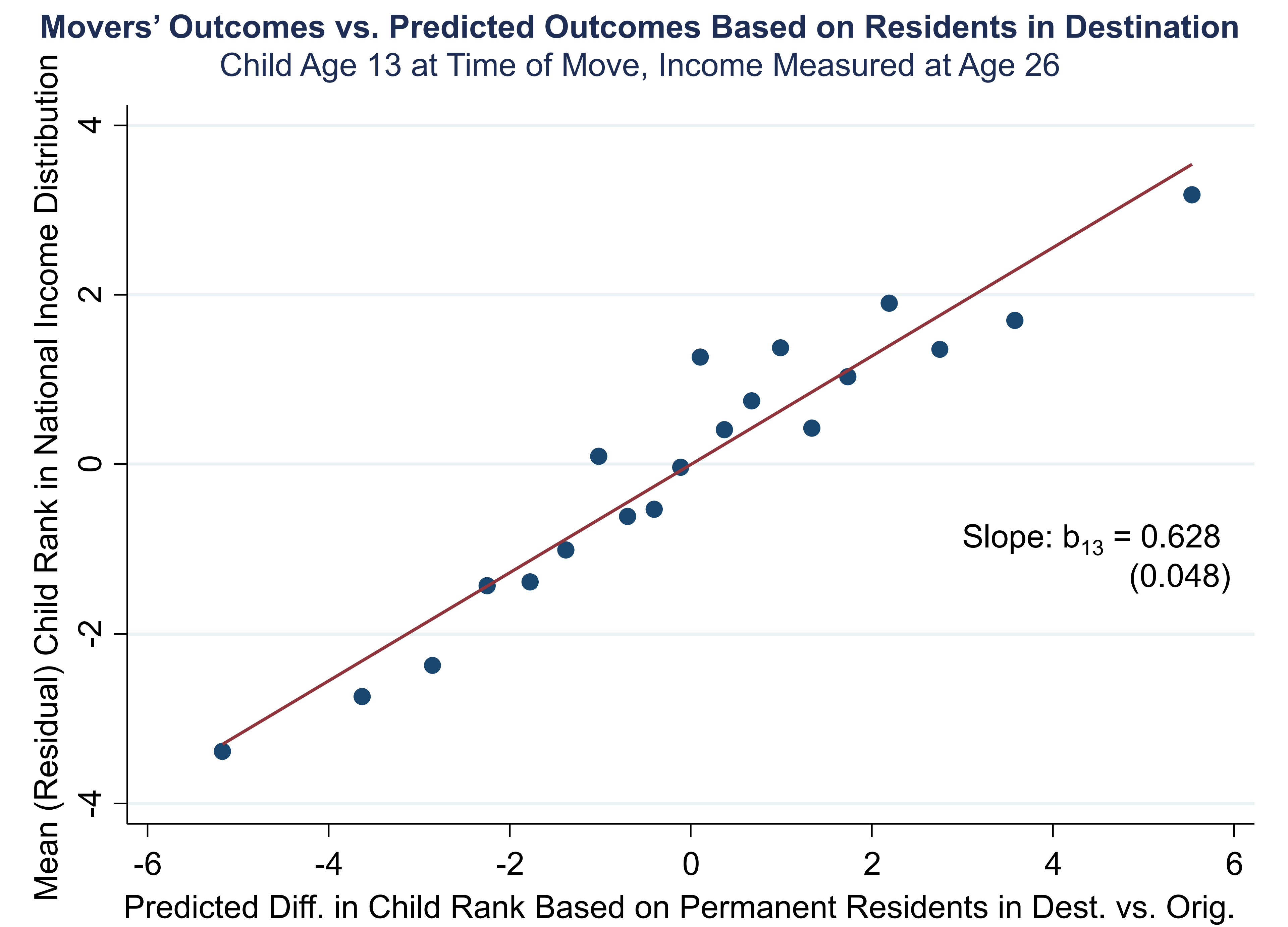
# Estimating Exposure Effects in Observational Data

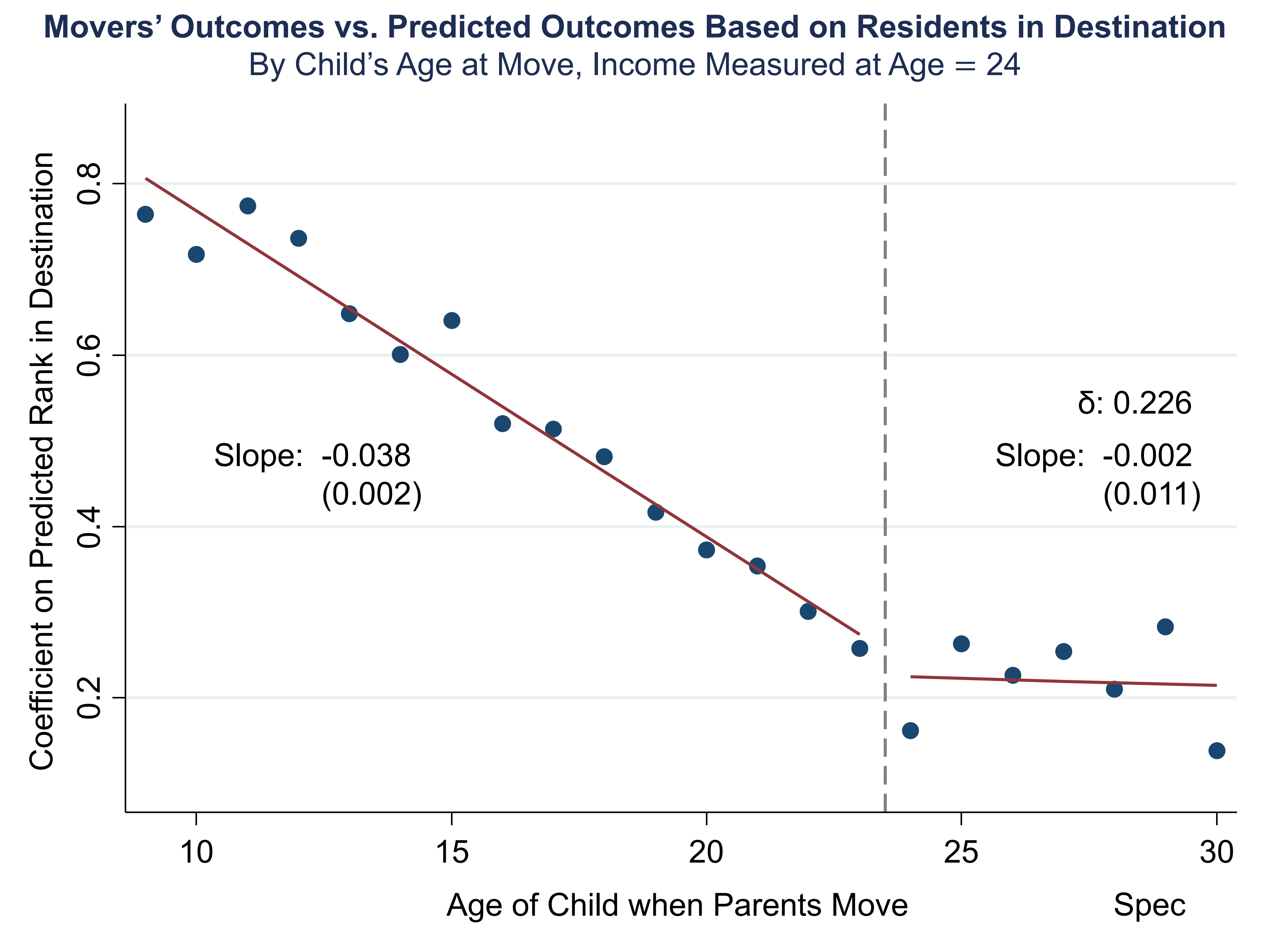
- To begin, consider subset of families who move with a child who is exactly 13 years old

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

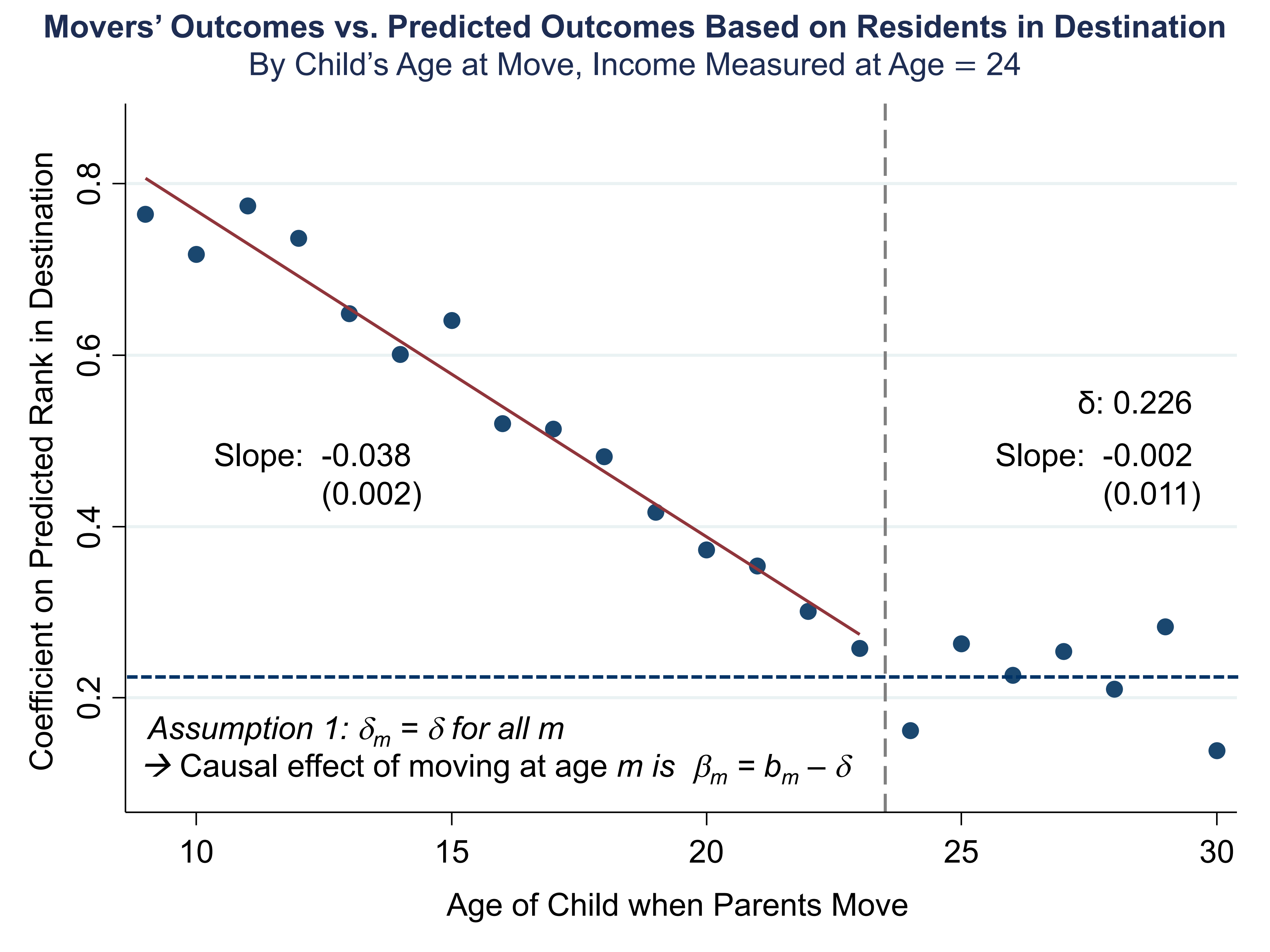
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

- 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 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

# Identifying Causal Exposure Effect

- Key identification assumption: *timing* of moves to better/worse areas uncorrelated with child's potential outcomes

- Primary contribution of the paper is to provide evidence in support of this identification condition in observational data

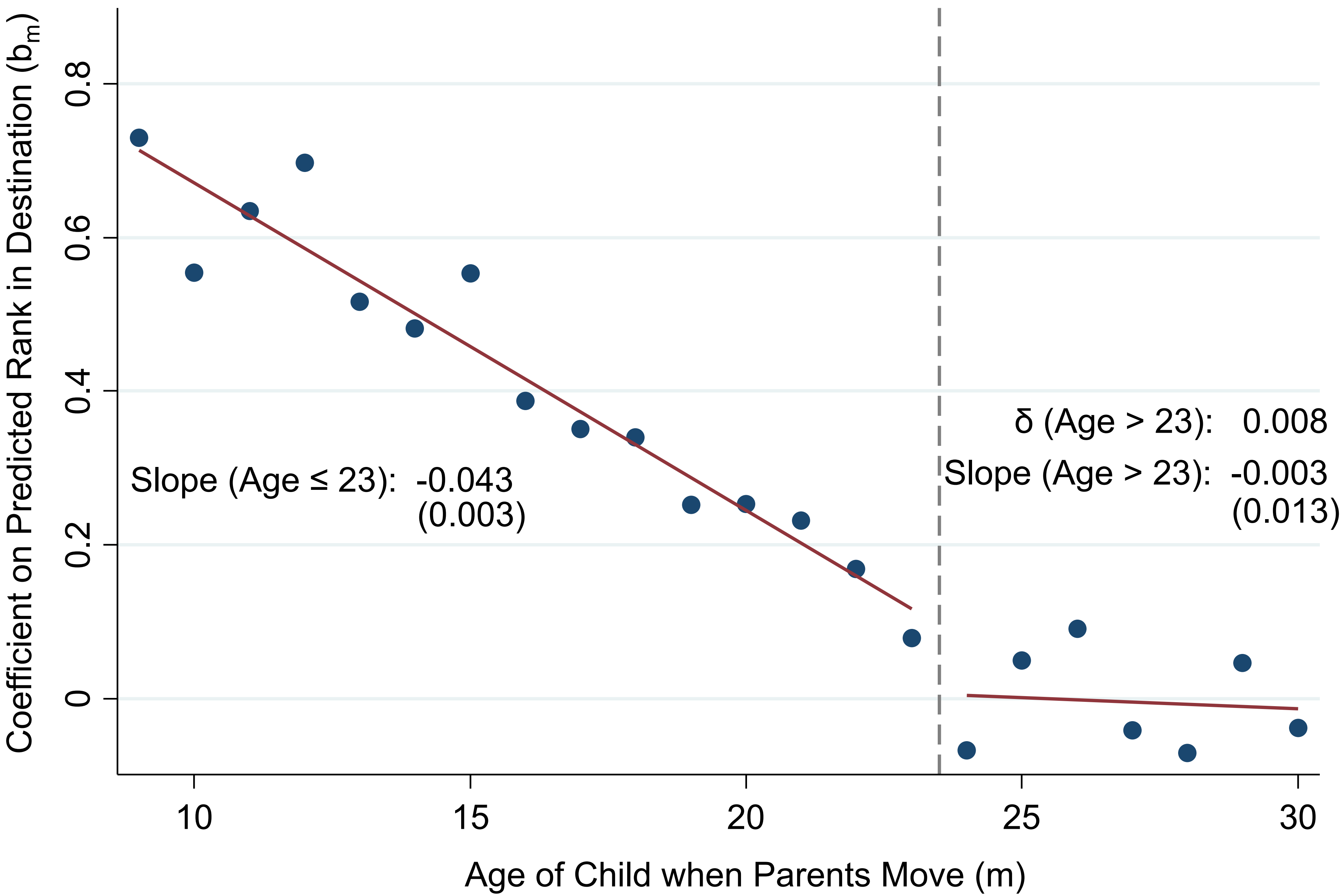
  - Without existence of an "instrument"

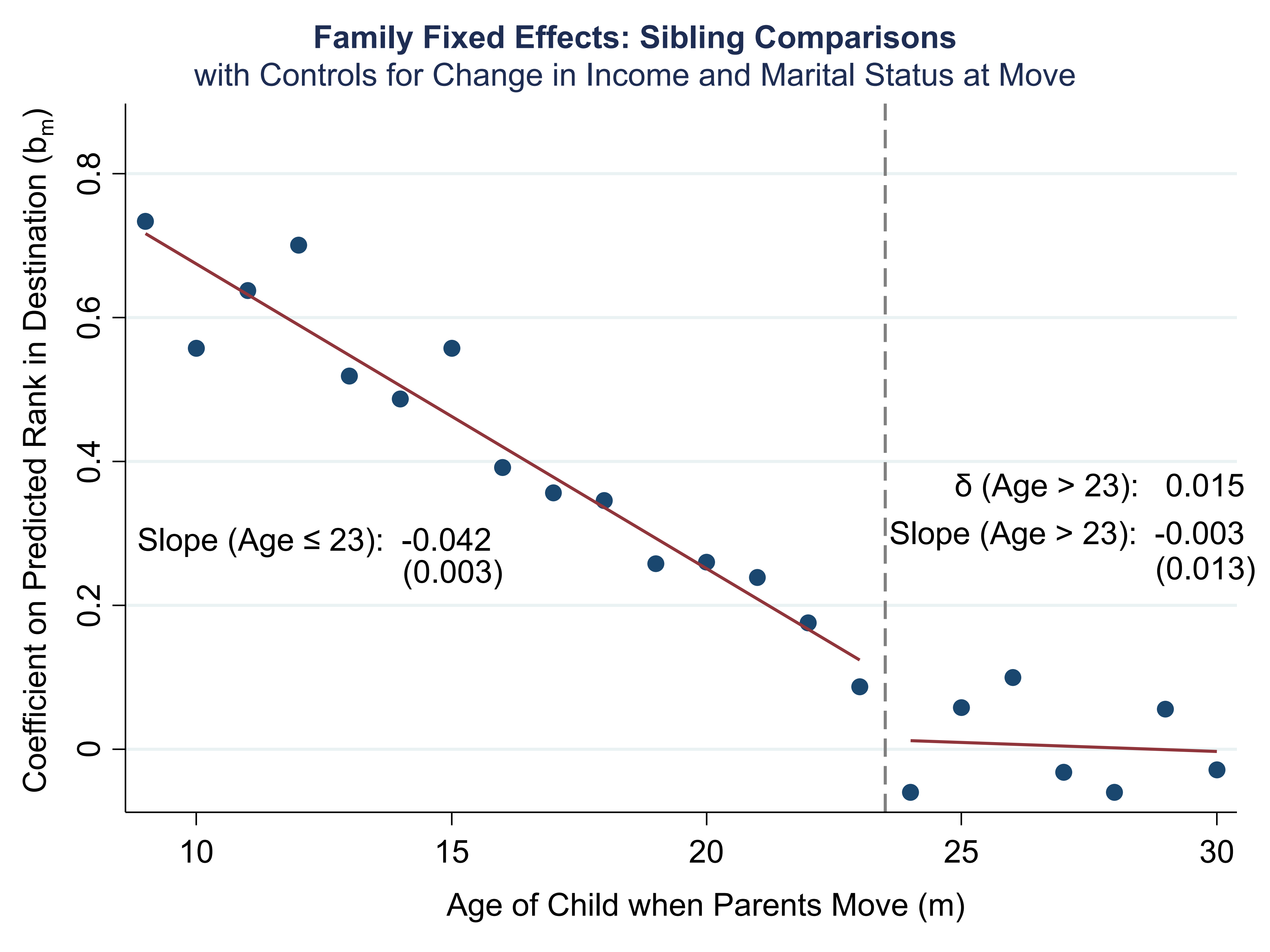
- Two main concerns (Jencks and Mayer, 1990)

  1. Sorting of families to different areas
  2. Shocks driving movement to different areas

- Begin with within-family design

## 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 ($b_m$)
0.8
0.6
0.4
0.2
0
Slope (Age ≤ 23): -0.042
(0.003)
δ (Age > 23): 0.015
Slope (Age > 23): -0.003
(0.013)
10
15
20
25
30
Age of Child when Parents Move (m)

# Time-Varying Unobservables

- Family fixed effects do not rule out time-varying unobservables that affect children in proportion to exposure time

  - Wealth shocks

  - “Parental capital” shocks correlated with where you move

- Key challenge faced by previous observational studies that have analyzed movers to identify nbhd. effects [e.g., Aaronson 1998]

# Distinguishing Neighborhood Effects from Other Shocks

- Prior observational studies of movers define "good" neighborhoods based on observable characteristics (e.g., low poverty rates)

- Chetty and Hendren (2016) approach differs by measuring nbhd. quality based on **outcomes** of permanent residents, analogous to value-added models

  - Generates sharp predictions that allow us distinguish causal effects of neighborhoods from other factors

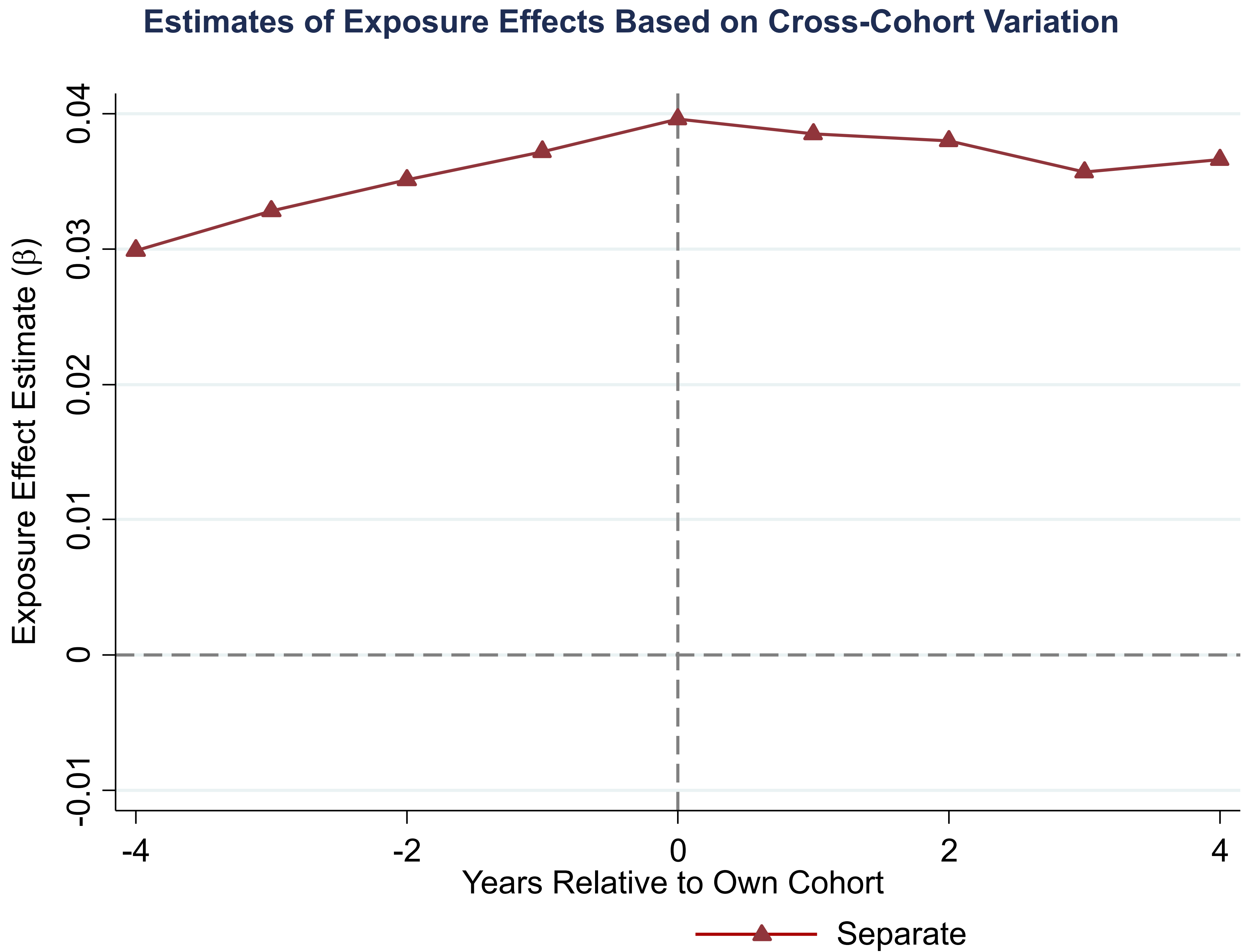
# Outcome-Based Placebo Tests

- 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

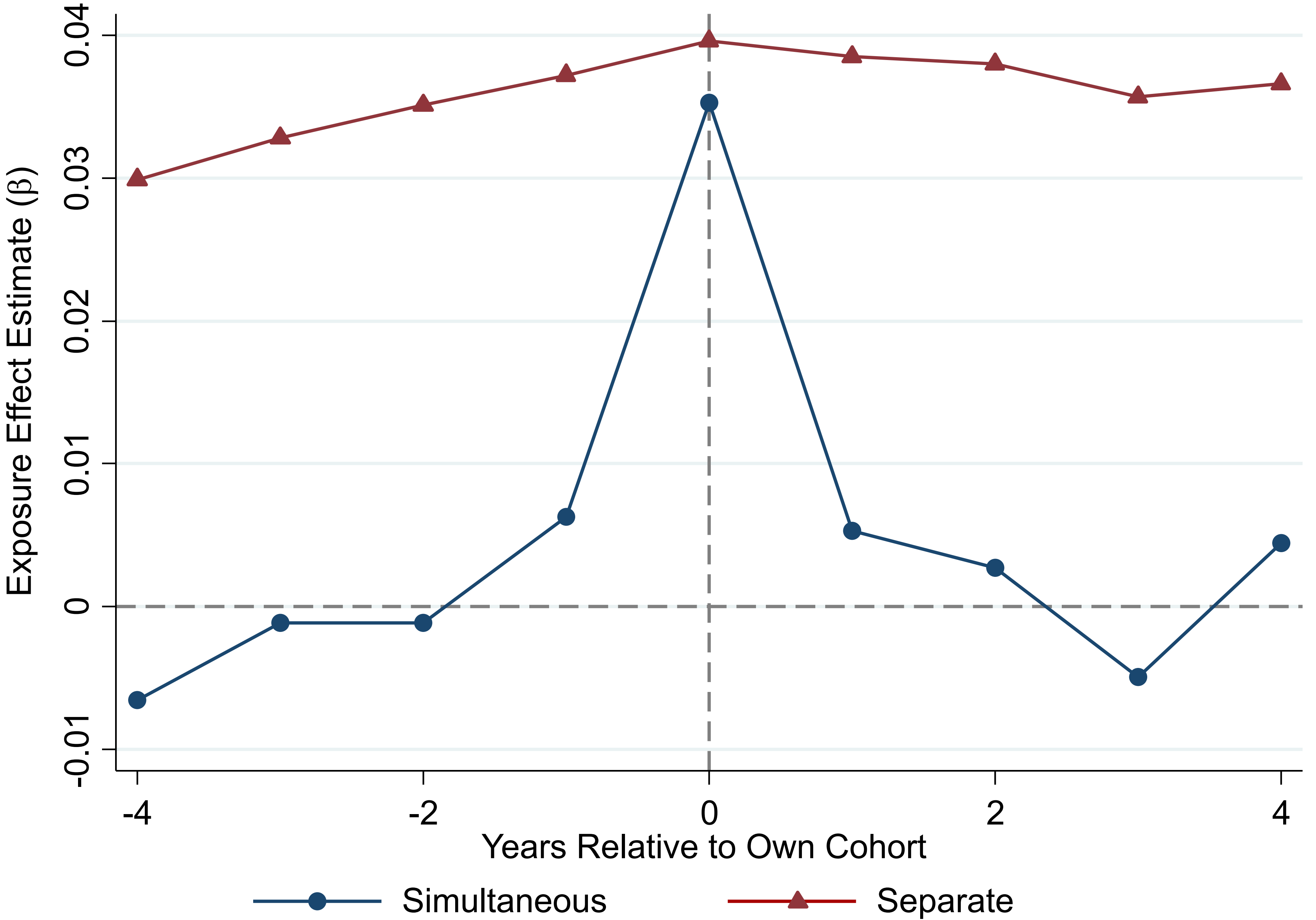
# Outcome-Based Placebo Tests

- 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
- Parents choose neighborhoods based on their preferences and information set at time of move
  - Difficult to predict high-frequency differences for outcomes 15 years later
  - Unlikely unobs. shock $\theta_i$ replicates cohort variation perfectly



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

- Boston and San Francisco generate similar mean outcomes for children with parents at 25$^{th}$ pctile., but more children in SF reach tails (top 10%, bottom 10%)

- 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

    - Again, unlikely that unobserved factor $\theta_i$ would replicate distribution of outcomes in each 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 (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 $\theta_i$ 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 |

# Identification of Exposure Effects: Summary

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

    1. Operate within family in proportion to exposure time
    2. Be fully orthogonal to changes in parent income and marital status over 17 years
    3. Replicate prior residents' outcomes by birth cohort, quantile, and gender in proportion to exposure time *conditional* on other predictions
    4. Replicate impacts across outcomes (income, college attendance, teen labor, marriage)

- Unlikely?

# Part 2: Causal Effects of Each County

- Estimate causal effects of each county and CZ in the U.S. on children's earnings in adulthood

  - Estimate ~3,000 treatment effects (one per county) instead of one average exposure effect as in first paper

# Estimating County Fixed Effects

- Begin by estimating effect of each county using a fixed effects model that is identified using variation in timing of moves between areas

- Intuition for identification: 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

# Estimating County Fixed Effects

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

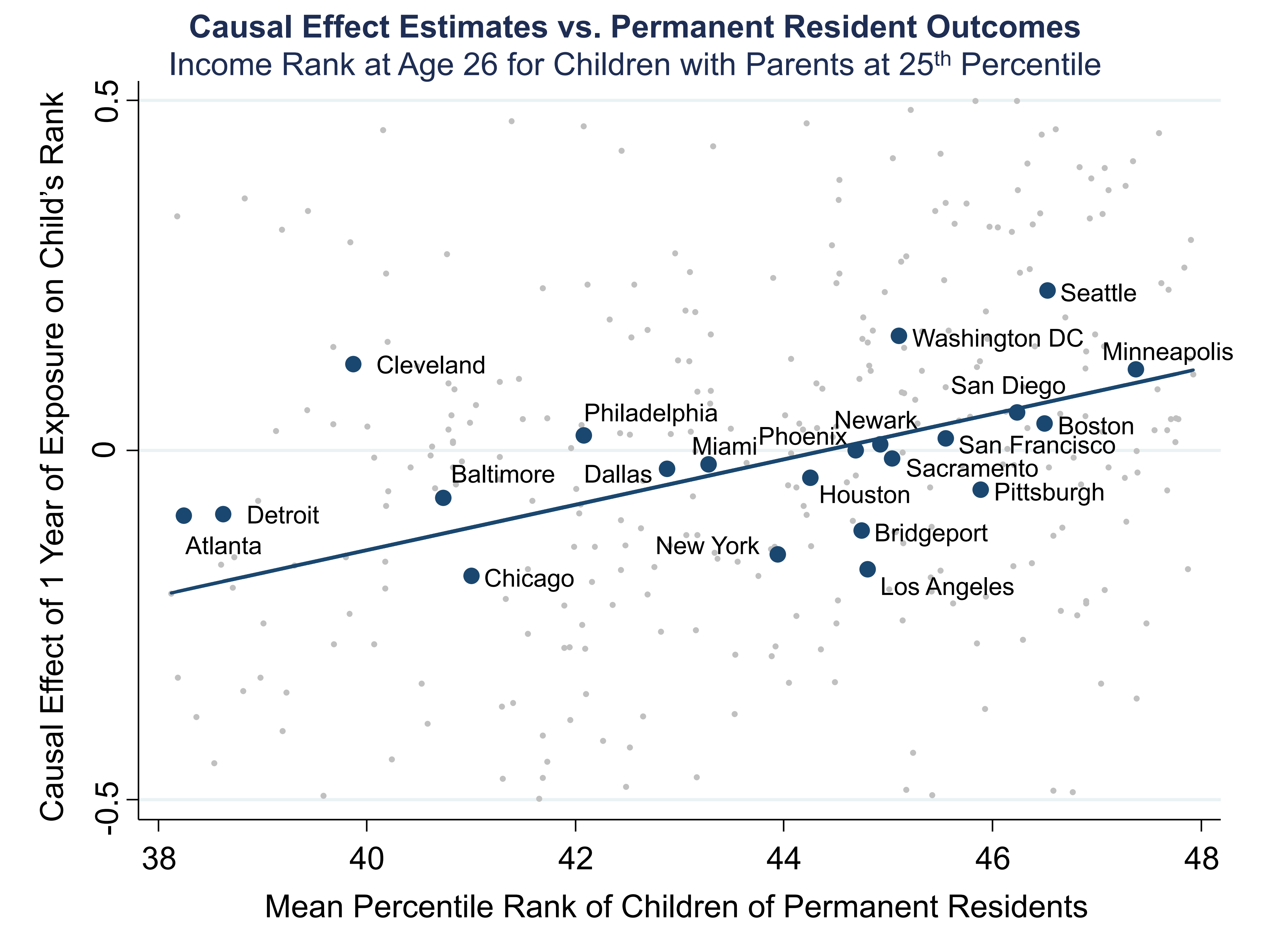
$$y_i = \underbrace{(T_c - m)}_{\text{Exposure}} \left[ \underbrace{\mu_d 1\{d(i) = d\}}_{\text{Dest. FE}} - \underbrace{\mu_o 1\{o(i) = o\}}_{\text{Orig. FE.}} \right] + \underbrace{\alpha_{odps}}_{\text{orig x Dest FE}} + \eta_i$$

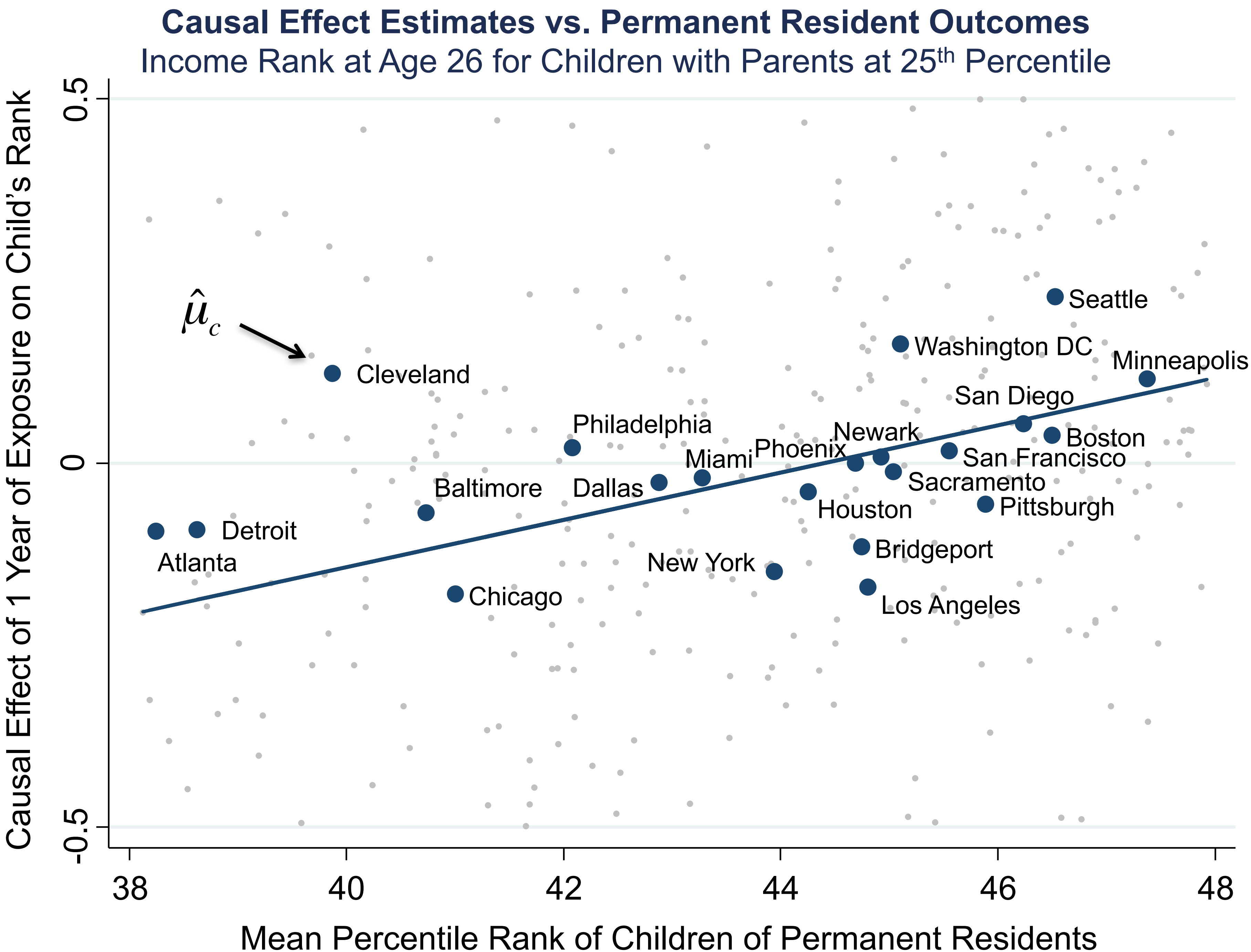
- Place effects are allowed to vary linearly with parent income rank:

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

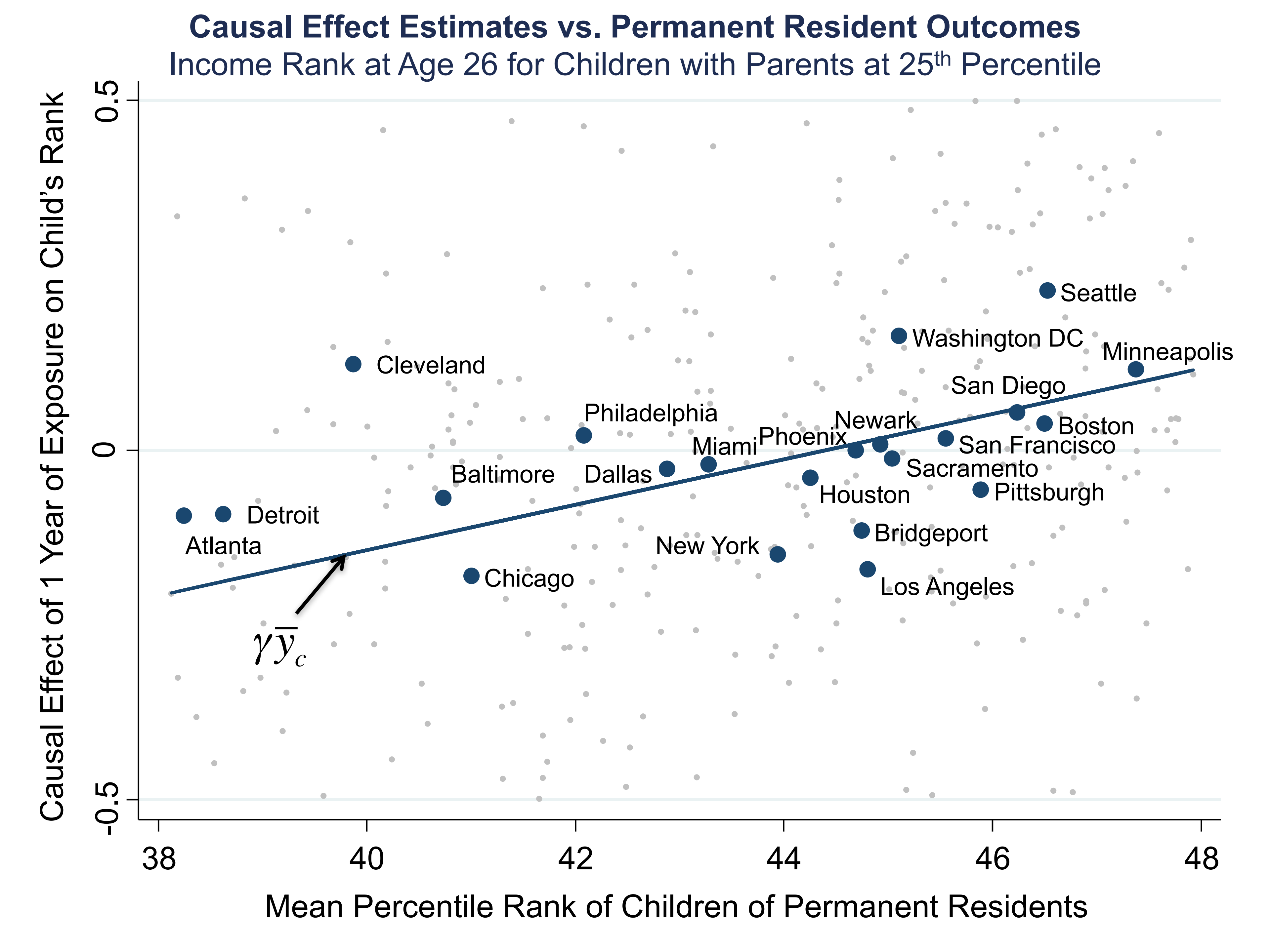
- Include origin-by-destination fixed effects to isolate variation in exposure

- What is the identification condition?


Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of 1 Year of Exposure on Child's Rank
0.5
0
-0.5
Mean Percentile Rank of Children of Permanent Residents
38
40
42
44
46
48
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Sacramento
Baltimore
Dallas
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles

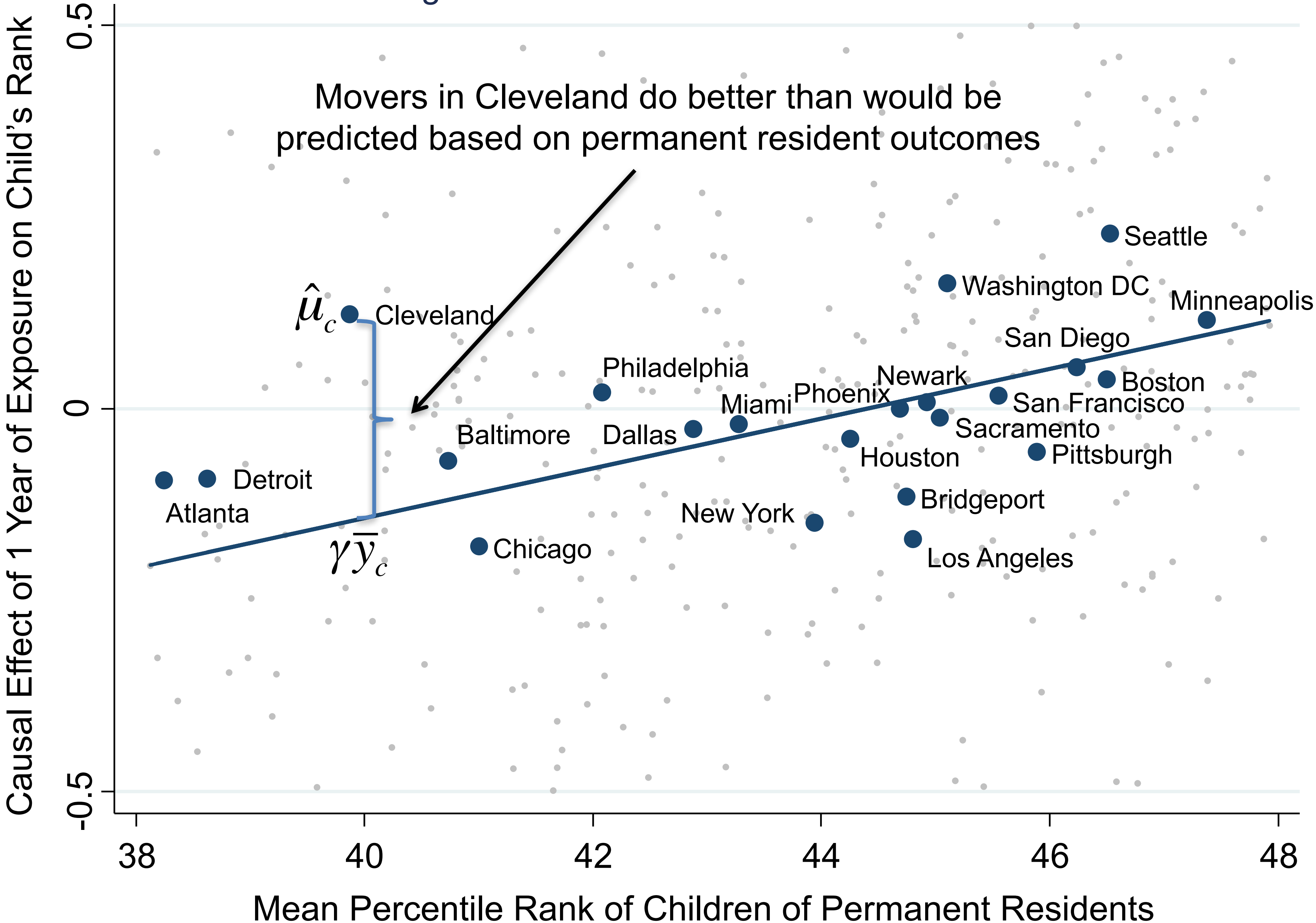


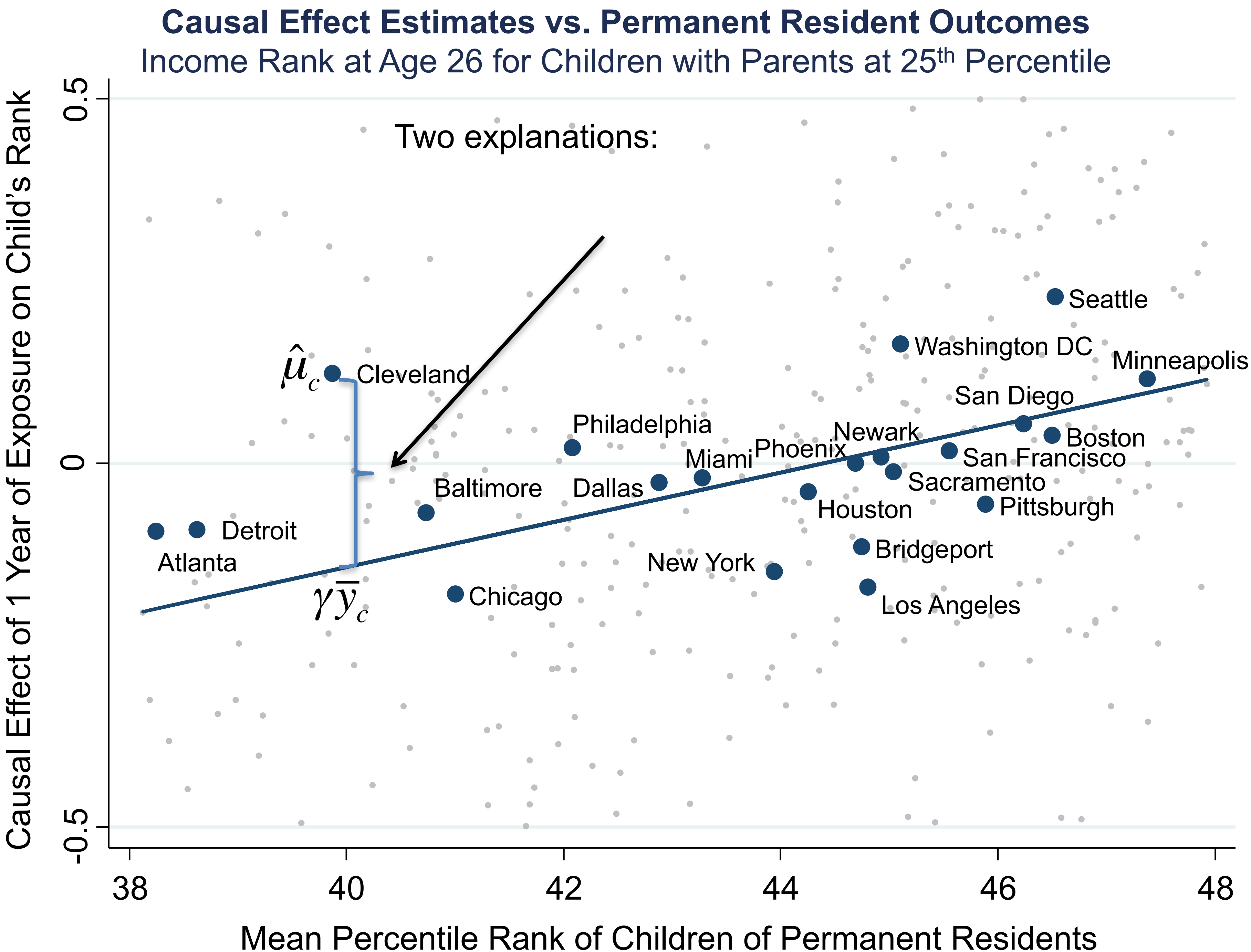
Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents
$\hat{\mu}_c$
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Baltimore
Dallas
Sacramento
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles
0.5
0
-0.5
38
40
42
44
46
48

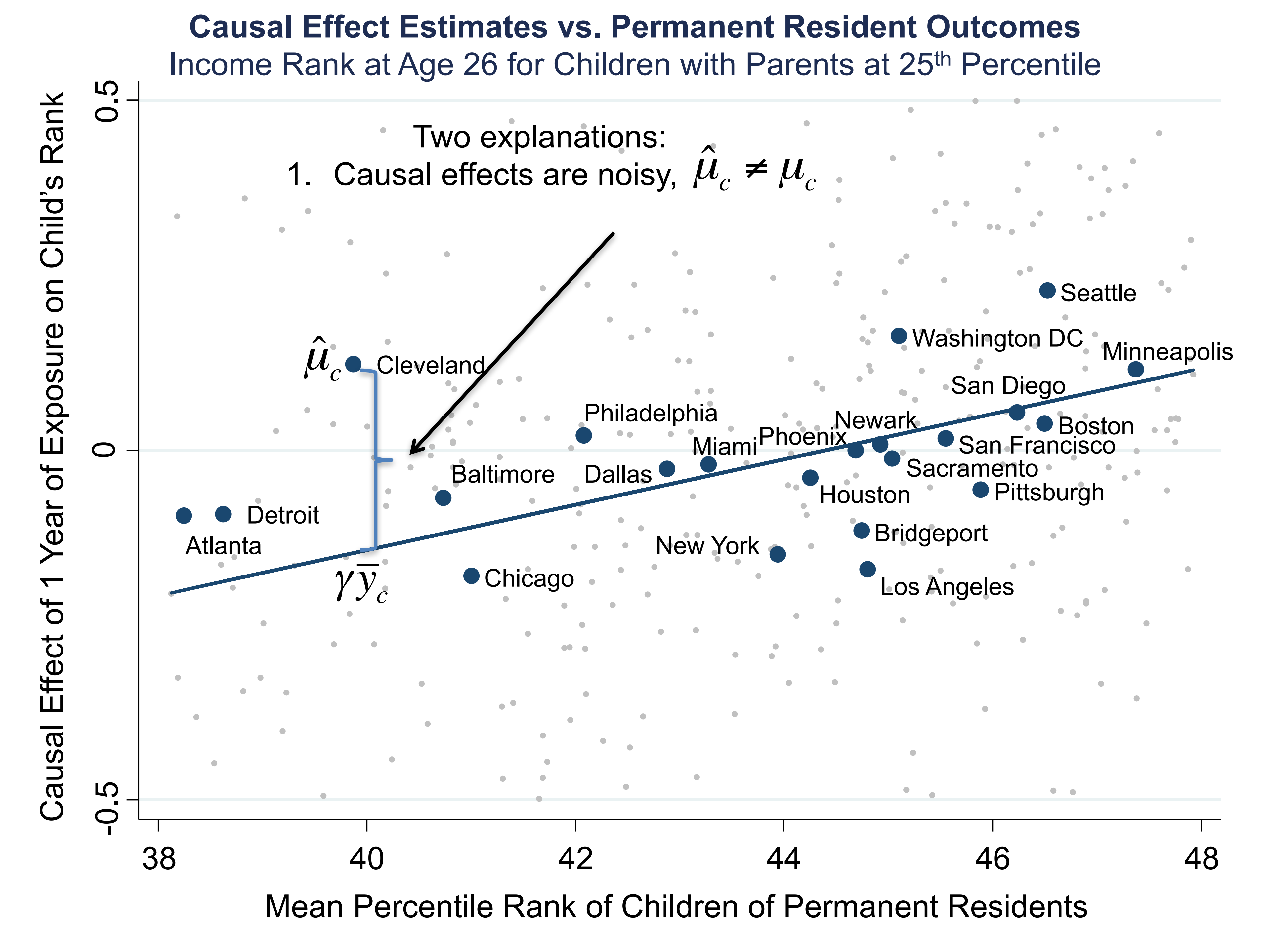

Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents
0.5
0
-0.5
38
40
42
44
46
48
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Baltimore
Dallas
Sacramento
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles
$\gamma \overline{y}_c$

## Causal Effect Estimates vs. Permanent Resident Outcomes

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



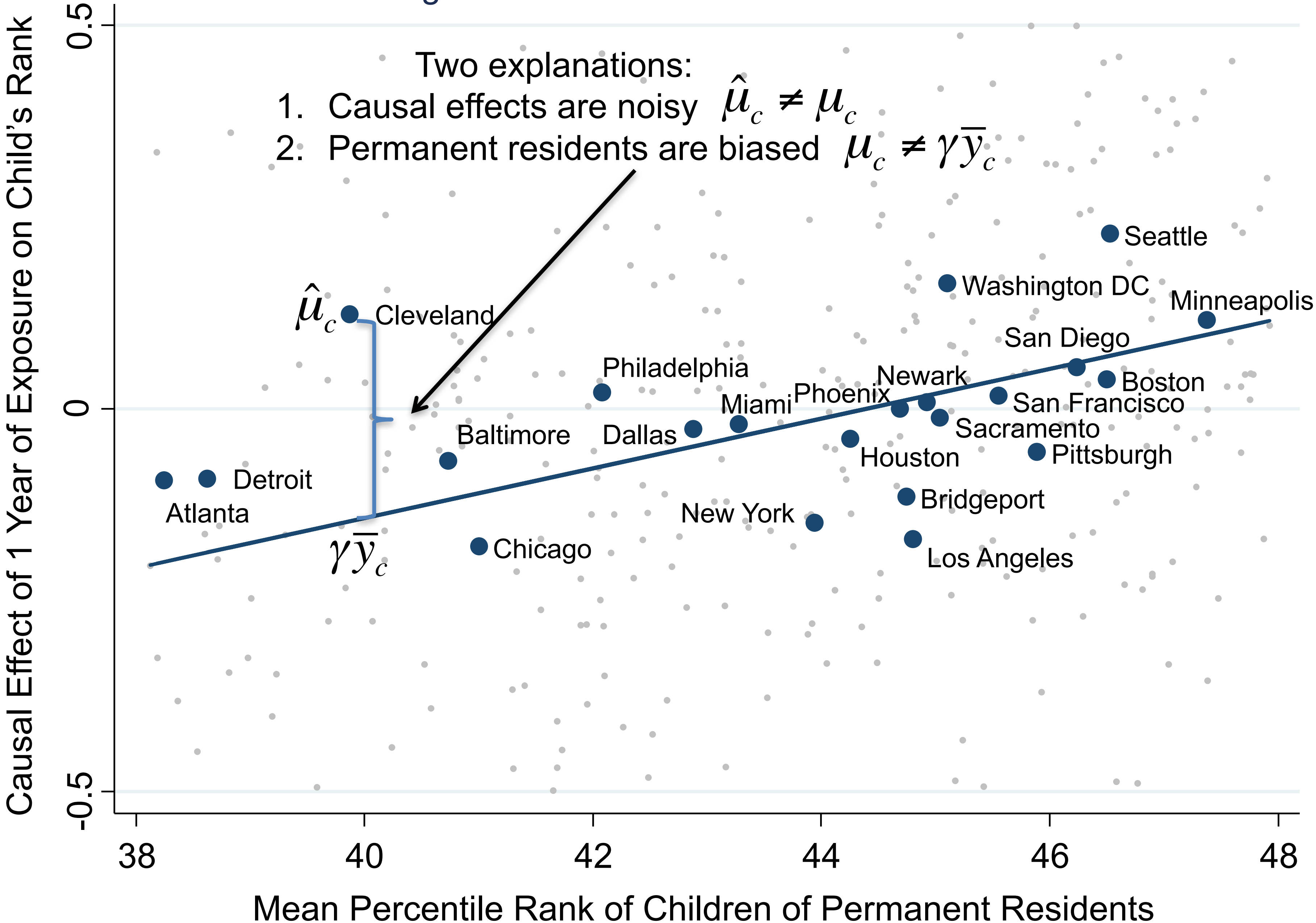

Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Two explanations:
$\hat{\mu}_c$
$\gamma \bar{y}_c$
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Sacramento
Baltimore
Dallas
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents
0.5
0
-0.5
38
40
42
44
46
48

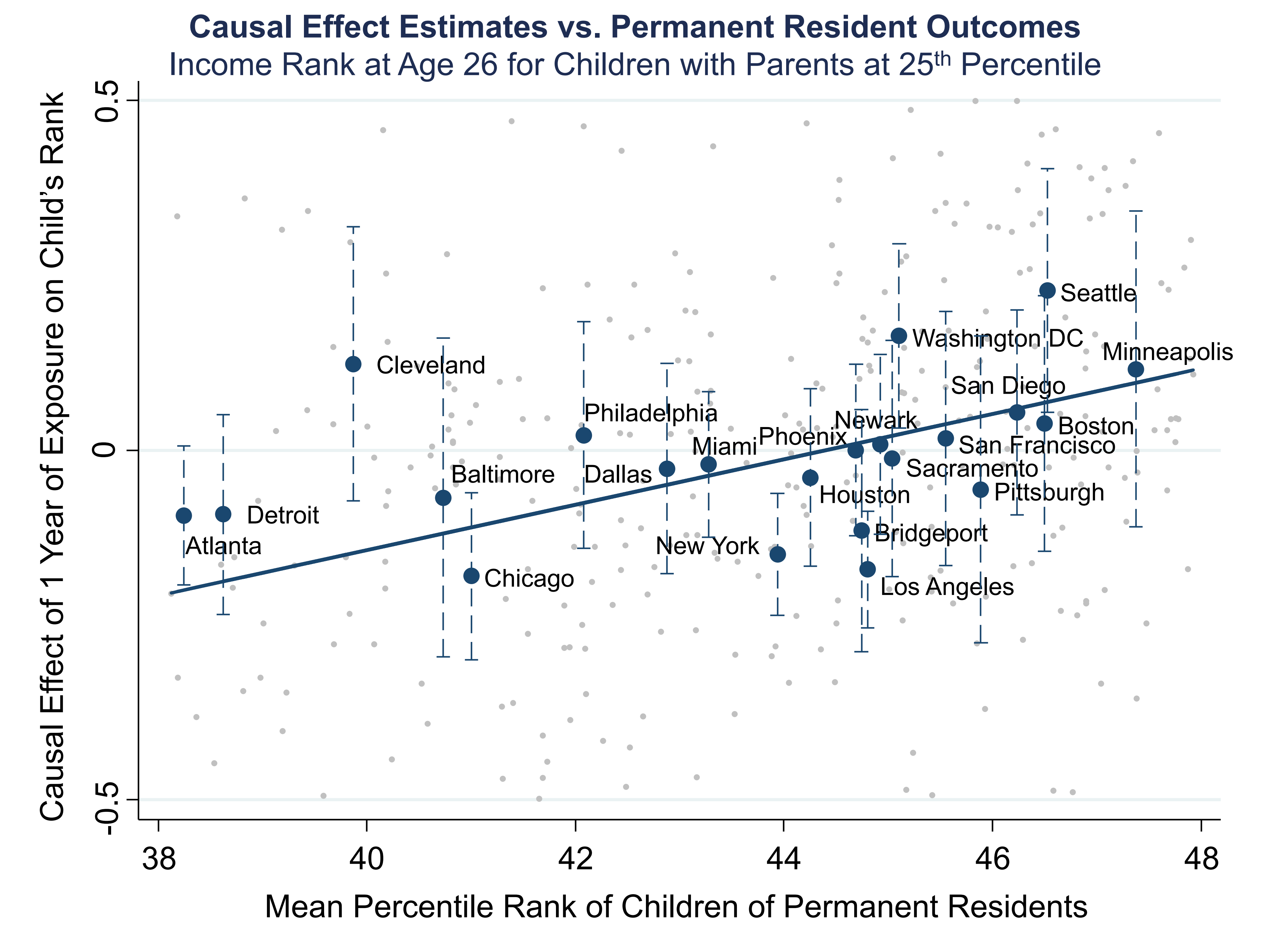


Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Two explanations:
1. Causal effects are noisy, $\hat{\mu}_c \neq \mu_c$
$\hat{\mu}_c$
$\gamma \bar{y}_c$
Seattle
Washington DC
Minneapolis
San Diego
Boston
San Francisco
Newark
Phoenix
Sacramento
Pittsburgh
Houston
Miami
Dallas
Philadelphia
Cleveland
Baltimore
Detroit
Atlanta
Chicago
New York
Bridgeport
Los Angeles
Causal Effect of 1 Year of Exposure on Child's Rank
0.5
0
-0.5
38
40
42
44
46
48
Mean Percentile Rank of Children of Permanent Residents

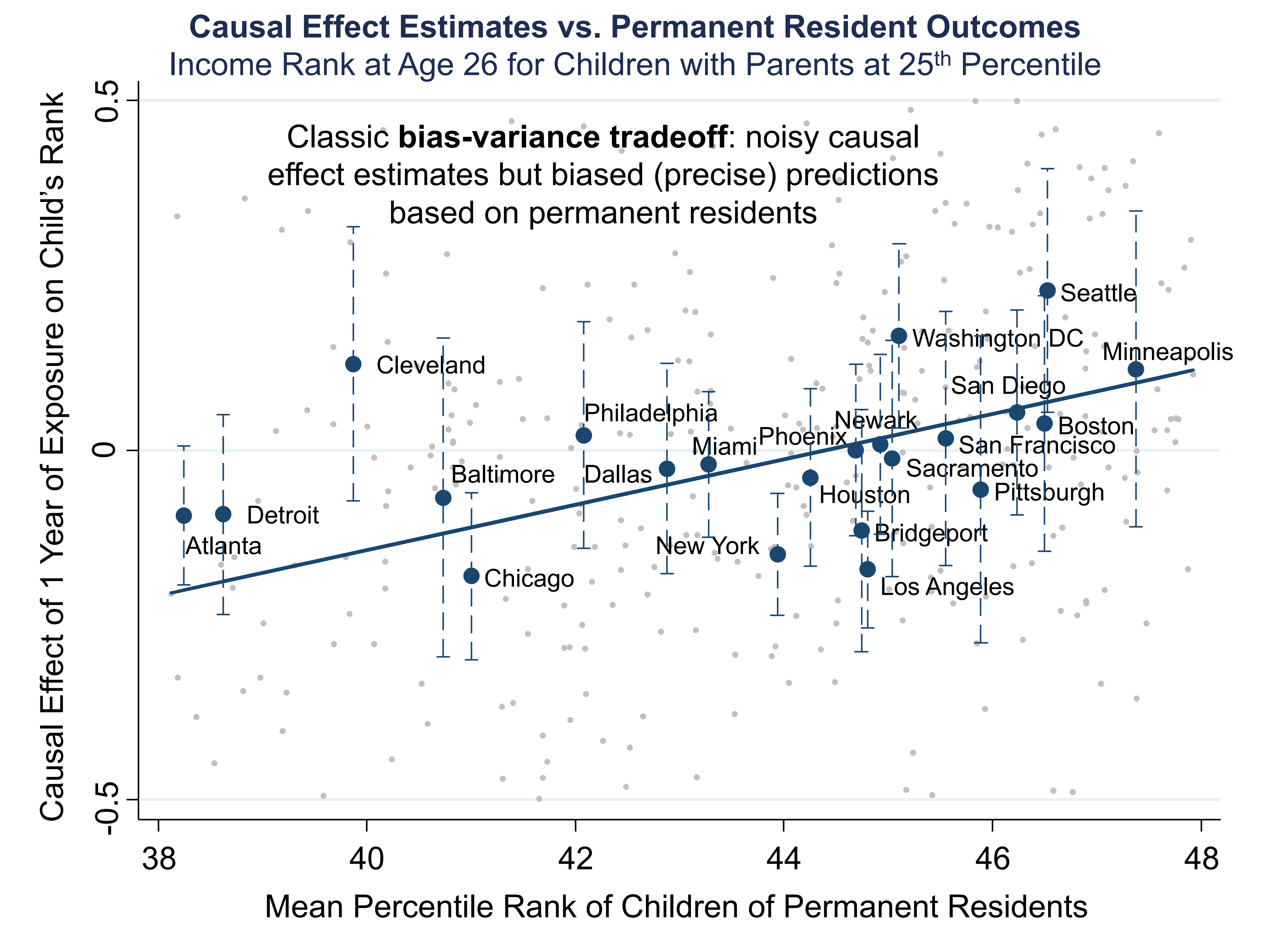
# Causal Effect Estimates vs. Permanent Resident Outcomes

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





Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents
0.5
0
-0.5
38
40
42
44
46
48
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Sacramento
Baltimore
Dallas
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles



Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Classic **bias-variance tradeoff**: noisy causal effect estimates but biased (precise) predictions based on permanent residents
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents
0.5
0
-0.5
38
40
42
44
46
48
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Baltimore
Dallas
Sacramento
Pittsburgh
Houston
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles

# Three Objectives

- Use fixed effect estimates for three purposes:

  1. Quantify the size of place effects: how much do places matter?

  2. Construct forecasts that can be used to guide families seeking to "move to opportunity"

  3. Characterize which types of areas produce better outcomes to provide guidance for place-based policies

# Objective 1: Magnitude of Place Effects

- Can we just look at the variance of fixed effect estimates, $\hat{\mu}_c$ ?
- No….we can write: $\hat{\mu}_c = \mu_c + \varepsilon_c$ where $\varepsilon_c$ is orthogonal sampling error
- Total variance has two components:

$$Var(\hat{\mu}_c) = Var(\mu_c) + Var(\varepsilon_c)$$

- Let $s_c$ be the std error of the causal effect in place c, $E\left[\varepsilon_c^2 \mid s_c\right] = s_c^2$
- So, $Var(\varepsilon_c) = E\left[\varepsilon_c^2\right] = E_c\left[E\left[\varepsilon_c^2 \mid s_c\right]\right] = E_c\left[s_c^2\right]$
- Variance of true place effects is given by

$$Var(\mu_c) = \underbrace{Var(\hat{\mu}_c)}_{Total} - \underbrace{E_c\left[s_c^2\right]}_{Noise}$$

# Objective 1: Magnitude of Place Effects

- Chetty and Hendren (2016) estimate across counties for parents at 25th percentile:

$$Var\left(\hat{\mu}_c\right) = 0.434 \qquad E_c\left[s_c^2\right] = 0.402$$

- So, $Var\left(\mu_c\right) = 0.032$ or $Std\left(\mu_c\right) = 0.18$

- 1 year of exposure to a 1SD better place increases earnings by 0.18 percentiles

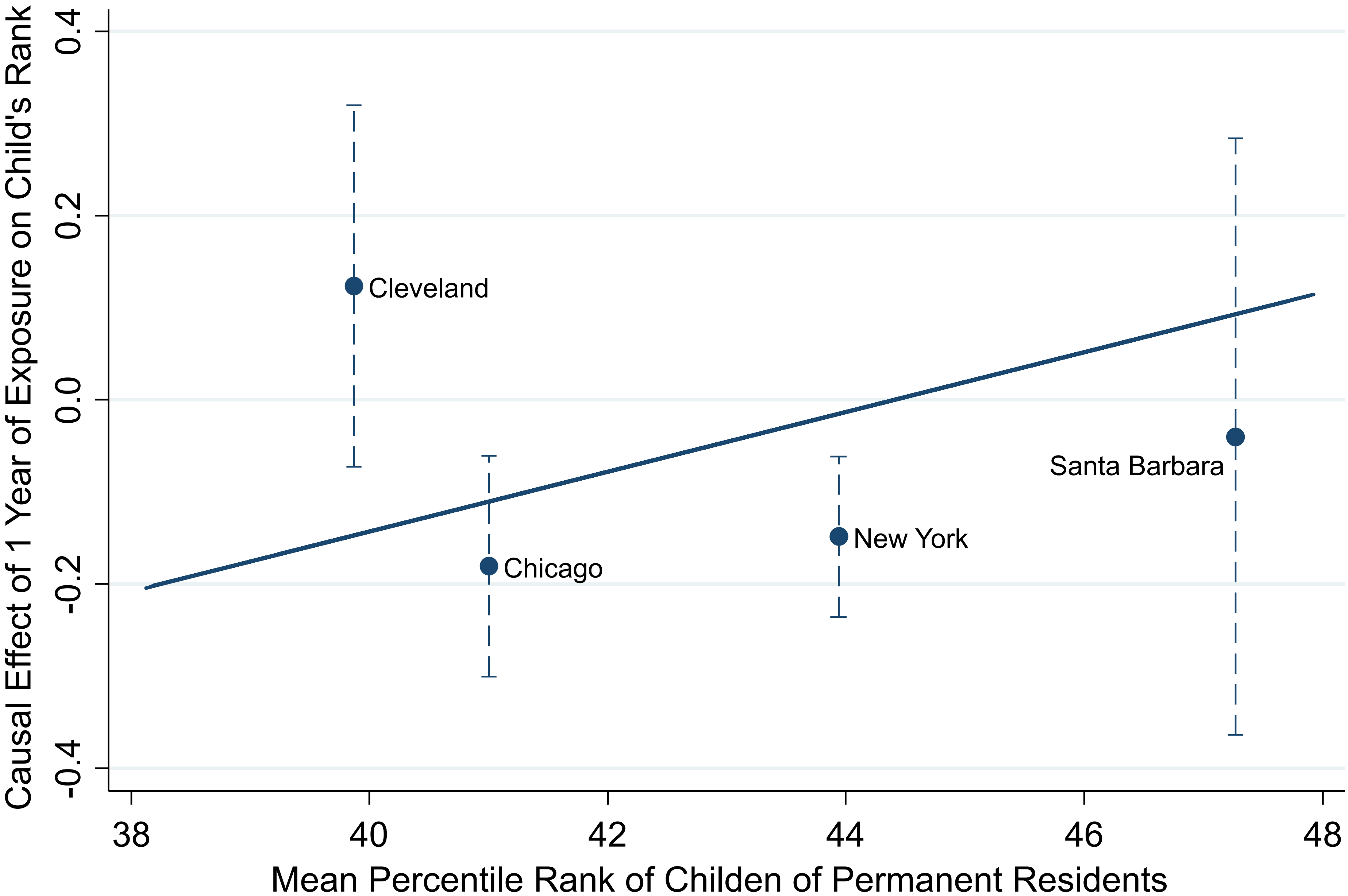
  - To interpret units, note that 1 percentile ~= 3% change in earnings

- For children with parents at 25th percentile: 1 SD better county from birth (20 years) → 3.6 percentiles → 10% earnings gain

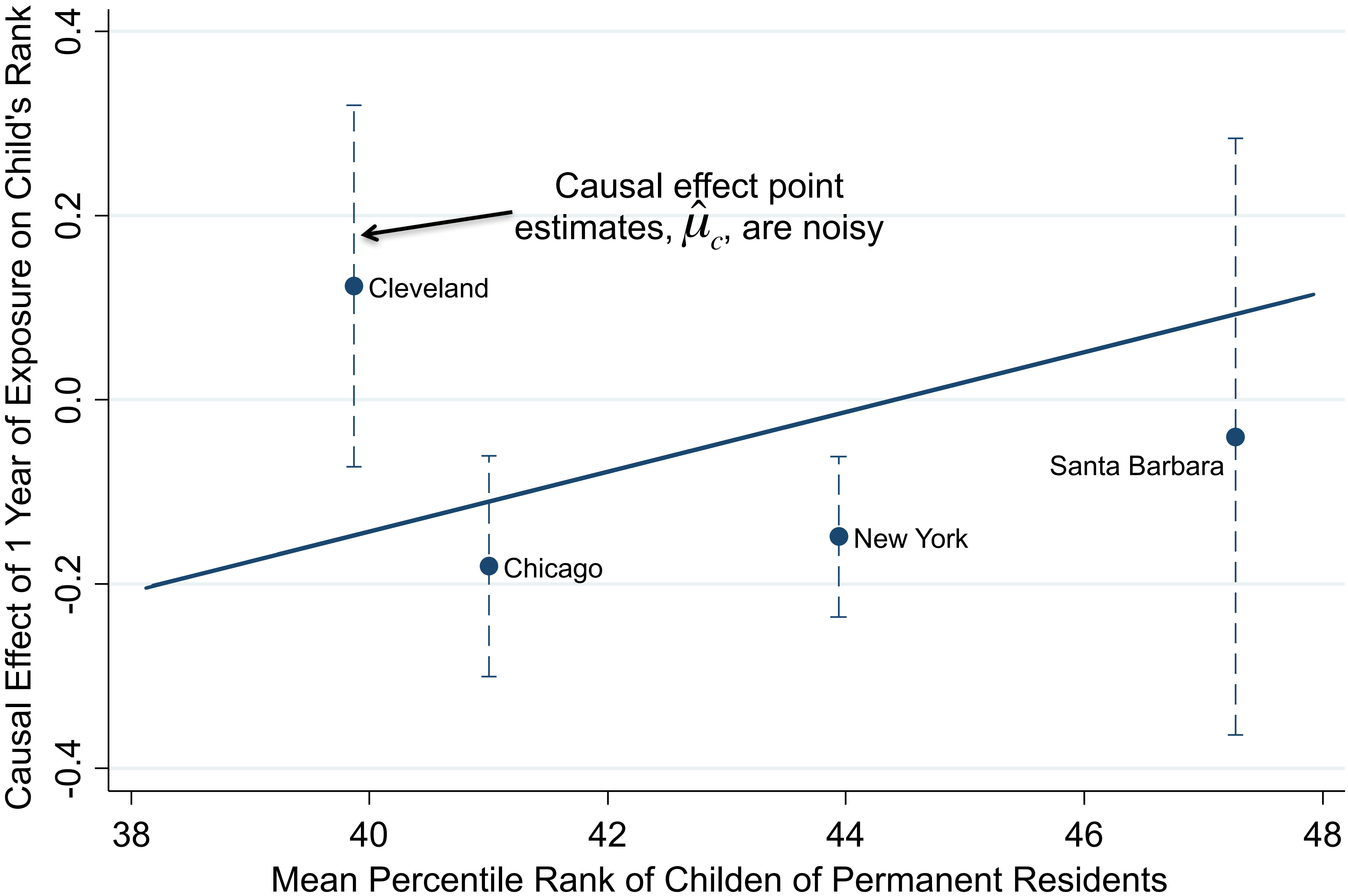
# Objective 2: Forecasts of Best and Worst Areas

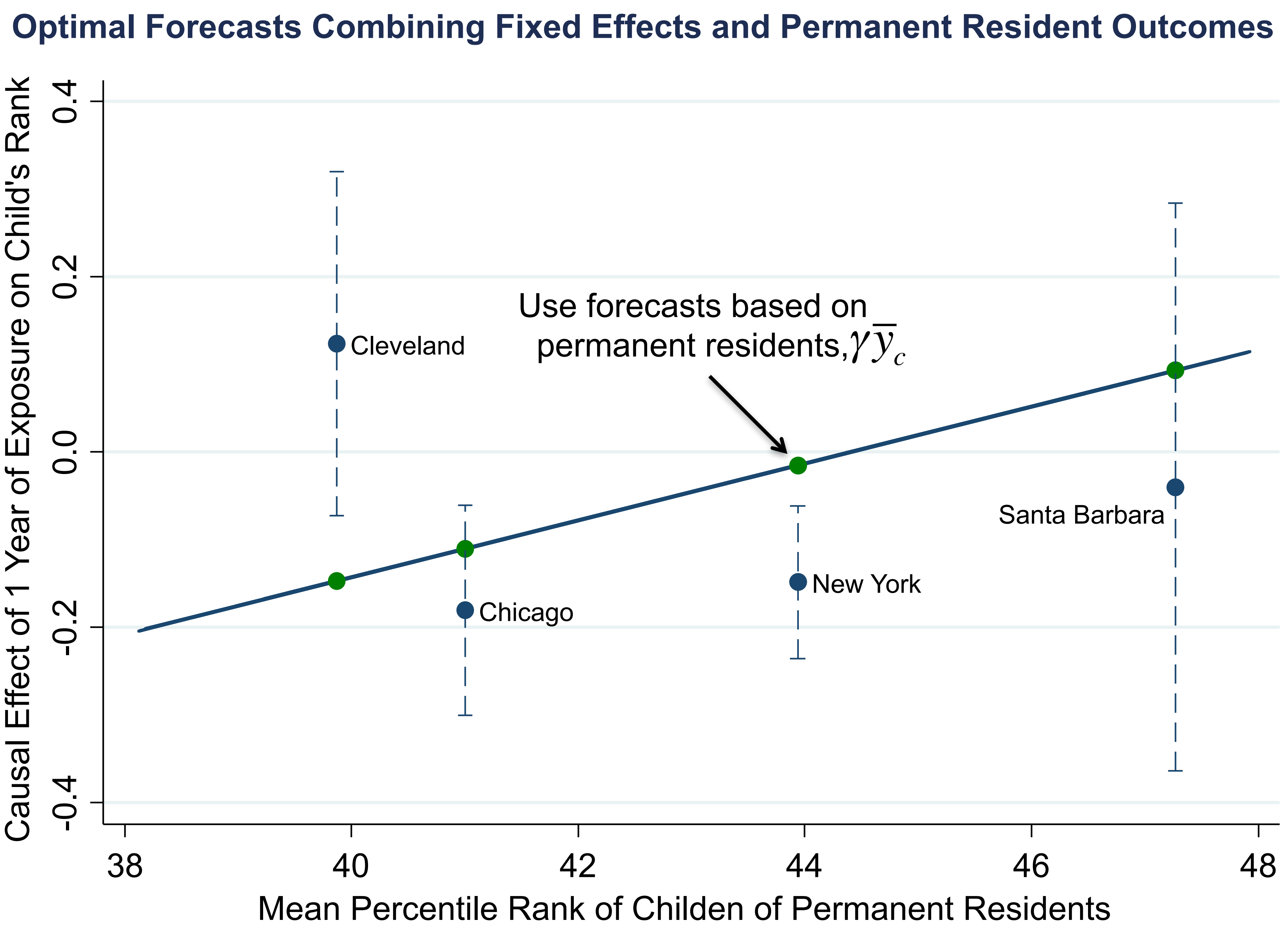
- What are the best and worst places to grow up?
- Construct forecasts that minimize mean-squared-error of predicted impact for a family moving to a new area
- Raw fixed effect estimates have high MSE because of sampling error
- Reduce MSE by combining fixed effects (unbiased, but imprecise) with permanent resident outcomes (biased, but precise)
- Common approach in recent literature:
  - E.g. School effects combining causal effects from lotteries with school value-added estimates [Angrist, et al. 2016, QJE: “Leveraging Lotteries for School Value-Added: Testing and Estimation]

**Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes**



## Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes





Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Use forecasts based on permanent residents, $\gamma \bar{y}_c$
Cleveland
Chicago
New York
Santa Barbara
Causal Effect of 1 Year of Exposure on Child's Rank
-0.4
-0.2
0.0
0.2
0.4
38
40
42
44
46
48
Mean Percentile Rank of Childen of Permanent Residents

# 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, $\hat{\mu}_c$, and stayers prediction, $\gamma \bar{y}_c$ where $\bar{y}_c$ is de-meaned across places

$$y_i = \alpha + \rho_{1,c}\left(\gamma \bar{y}_c\right) + \rho_{2,c}\hat{\mu}_c + \eta_i$$

- Part 1 shows that $E\left[y_i \mid \bar{y}_c\right] = \gamma \bar{y}_c$, so that the regression coeffs are:

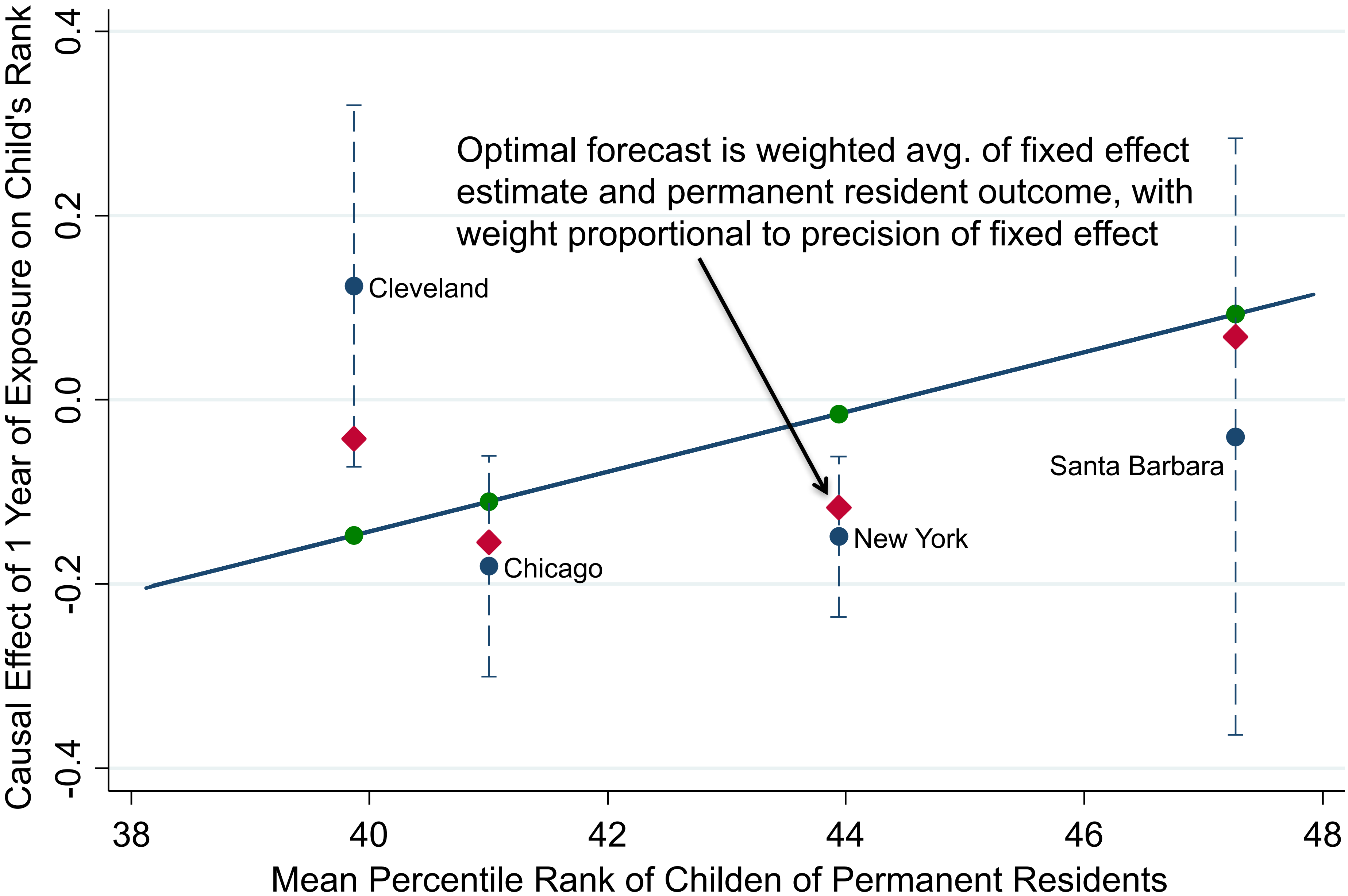
$$\rho_{1,c} = \frac{\sigma^2_{bias}}{\sigma^2_{noise,c} + \sigma^2_{bias}} \qquad \rho_{2,c} = \frac{\sigma^2_{noise,c}}{\sigma^2_{noise,c} + \sigma^2_{bias}}$$

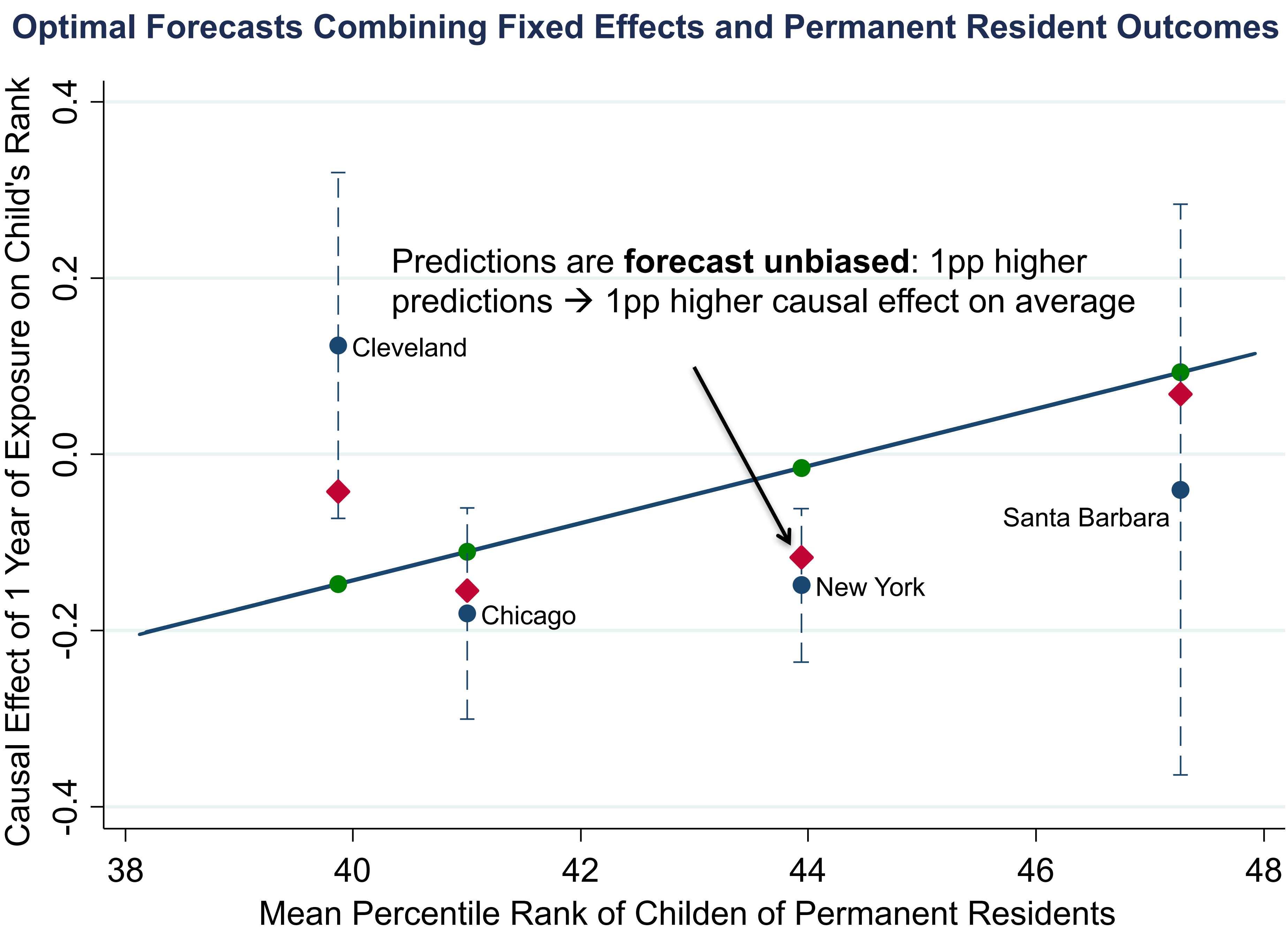
where:

  - $\sigma^2_{bias} = Var\left(\mu_c - \gamma \bar{y}_c\right)$ is residual variance of fixed effects

  - $\sigma^2_{noise,c} = s^2_c$ is the noise variance of the fixed effects (=square of std error)

# Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes




Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Childen of Permanent Residents
0.4
0.2
0.0
-0.2
-0.4
38
40
42
44
46
48
Predictions are **forecast unbiased**: 1pp higher predictions → 1pp higher causal effect on average
Cleveland
Chicago
New York
Santa Barbara

# 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, $\hat{\mu}_c$, and stayers prediction, $\gamma \bar{y}_c$ where $\bar{y}_c$ is de-meaned across places

$$y_i = \alpha + \rho_{1,c}\left(\gamma \bar{y}_c\right) + \rho_{2,c}\hat{\mu}_c + \eta_i$$

- Part 1 shows that $E\left[y_i \mid \bar{y}_c\right] = \gamma \bar{y}_c$, so that the regression coeffs are:

$$\rho_{1,c} = \frac{\sigma^2_{bias}}{\sigma^2_{noise,c} + \sigma^2_{bias}} \qquad \rho_{2,c} = \frac{\sigma^2_{noise,c}}{\sigma^2_{noise,c} + \sigma^2_{bias}}$$

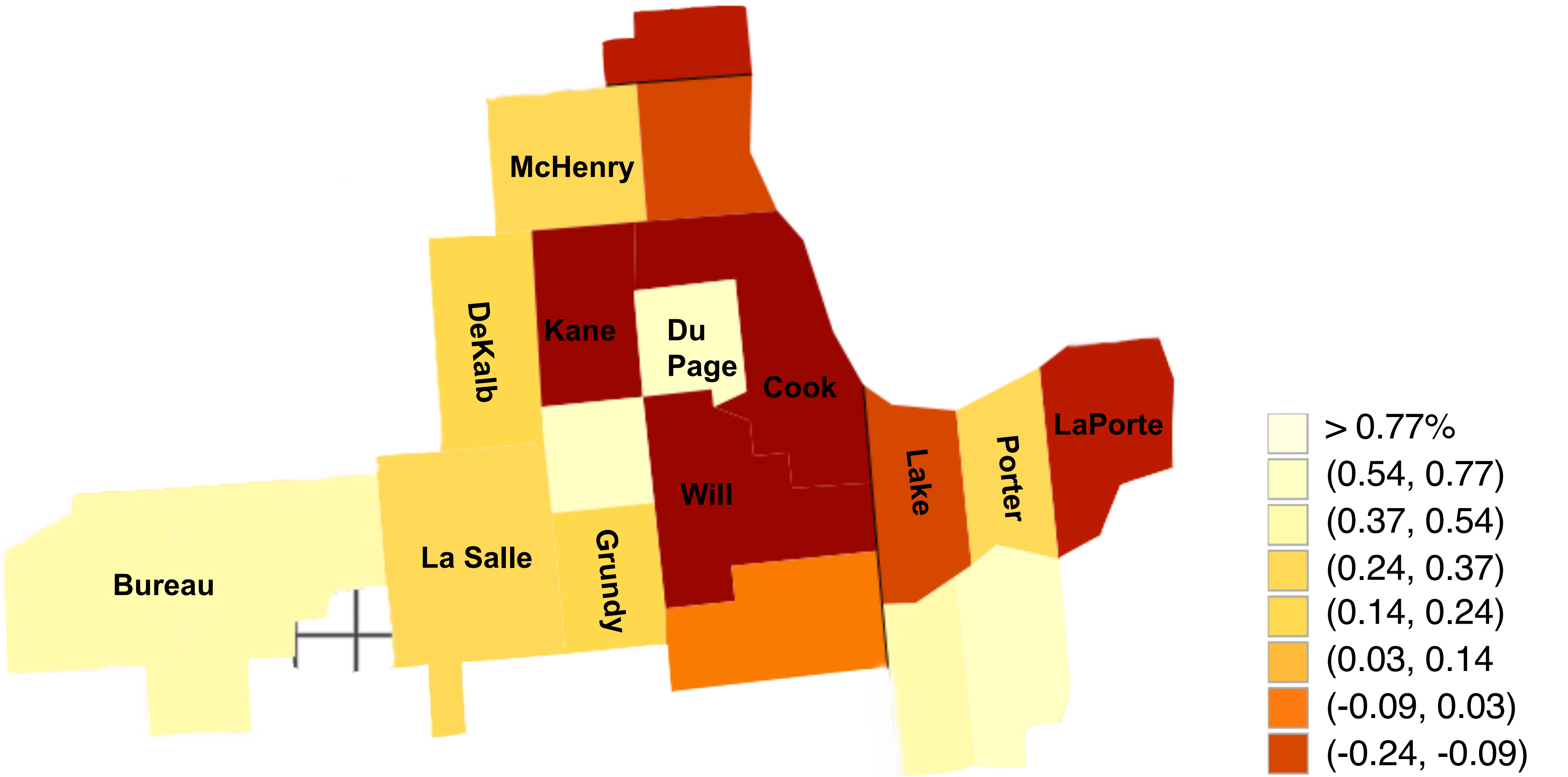
where:

  - $\sigma^2_{bias} = Var\left(\mu_c - \gamma \bar{y}_c\right)$ is residual variance of fixed effects (constant across places)

  - $\sigma^2_{noise,c} = s^2_c$ is the noise variance of the fixed effects (varies across places)

## Causal Effects of Growing up in Different Counties on Earnings in Adulthood

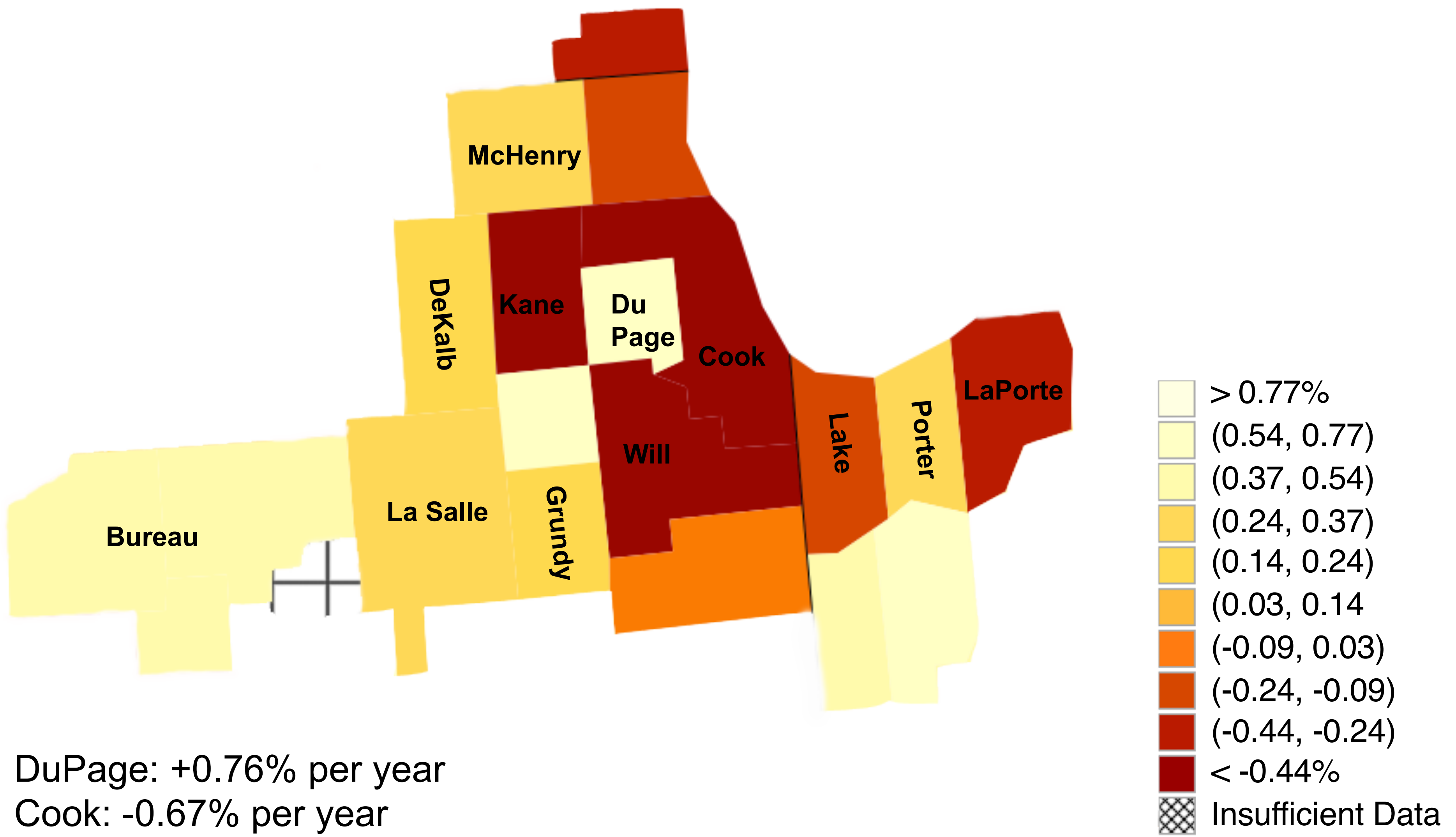
For Children in Low-Income (25th Percentile) Families in the Chicago Metro Area




DuPage: +0.76% per year
Cook: -0.67% per year

**Causal Effects of Growing up in Different Counties on Earnings in Adulthood**

For Children in Low-Income (25th Percentile) Families in the Chicago Metro Area



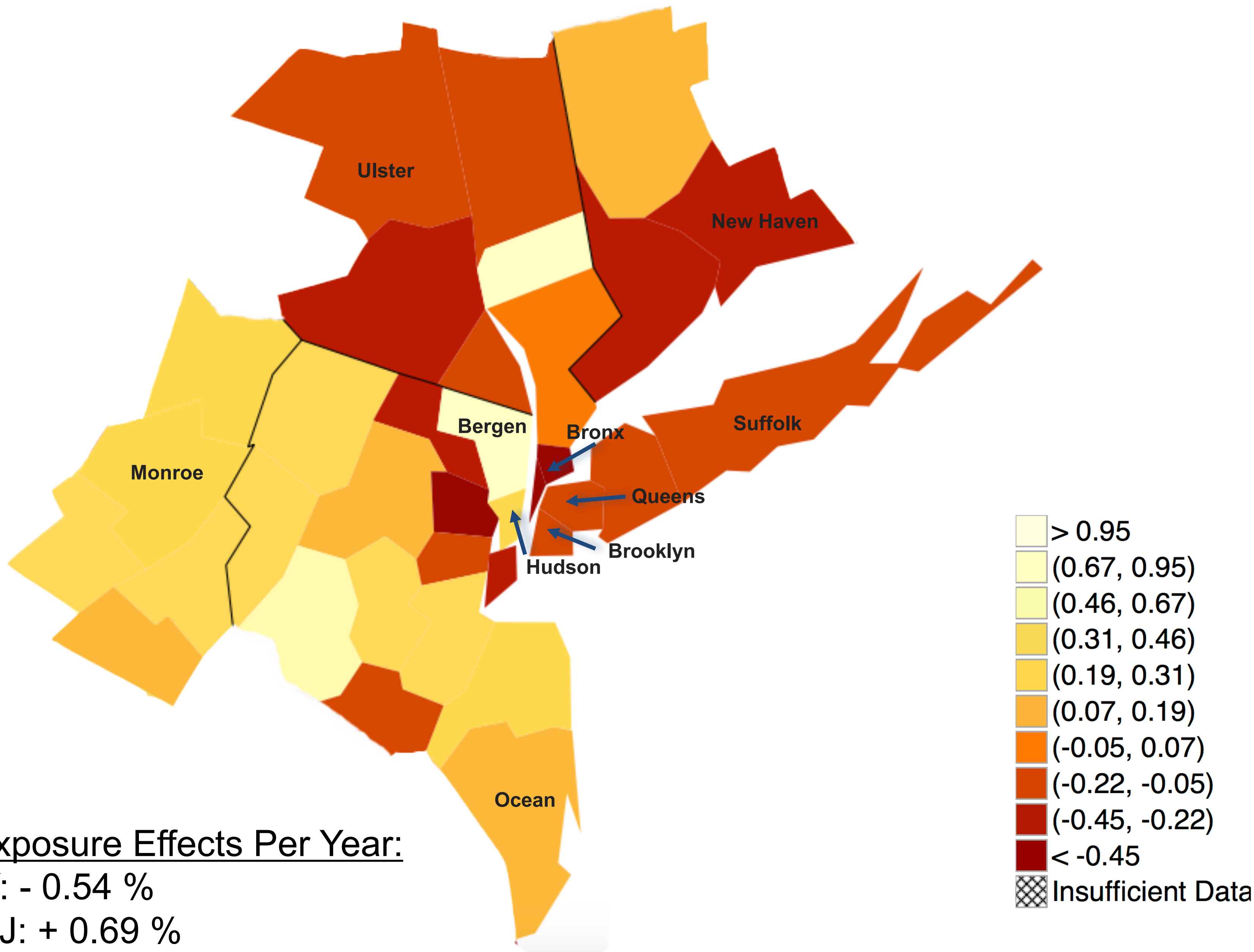

DuPage: +0.76% per year

Cook: -0.67% per year

20 Years of Exposure to DuPage vs. Cook County generates ~30% increase in earnings

# Exposure Effects on Income in the New York CSA

For Children with Parents at 25th Percentile of Income Distribution



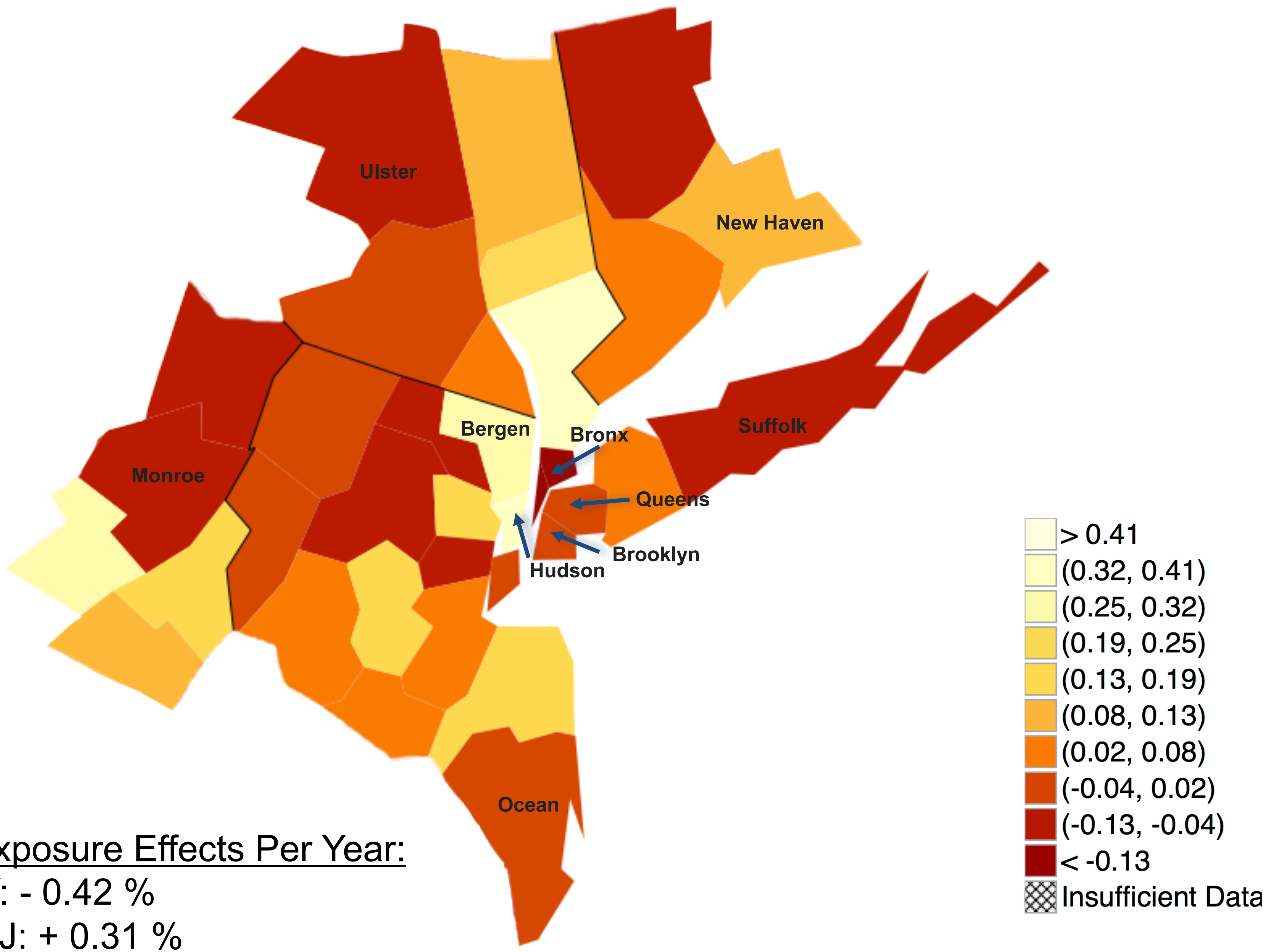

<u>Causal Exposure Effects Per Year:</u>

Bronx NY: - 0.54 %

Bergen NJ: + 0.69 %

# Exposure Effects on Income in the New York CSA

For Children with Parents at 75th Percentile of Income Distribution



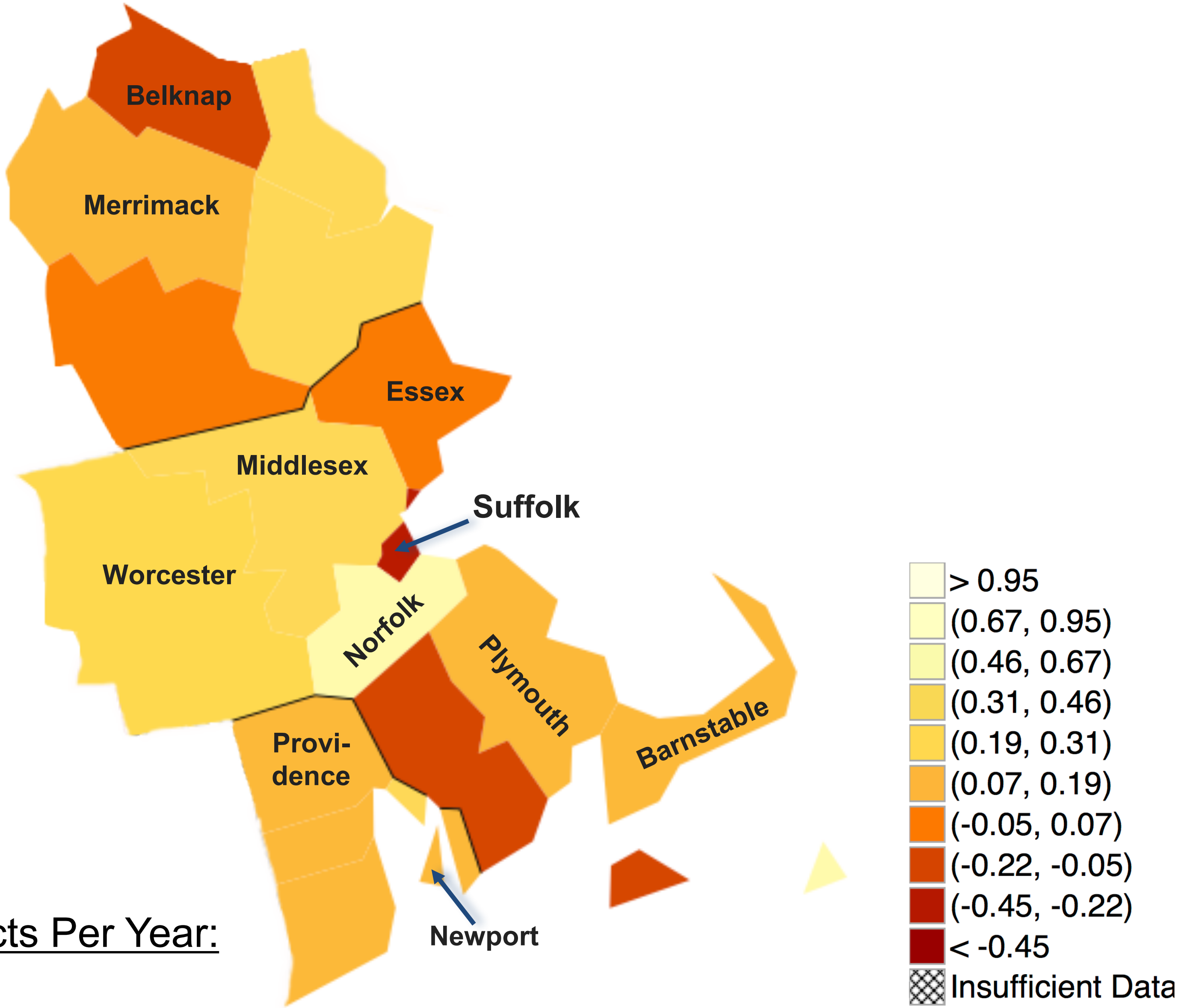

<u>Causal Exposure Effects Per Year:</u>

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



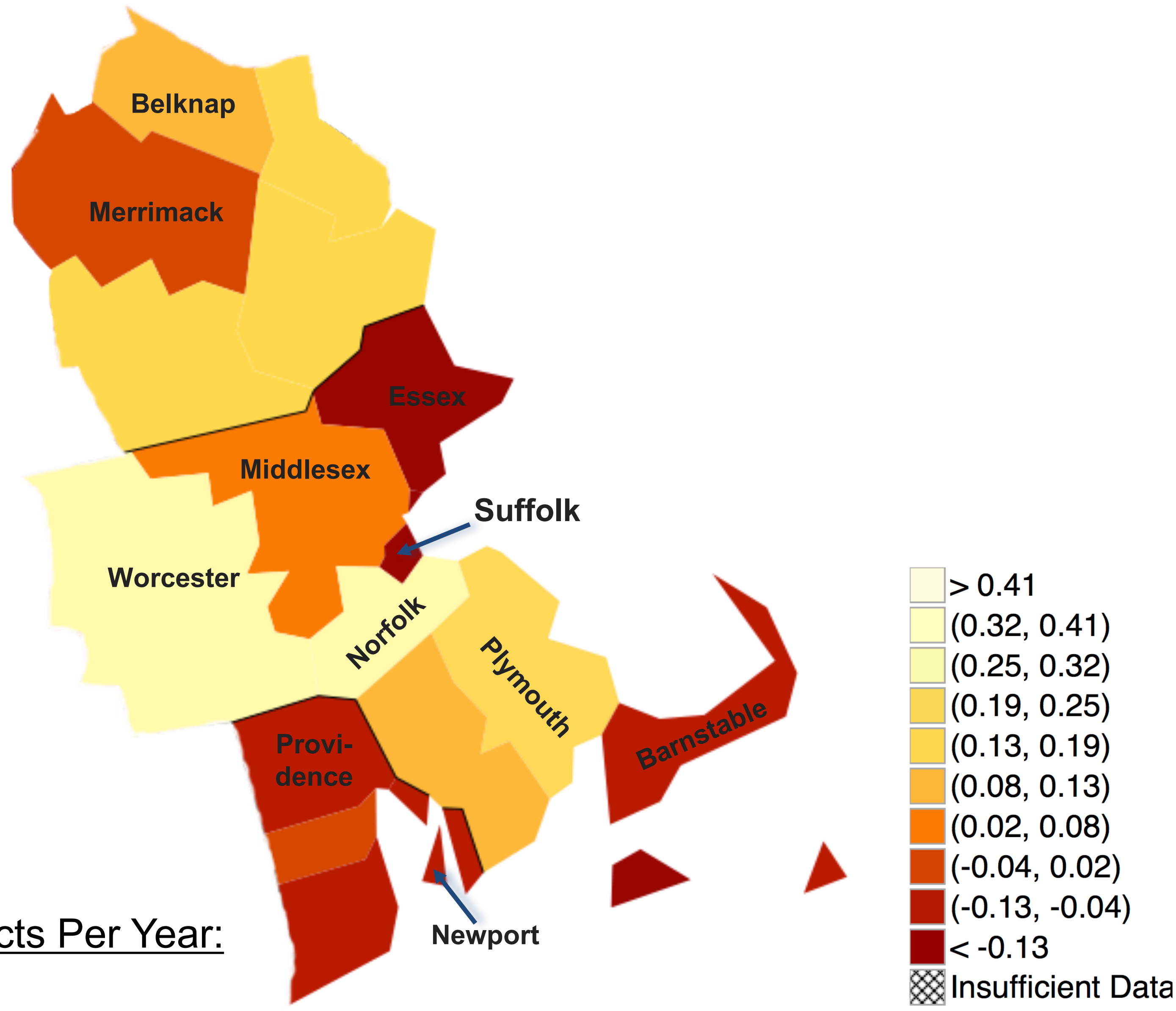

Causal Exposure Effects Per Year:

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*

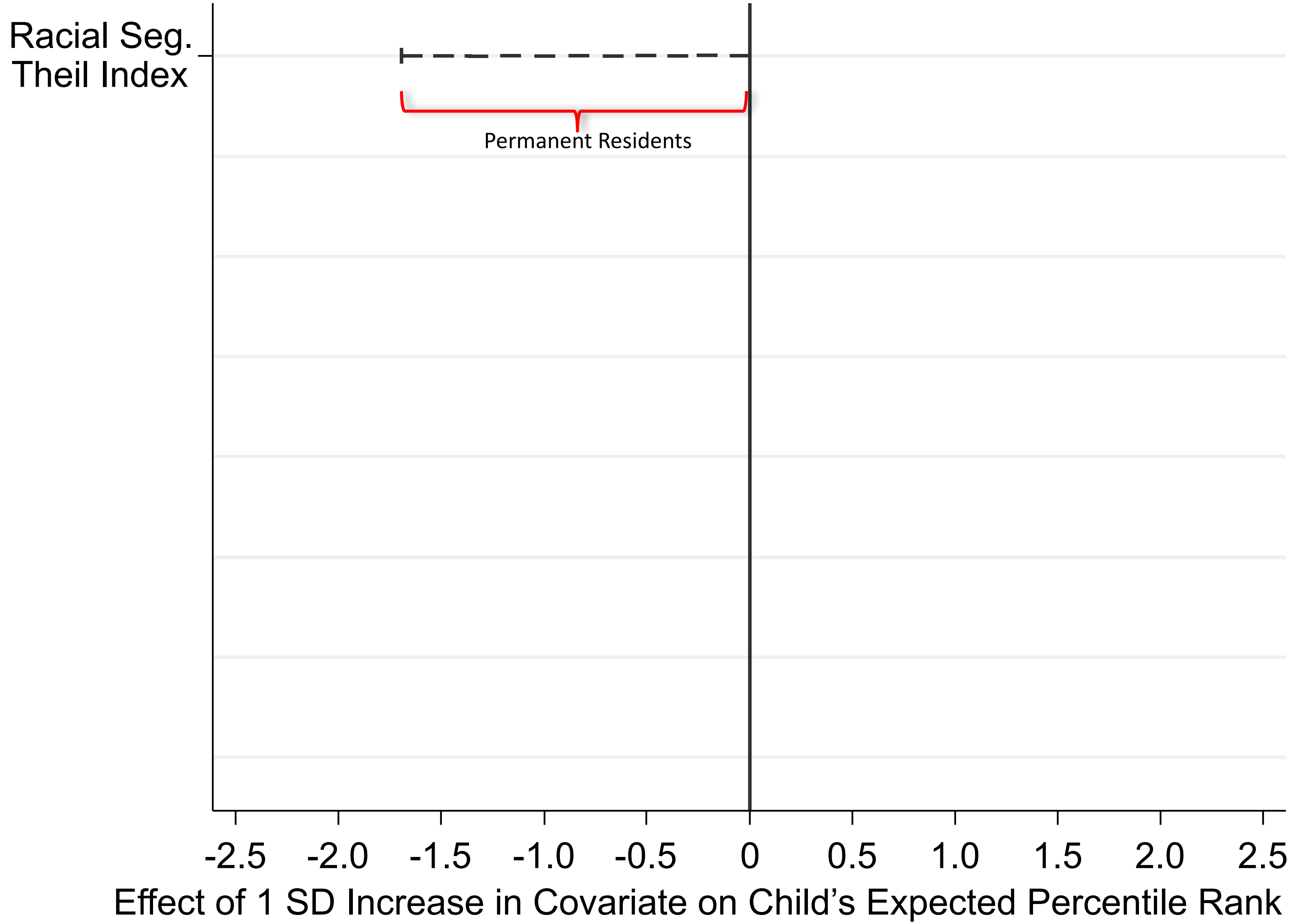
# Characteristics of Good Areas

- Are correlations documented in prior studies driven by causal effects?
  - Ex: children who grow up in "ghettos" with concentrated poverty have worse outcomes [Massey and Denton 1993, Cutler and Glaeser 1997]
  - Is growing up in a segregated area actually bad for a child or do people who live in segregated areas have worse unobservables?"
- Correlate fixed effect estimates with observable characteristics of areas

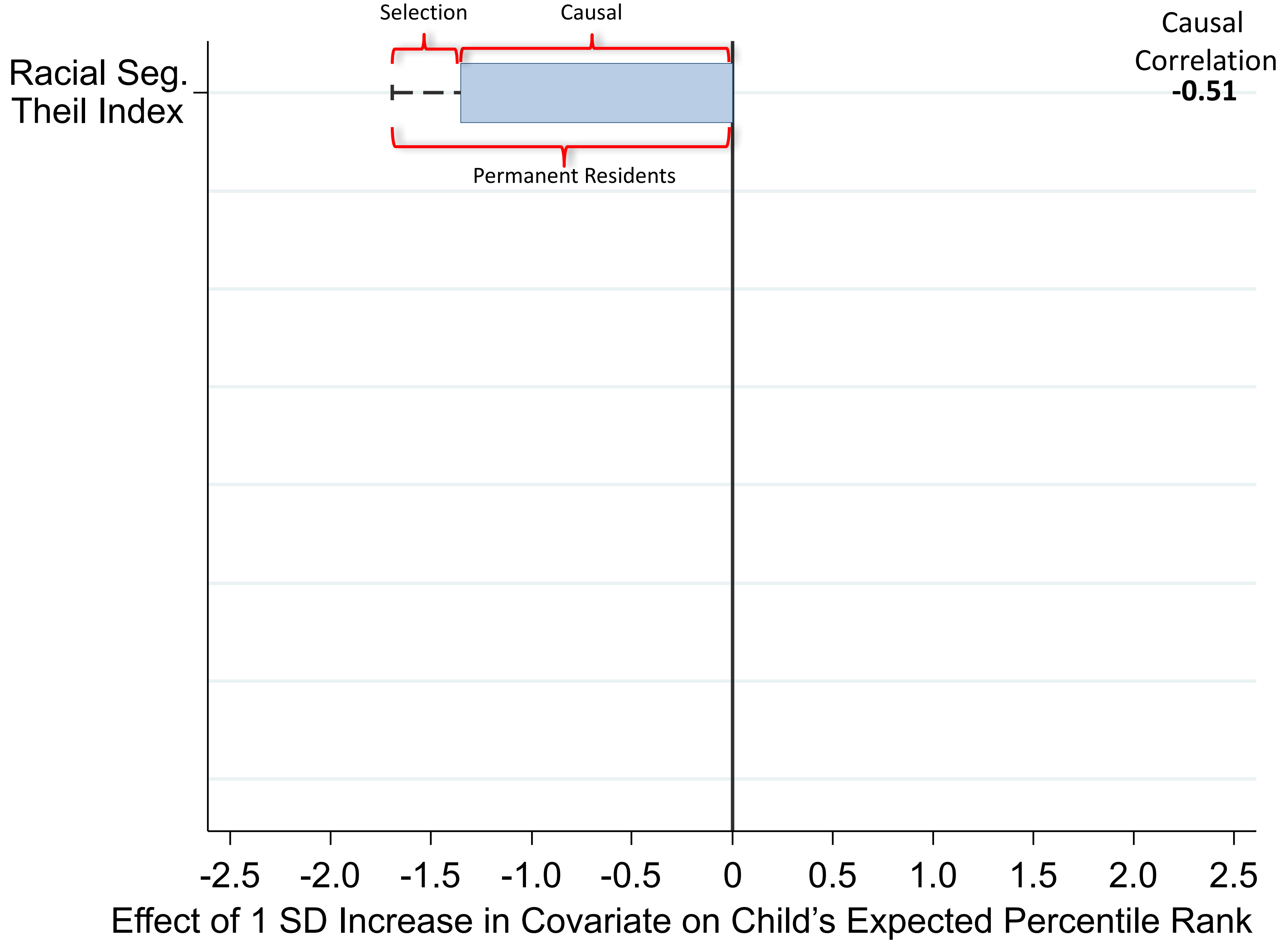
# Characteristics of Good Areas

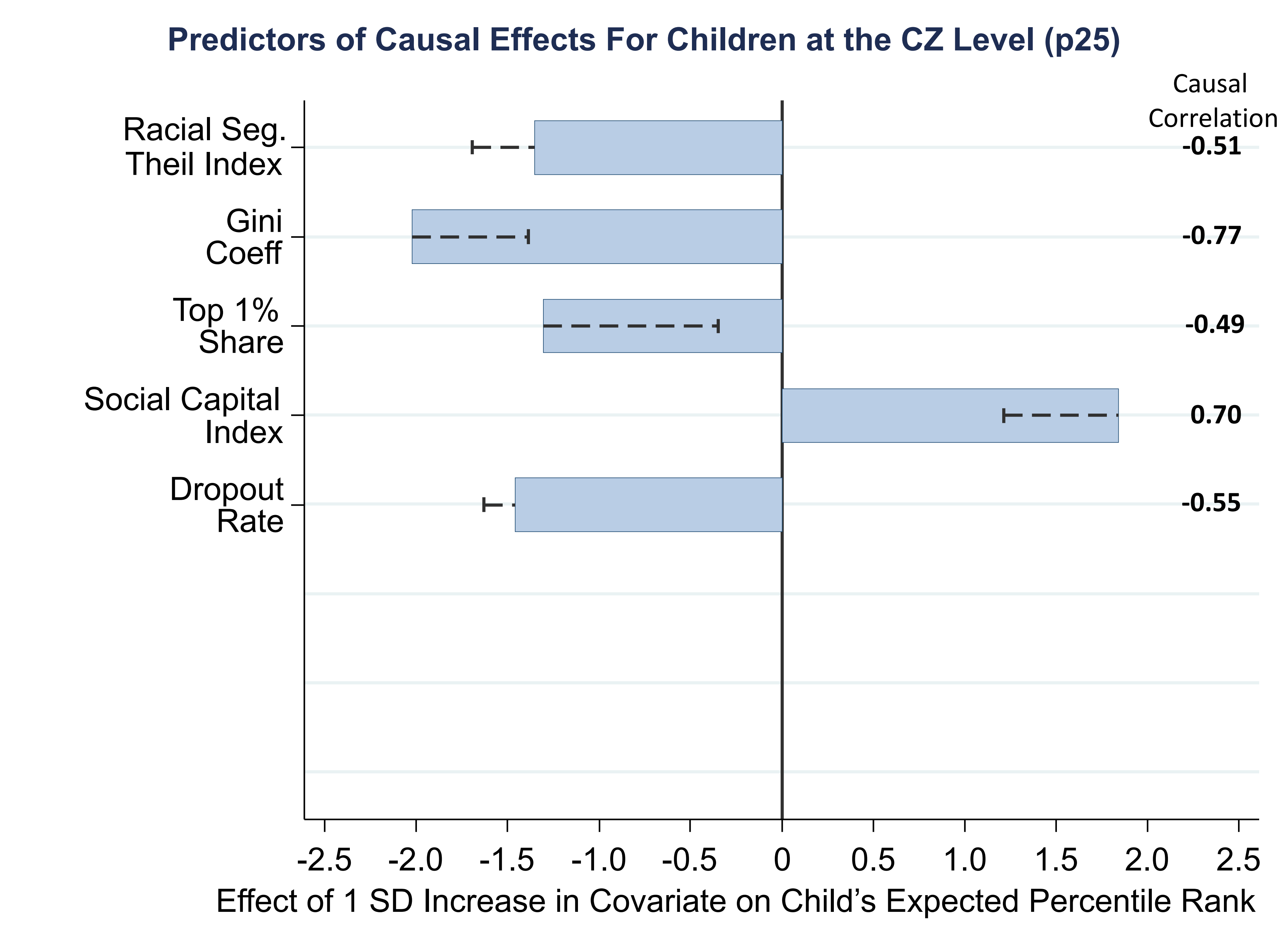
- Decompose observed rank for stayers ($y_{pc}$) into causal and sorting components by multiplying annual exposure effect $\mu_{pc}$ by 20:
  - Causal component = $20\mu_{pc}$
  - Sorting component = $y_{pc} - 20\mu_{pc}$
- Regress $y_{pc}$, causal, and sorting components on covariates
  - Standardize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

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



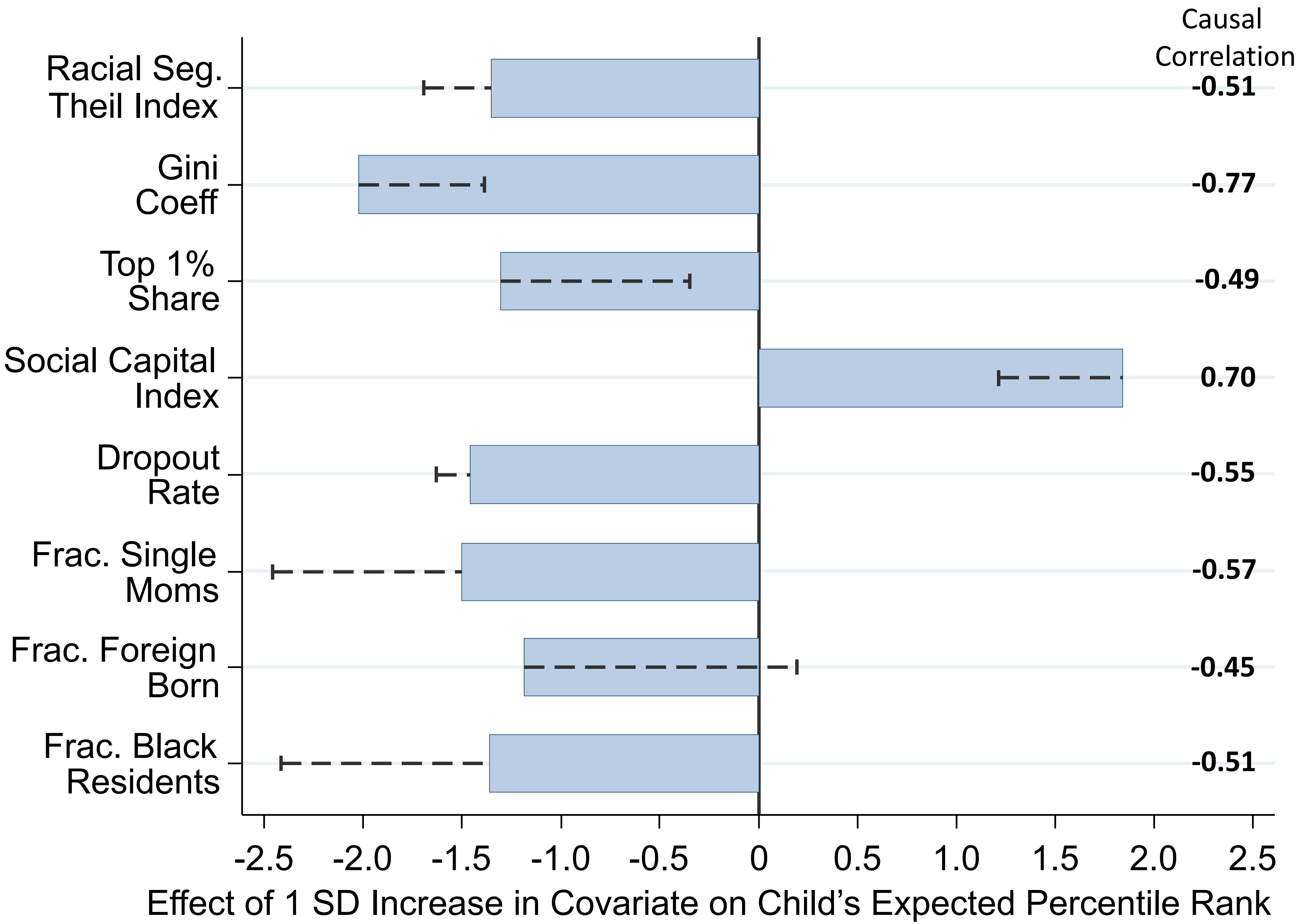
# Predictors of Causal Effects For Children at the CZ Level (p25)

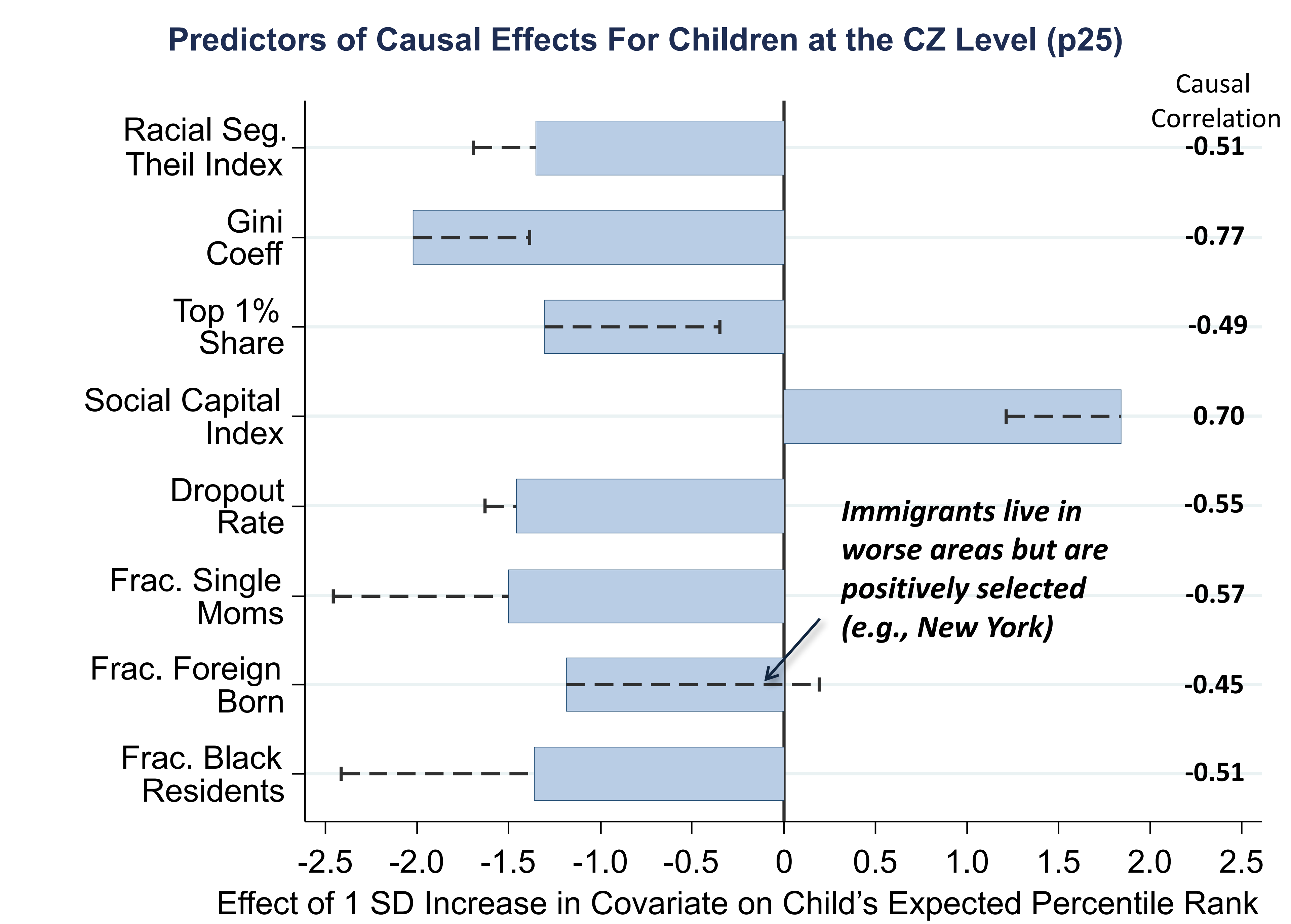




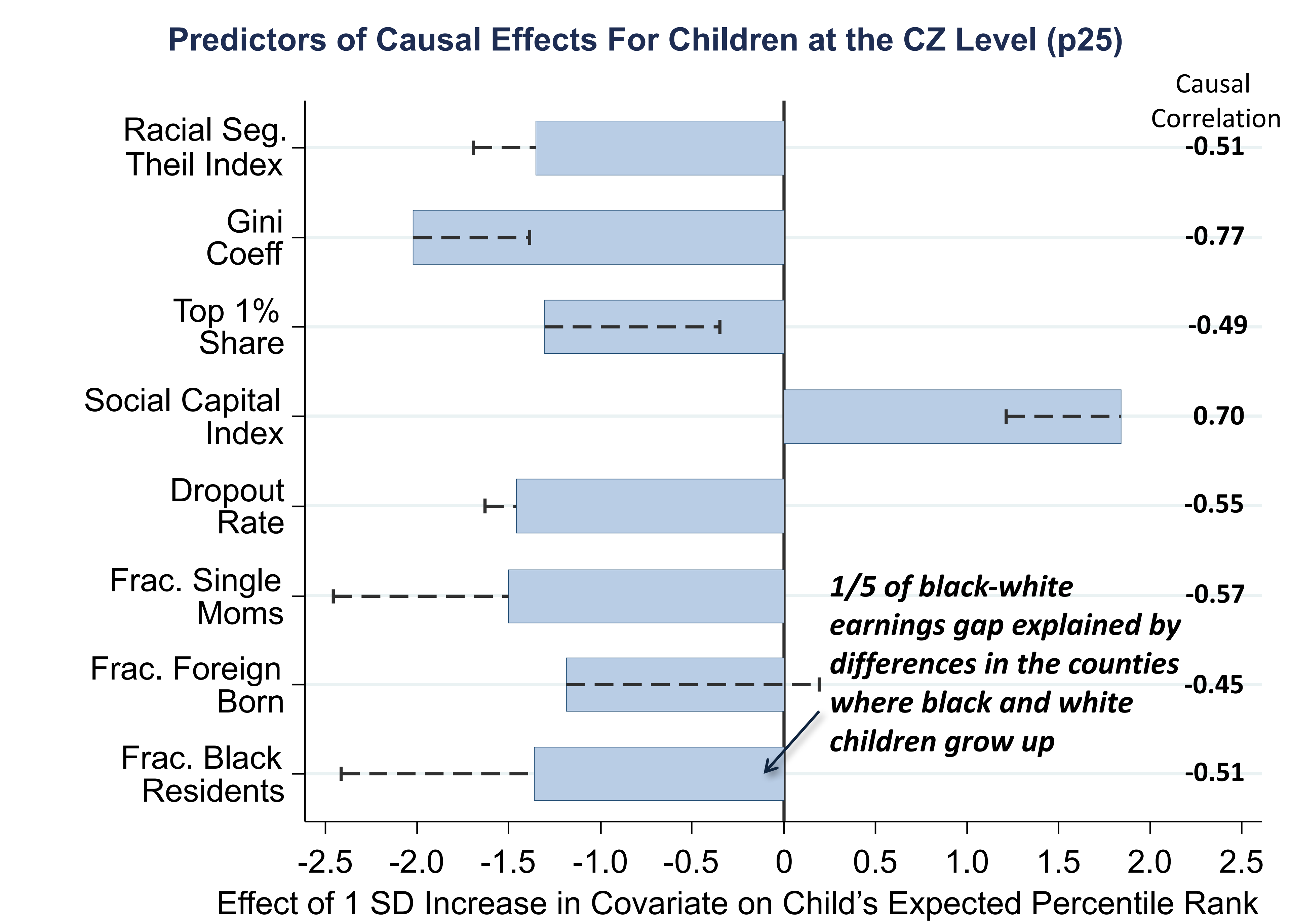
Predictors of Causal Effects For Children at the CZ Level (p25)
Causal Correlation
Racial Seg. Theil Index
-0.51
Gini Coeff
-0.77
Top 1% Share
-0.49
Social Capital Index
0.70
Dropout Rate
-0.55
-2.5
-2.0
-1.5
-1.0
-0.5
0
0.5
1.0
1.5
2.0
2.5
Effect of 1 SD Increase in Covariate on Child's Expected Percentile Rank

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





Predictors of Causal Effects For Children at the CZ Level (p25)
Causal Correlation
Racial Seg. Theil Index
-0.51
Gini Coeff
-0.77
Top 1% Share
-0.49
Social Capital Index
0.70
Dropout Rate
-0.55
Immigrants live in worse areas but are positively selected (e.g., New York)
Frac. Single Moms
-0.57
Frac. Foreign Born
-0.45
Frac. Black Residents
-0.51
-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 Causal Effects For Children at the CZ Level (p25)
Causal Correlation
Racial Seg. Theil Index
-0.51
Gini Coeff
-0.77
Top 1% Share
-0.49
Social Capital Index
0.70
Dropout Rate
-0.55
Frac. Single Moms
-0.57
Frac. Foreign Born
-0.45
Frac. Black Residents
-0.51
1/5 of black-white earnings gap explained by differences in the counties where black and white children grow up
-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

# Part B: Implications for Place-Based Policy

- Place matters for children's outcomes
- Two types of potential policy implications:
  - "Place based"
    - Policies that change places
    - e.g. investment in schools, community centers, etc.
  - "Choice based"
    - Change the allocation of people to places
    - E.g. housing vouchers ("Section 8")

# Place-Based Policy: Harlem Children's Zone

- Enormously difficult to estimate the causal effect of place-based policy
  - Need to randomize at the place level
- Nice Example: Harlem Children's Zone
  - Aimed to change entire neighborhood of Harlem
  - Bundle of services from birth to college (schools, community programs, …)
  - Expanded from their original 24-block area in central Harlem to a 64-block area in 2004 and a 97-block area in 2007
- Dobbie and Fryer (2011) estimate impact on test scores
  - Use lottery and distance instruments

Figure 1
The Harlem Children's Zone

## Large Impacts on Children's Test Scores

Table 3
Middle School Results

| | Lottery RF | Lottery FS | Lottery 2SLS | Distance 2SLS |
|---|---|---|---|---|
| Math | 0.284*** | 1.240*** | 0.229*** | 0.206** |
| | (0.050) | (0.075) | (0.037) | (0.092) |
| ELA | 0.059 | 1.241*** | 0.047 | −0.053 |
| | (0.041) | (0.074) | (0.033) | (0.049) |
| Absences | −2.783*** | 1.260*** | −2.199*** | −0.220 |
| | (0.833) | (0.079) | (0.650) | (2.544) |
| On Grade Level | −0.003 | 1.240*** | −0.002 | −0.011 |
| | (0.022) | (0.075) | (0.017) | (0.036) |
| Observations | 1449 | 1449 | 1449 | 41029 |

# Place-Based Policy: Harlem Children's Zone

- Results:
- Winning the lottery to enter the HCZ dramatically alters test scores
  - Closes half the gap in white-black test scores!
- Similar effects for those inside and outside original HCZ boundary
  - Suggests schools can explain much of the impact
    - What about baseline level differences inside and outside the zone?

# Place vs. Choice Based Policy

- HCV improves children’s outcomes
  - Suggests can improve places
- Other policy: provide families opportunities to move to better neighborhoods
  - Moving to Opportunity Experiment

# Choice-Based Policy: Moving to Opportunity

- 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
    - Rejects “Spatial Mismatch Hypothesis” of Kain (1968)
  - But 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?

# Data

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

# Estimating MTO Treatment Effects

- In baseline analysis, estimate treatment effects for two groups:
  - Young children: below age 13 at random assignment (RA)
  - Older children: age 13-18 at random assignment

- Average age at move: 8.2 for young children vs. 15.1 for older children

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

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

# Estimating MTO Treatment Effects

- Replicate standard regression specifications used in earlier work [Kling, Katz, Liebman 2007]

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

**Treatment Indicators**

**Site Indicators**

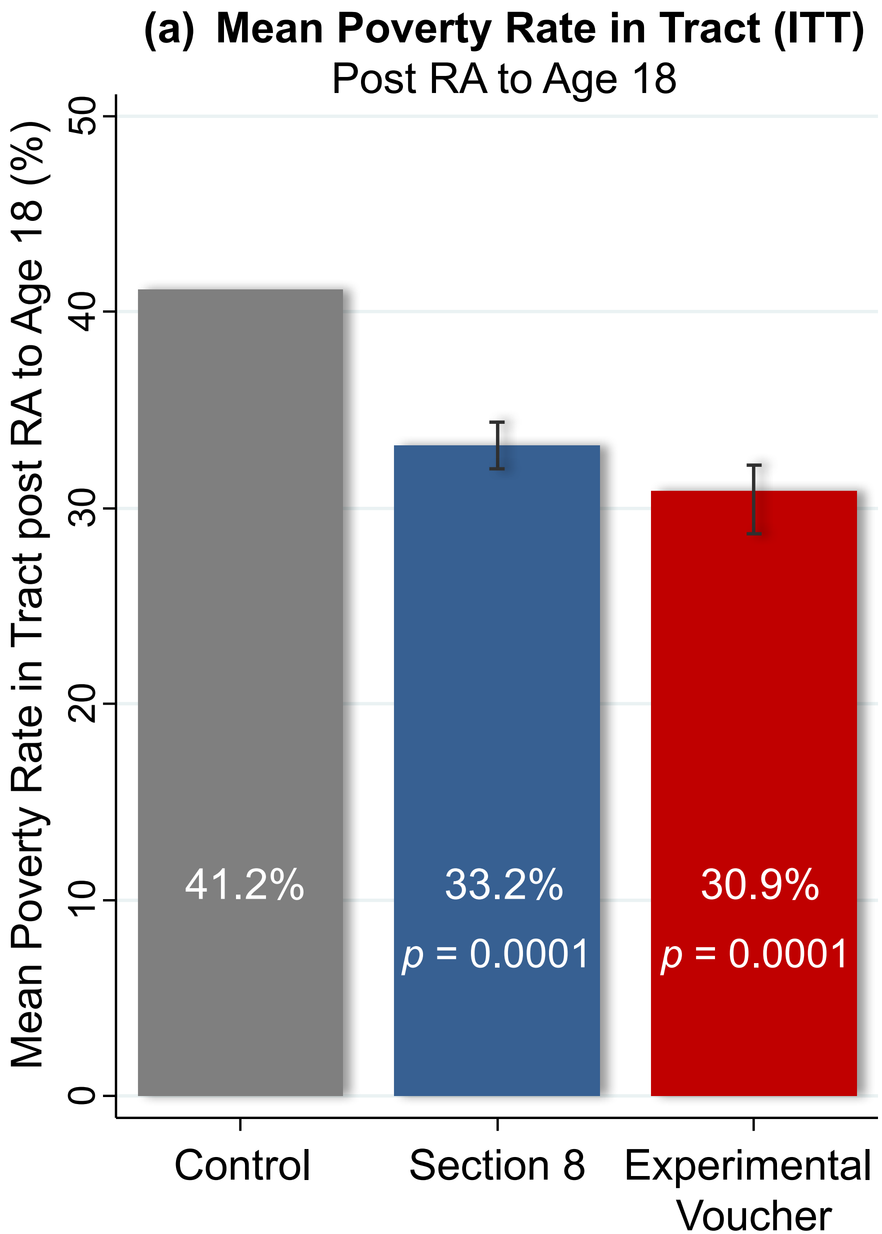
- These intent-to-treat (ITT) estimates identify effect of being *offered* a voucher to move through MTO

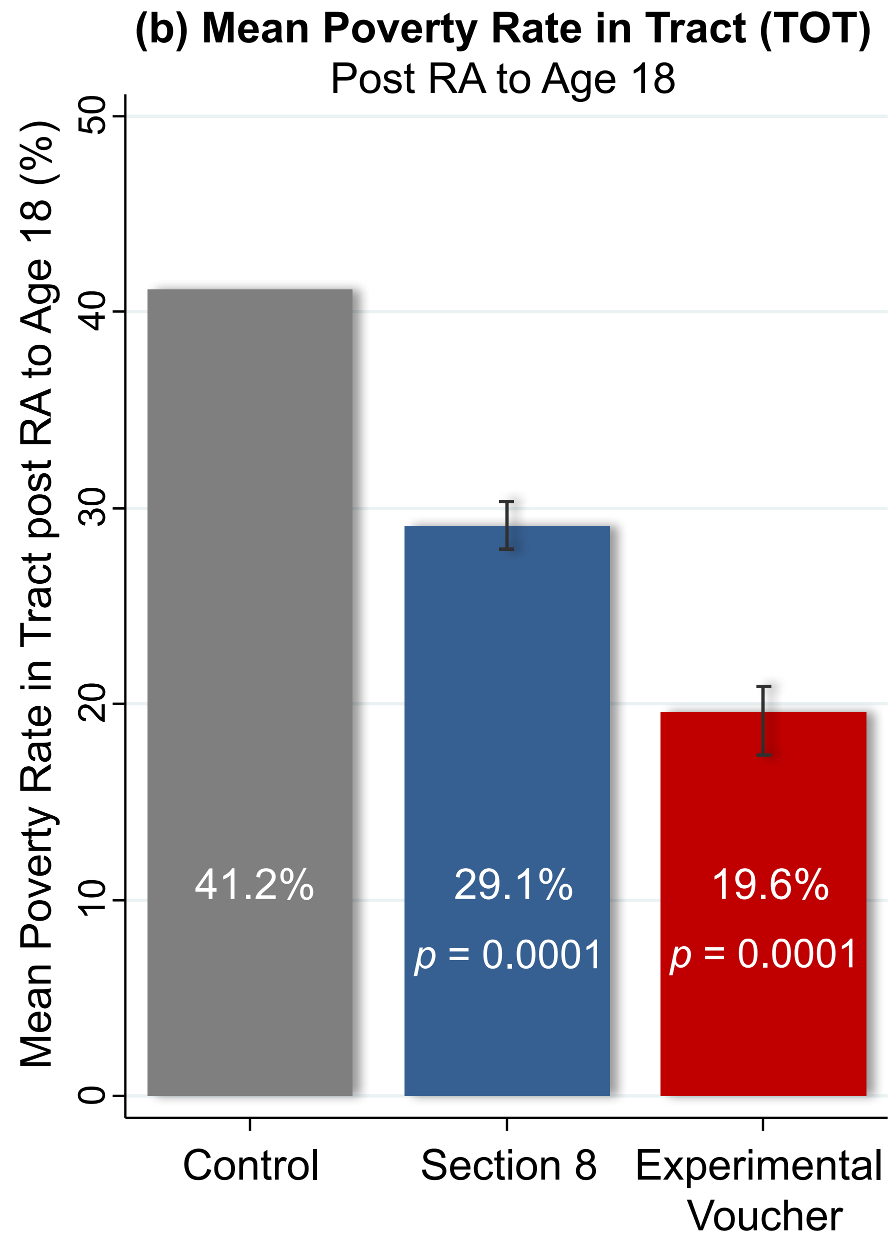
- Estimate treatment-on-treated (TOT) effects using 2SLS, instrumenting for voucher takeup with treatment indicators
  - Experimental take-up: 48% for young children, 40% for older children
  - Section 8 take-up: 65.8% for young children, 55% for older children

# Treatment Effects on Neighborhood Poverty

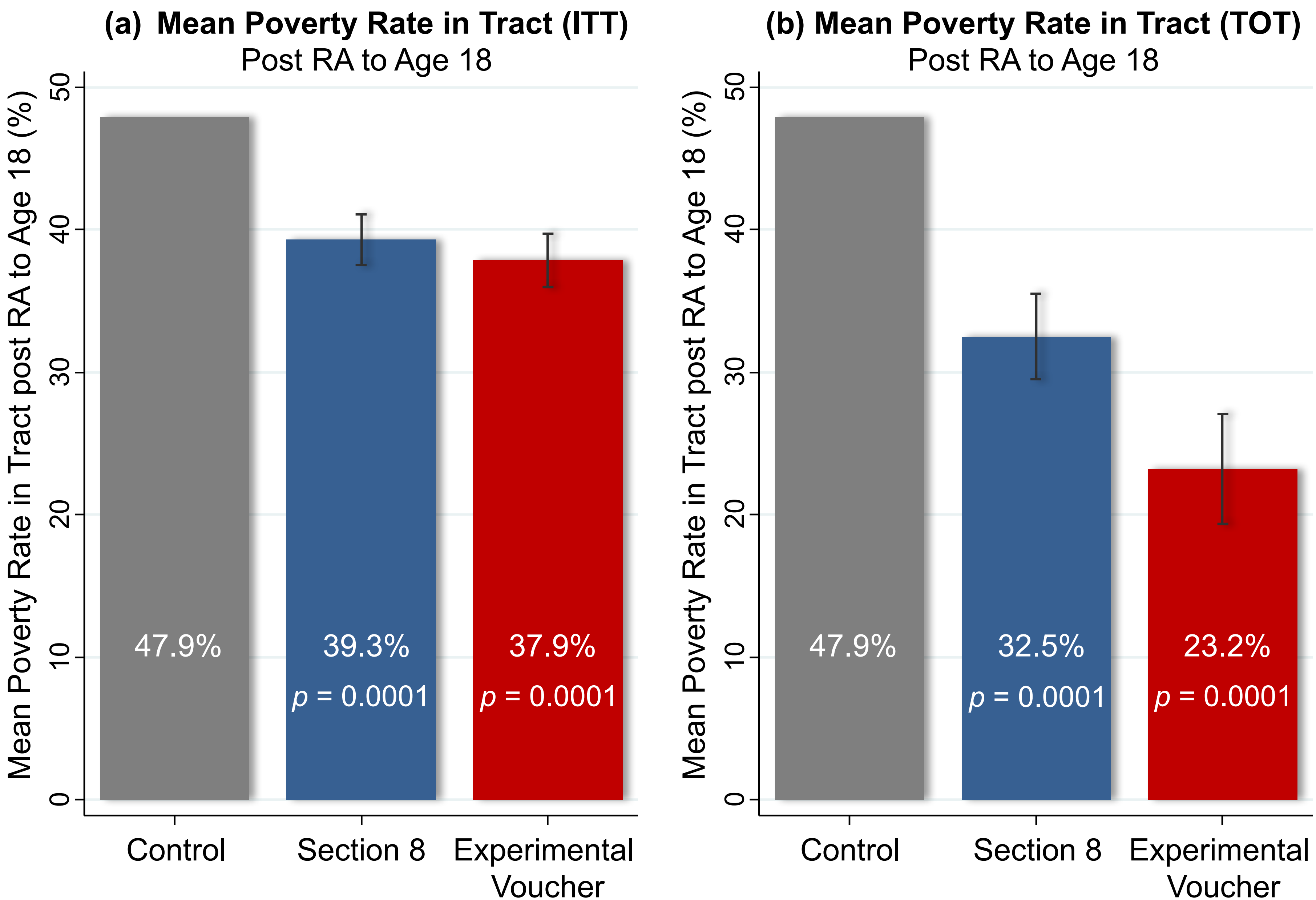
- Begin with “first stage” effects of MTO experiment on poverty rates
  - Measure mean poverty rates from random assignment to age 18 at tract level using Census data
- Use poverty rates as an index of nbhd. quality, but note that MTO treatments naturally changed many other features of neighborhoods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

# Impacts of MTO on Children Below Age 13 at Random Assignment



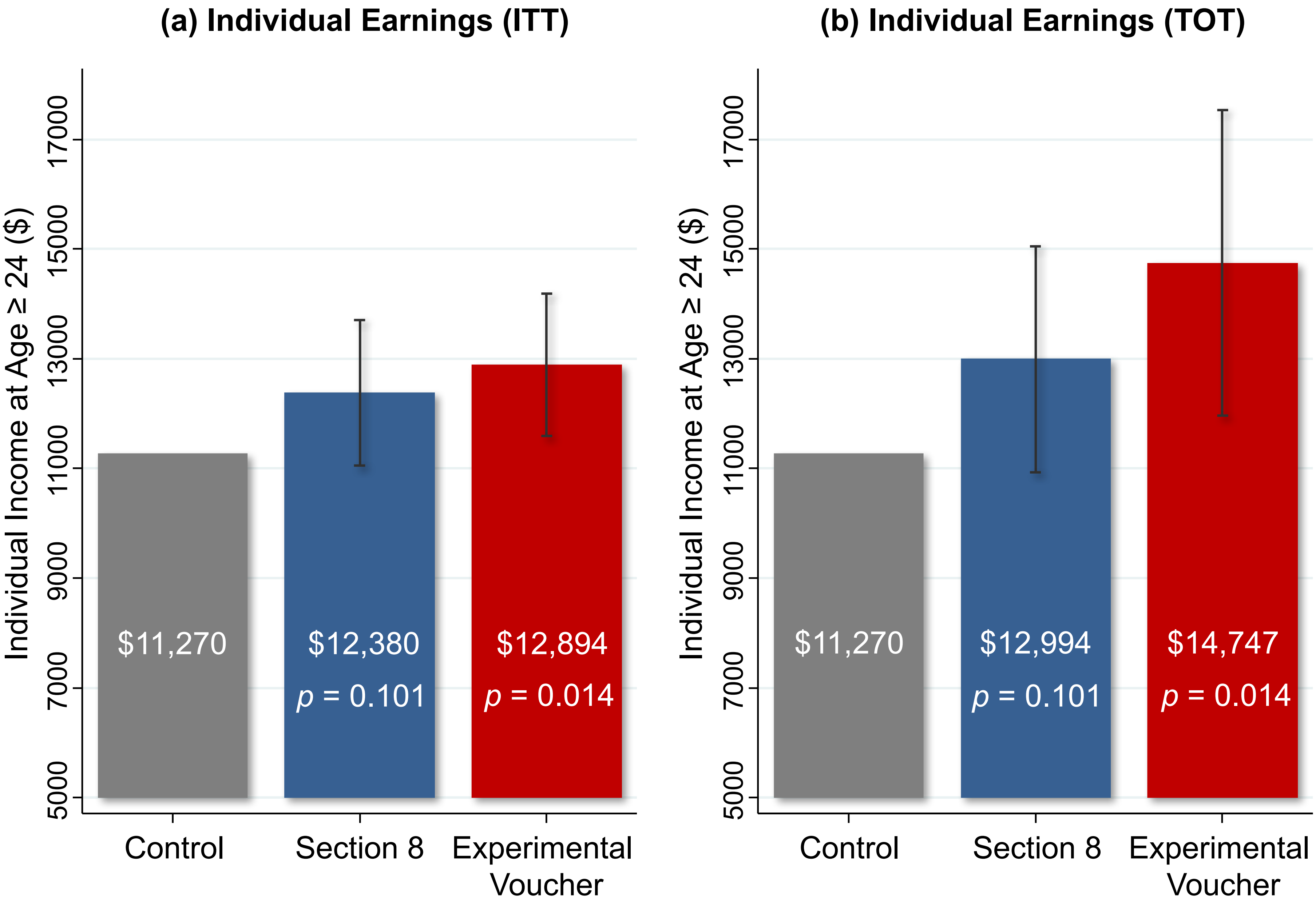
## Impacts of MTO on Children Age 13-18 at Random Assignment

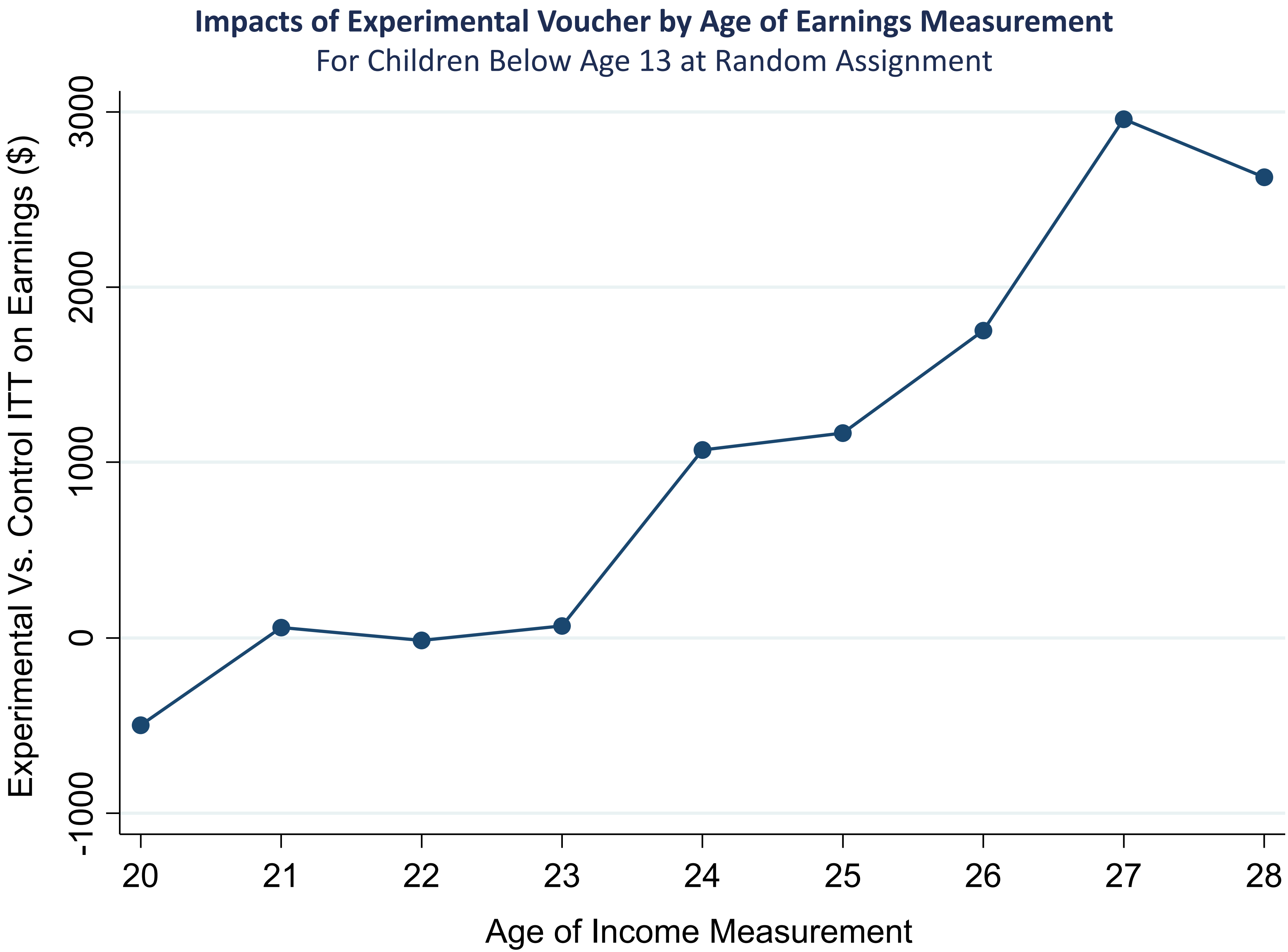


# Treatment Effects on Outcomes in Adulthood

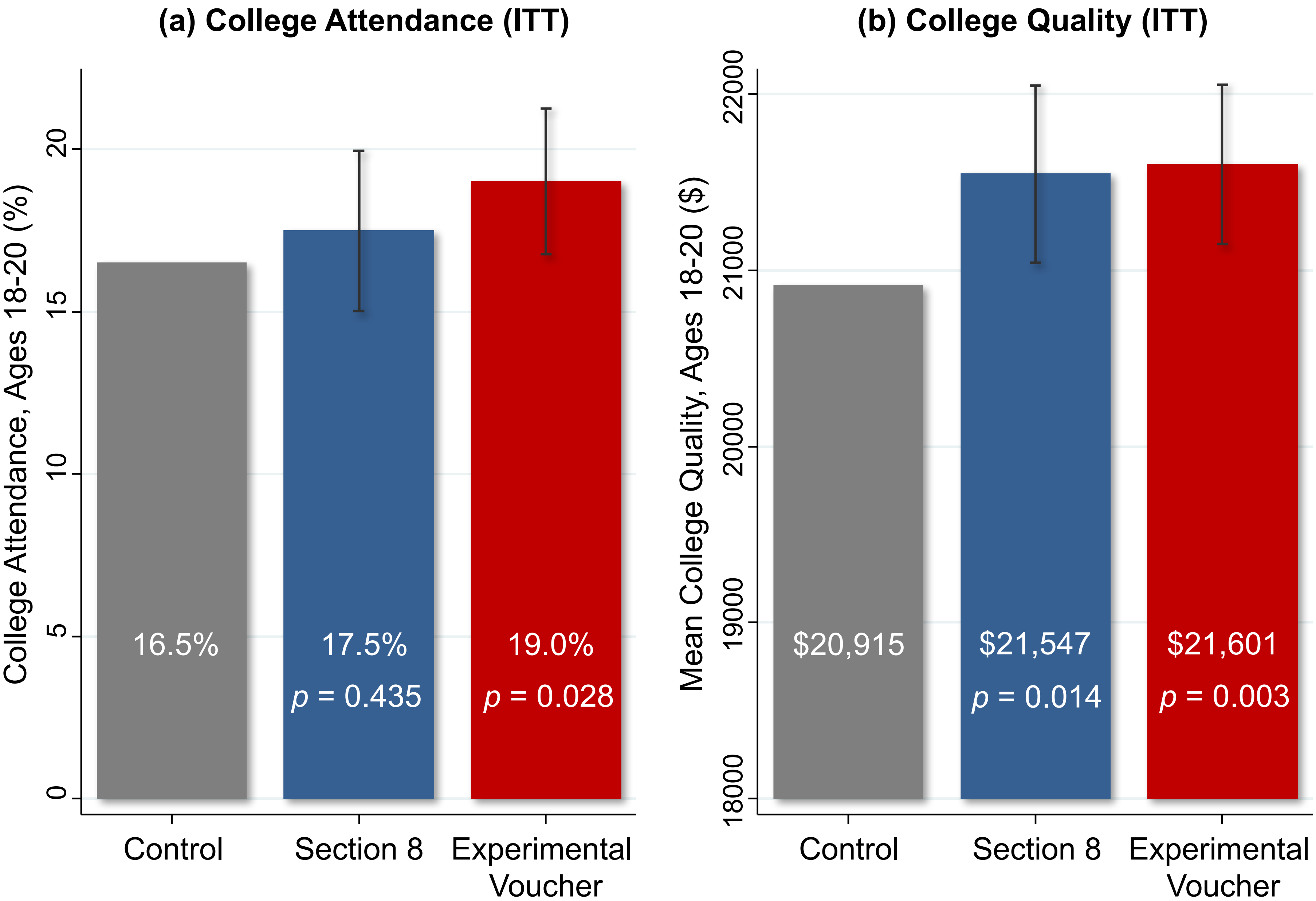
- Now turn to impacts on outcomes in adulthood
- Begin by analyzing effects on children below age 13 at RA
- Start with individual earnings (W-2 earnings + self-employment income)
  - Includes those who don’t file tax returns through W-2 forms
- Measured from 2008-12, restricting to years in which child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

# Impacts of MTO on Children Below Age 13 at Random Assignment

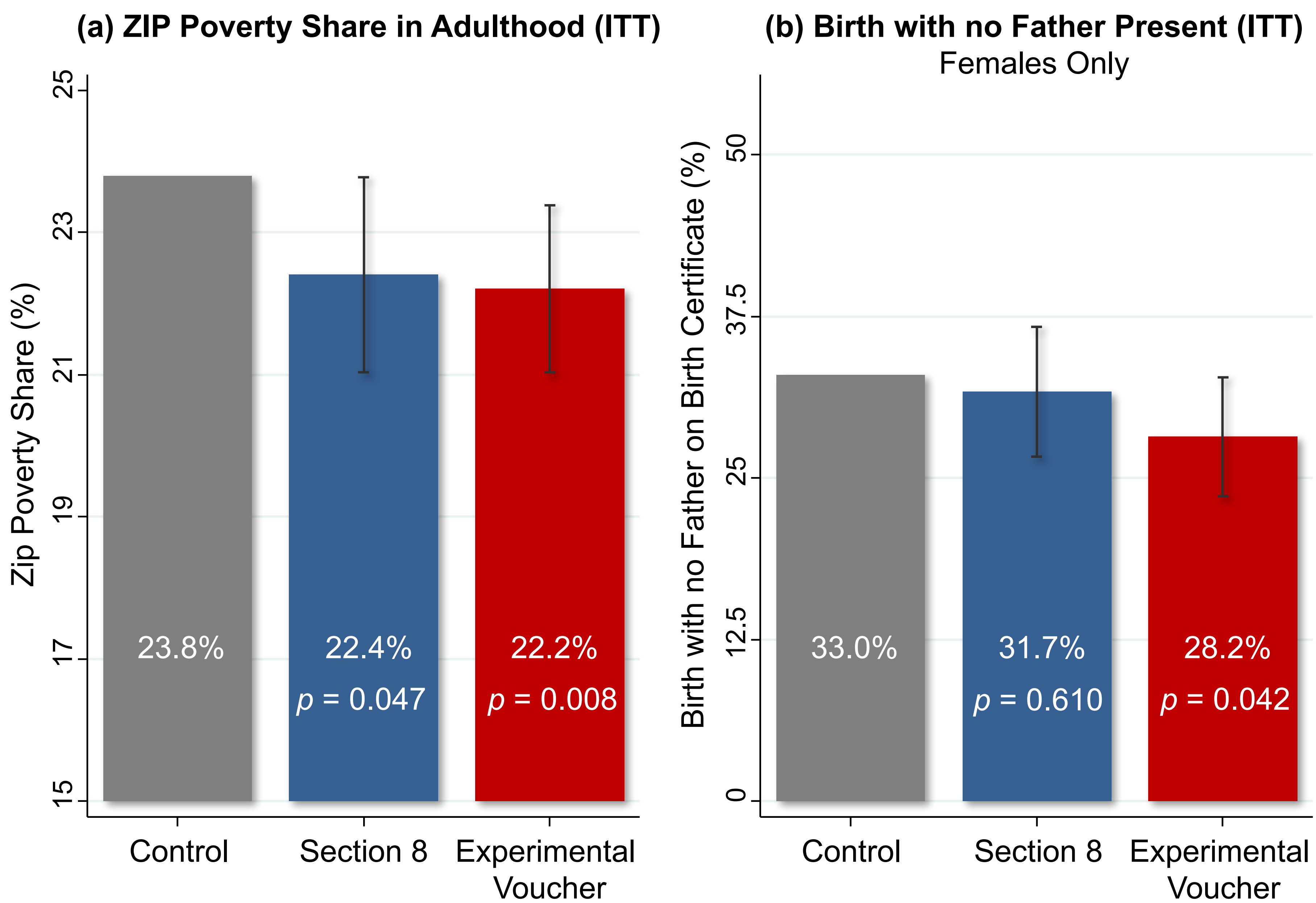



Impacts of Experimental Voucher by Age of Earnings Measurement
For Children Below Age 13 at Random Assignment
Experimental Vs. Control ITT on Earnings ($)
-1000
0
1000
2000
3000
20
21
22
23
24
25
26
27
28
Age of Income Measurement

## Impacts of MTO on Children Below Age 13 at Random Assignment



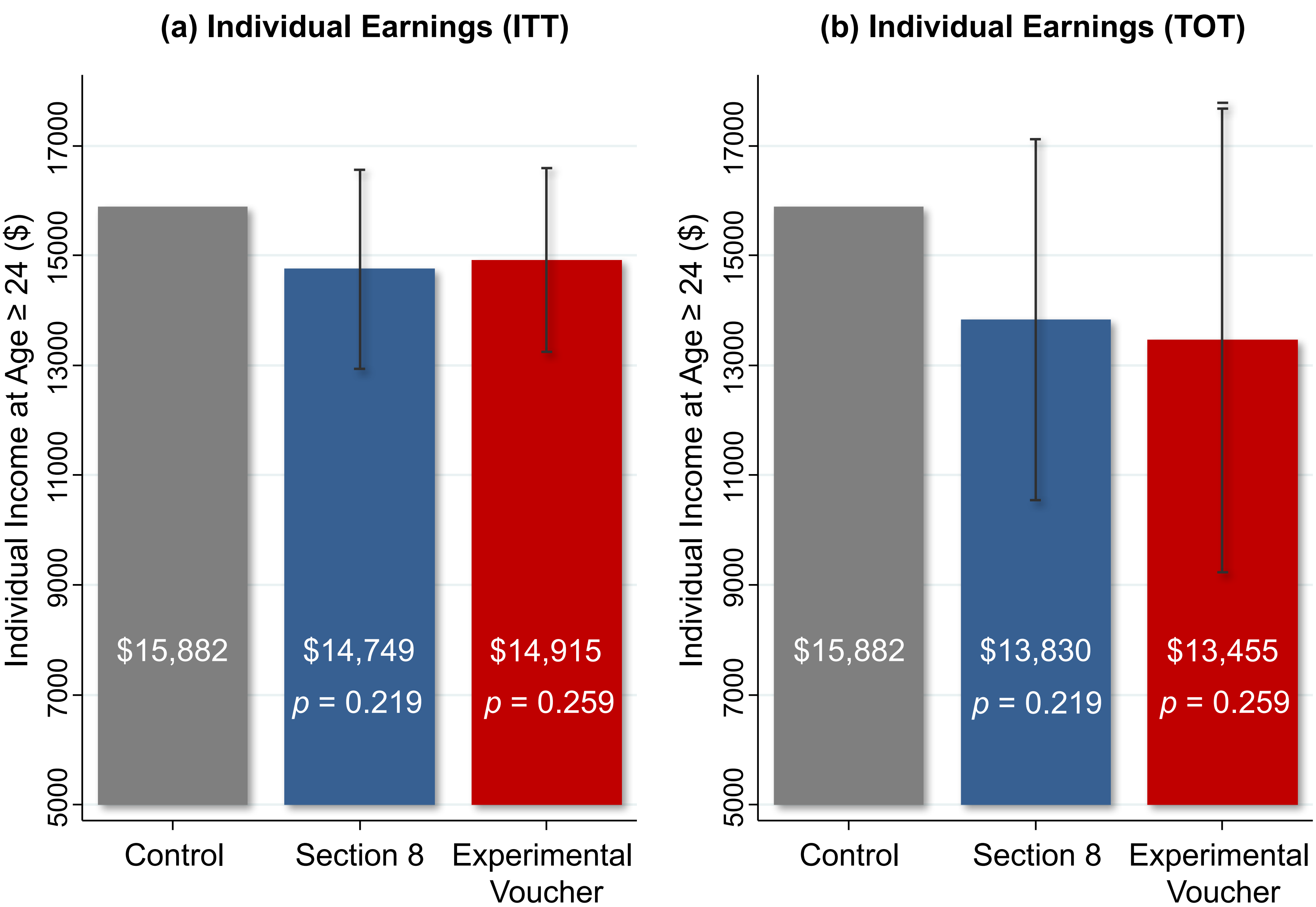
## Impacts of MTO on Children Below Age 13 at Random Assignment

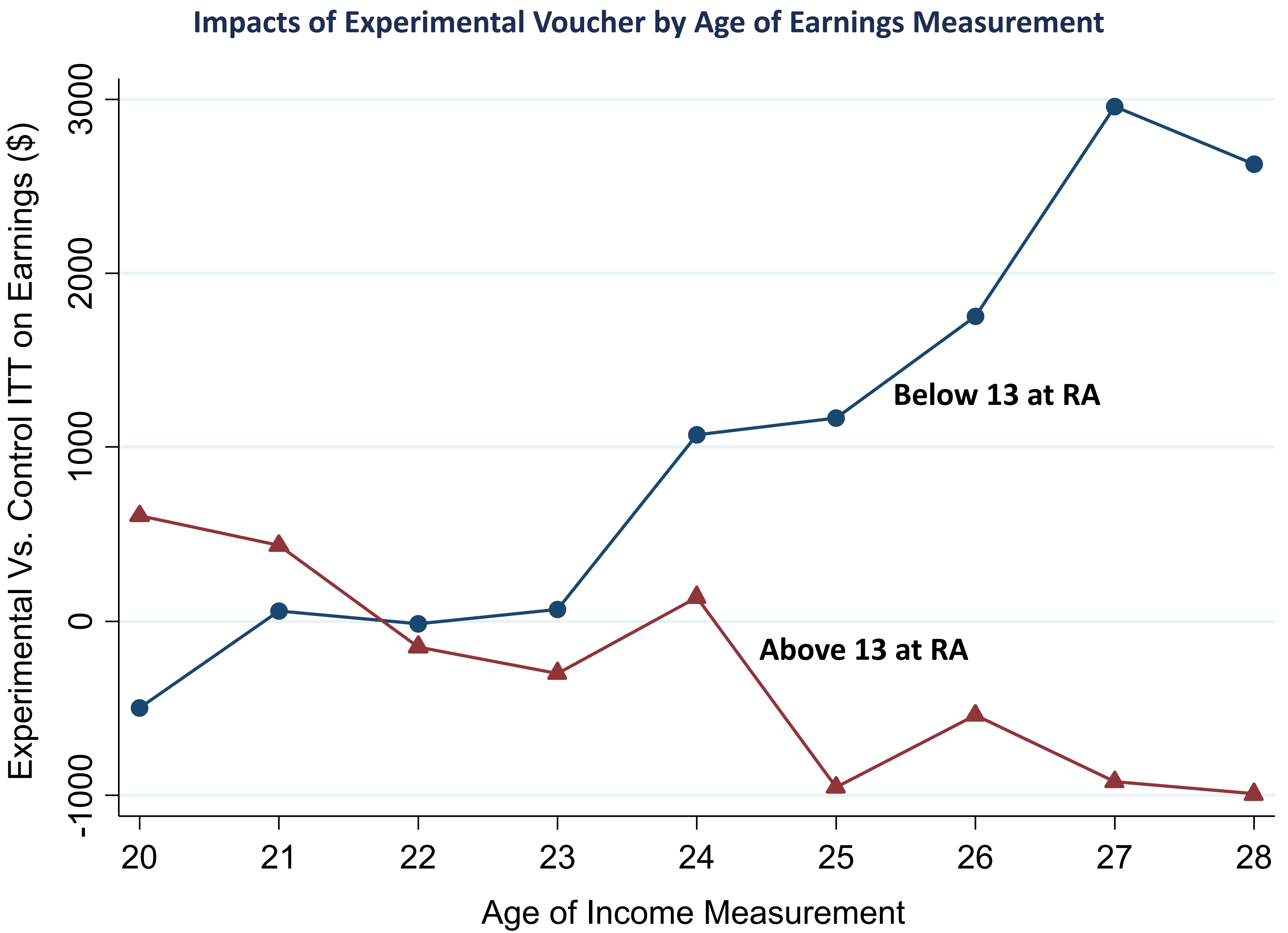


# Treatment Effects on Older Children

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

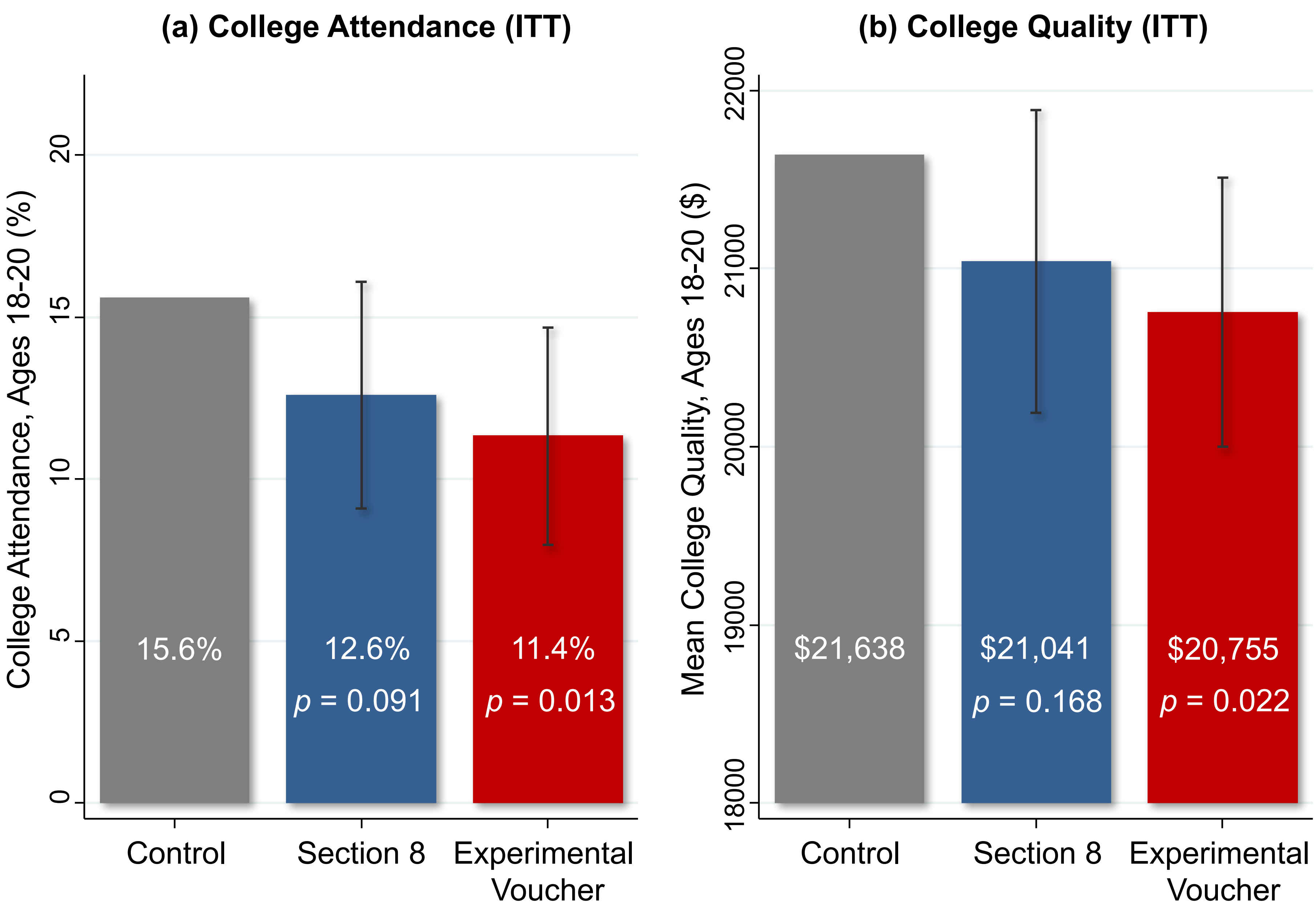
# Impacts of MTO on Children Age 13-18 at Random Assignment



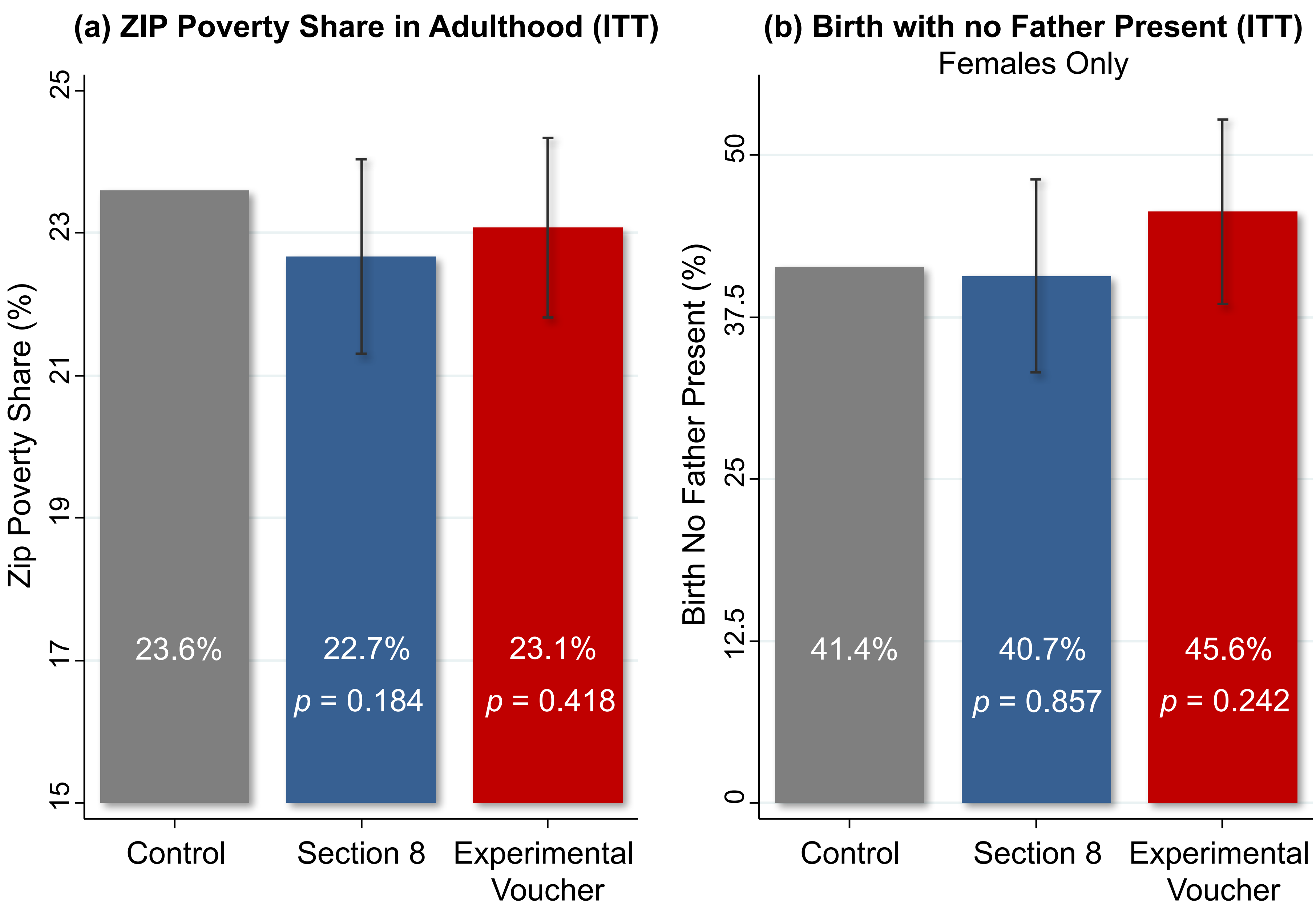


Impacts of Experimental Voucher by Age of Earnings Measurement
Experimental Vs. Control ITT on Earnings ($)
3000
2000
1000
0
-1000
20
21
22
23
24
25
26
27
28
Age of Income Measurement
Below 13 at RA
Above 13 at RA

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

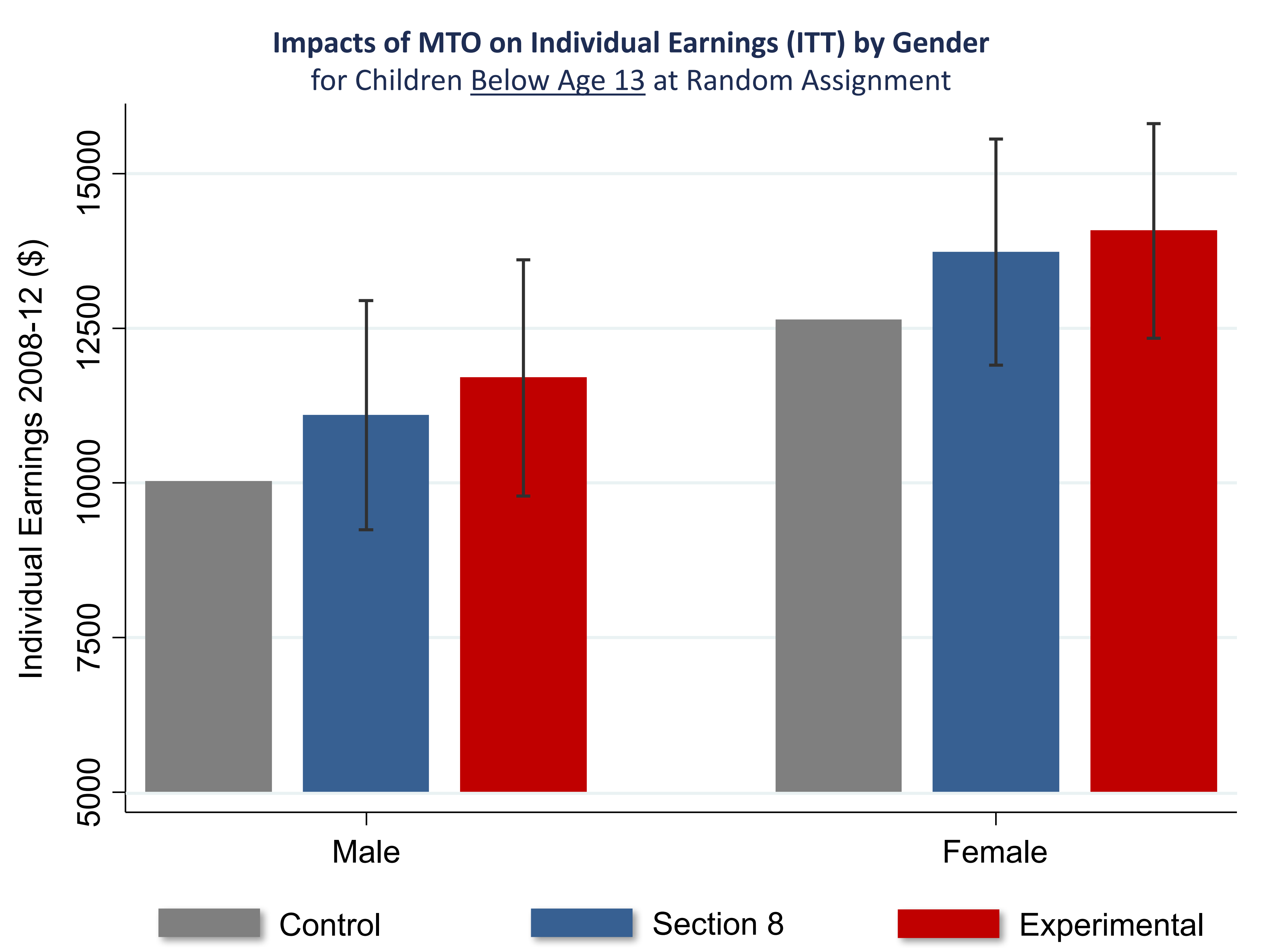


# Impacts of MTO on Children Age 13-18 at Random Assignment

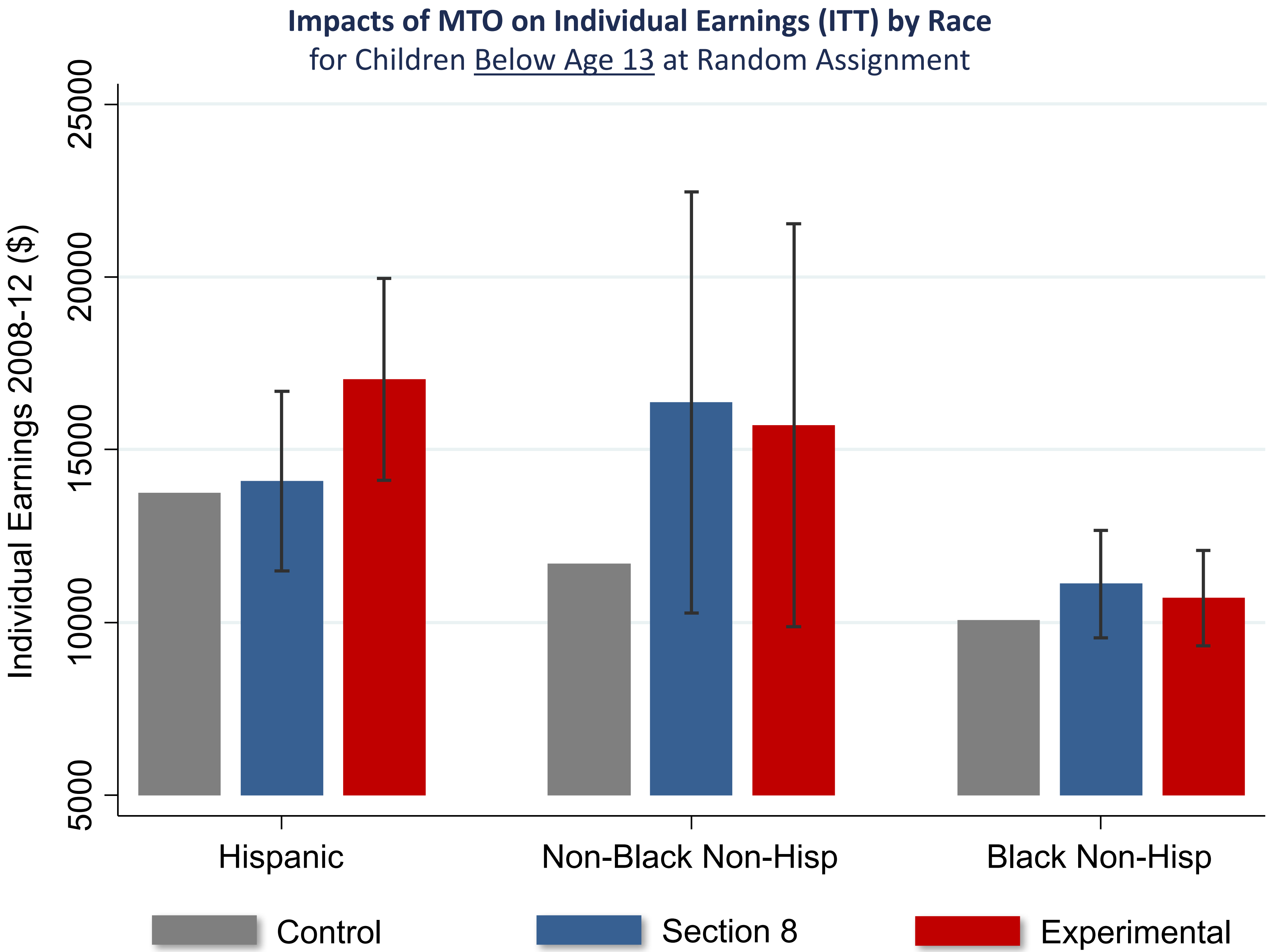


# Heterogeneity

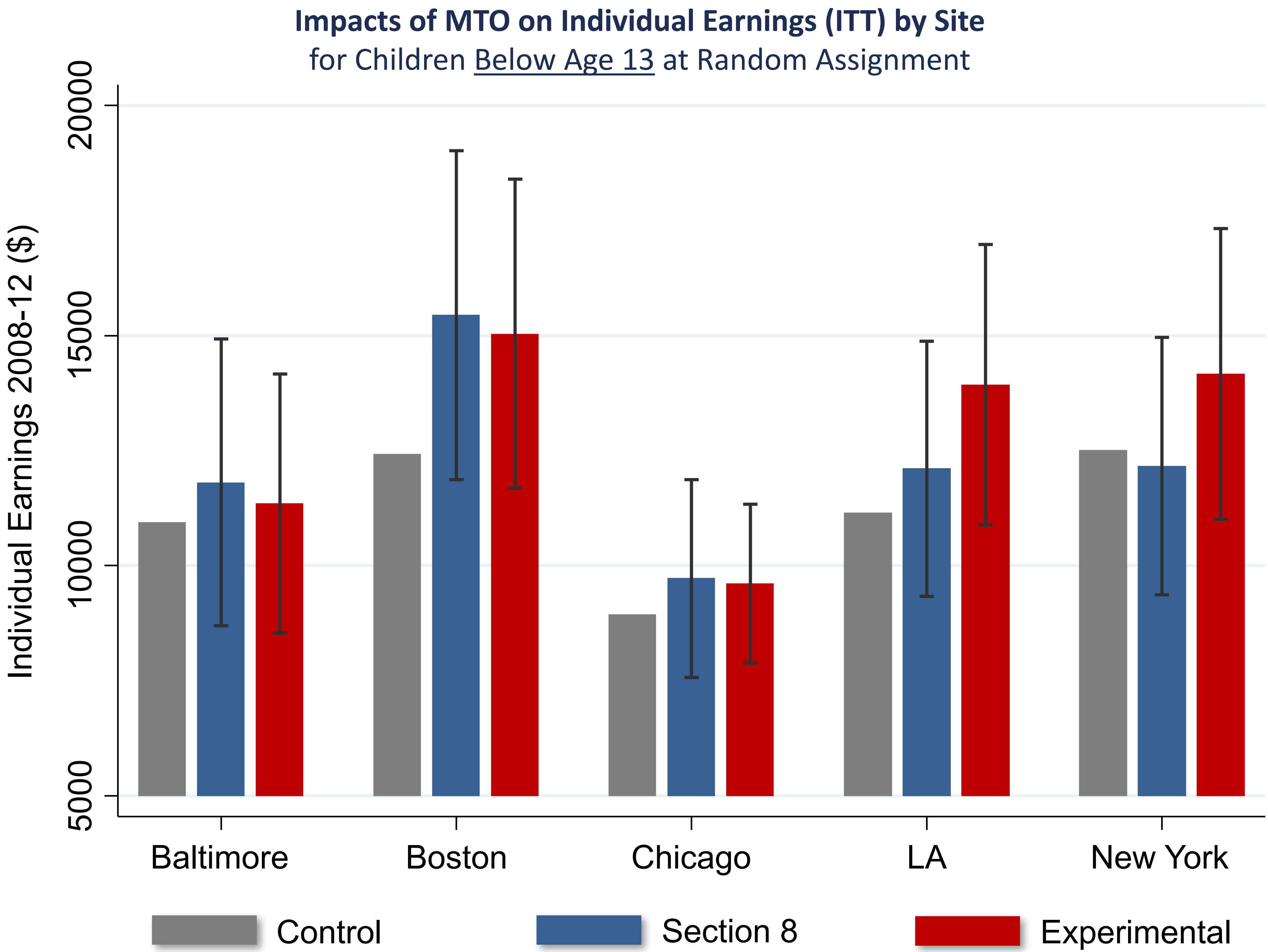
- Prior work has analyzed variation in treatment effects across sites, racial groups, and gender
- Replicate analysis across these groups for children below age 13 at RA



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



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



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

# Multiple Hypothesis Testing

- Given extent to which heterogeneity has been explored in MTO data, one should be concerned about multiple hypothesis testing

- Our study simply explores one more dimension of heterogeneity: age of child

- Any post-hoc analysis will detect "significant" effects ($p < 0.05$) even under the null of no effects if one examines a sufficiently large number of subgroups

- Can account for multiple tests by testing omnibus null that treatment effect is zero in all subgroups studied to date (gender, race, site, and age)

    - Two approaches: parametric F test and non-parametric permutation test

## Multiple Comparisons: F Tests for Subgroup Heterogeneity

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

# Multiple Comparisons: Permutation Tests for Subgroup Heterogeneity

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

## Multiple Comparisons: How to Construct Permutation Tests for Subgroup Heterogeneity
## EXAMPLE

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

**Adjusted p-value (example) 0.100**

# Multiple Hypothesis Testing

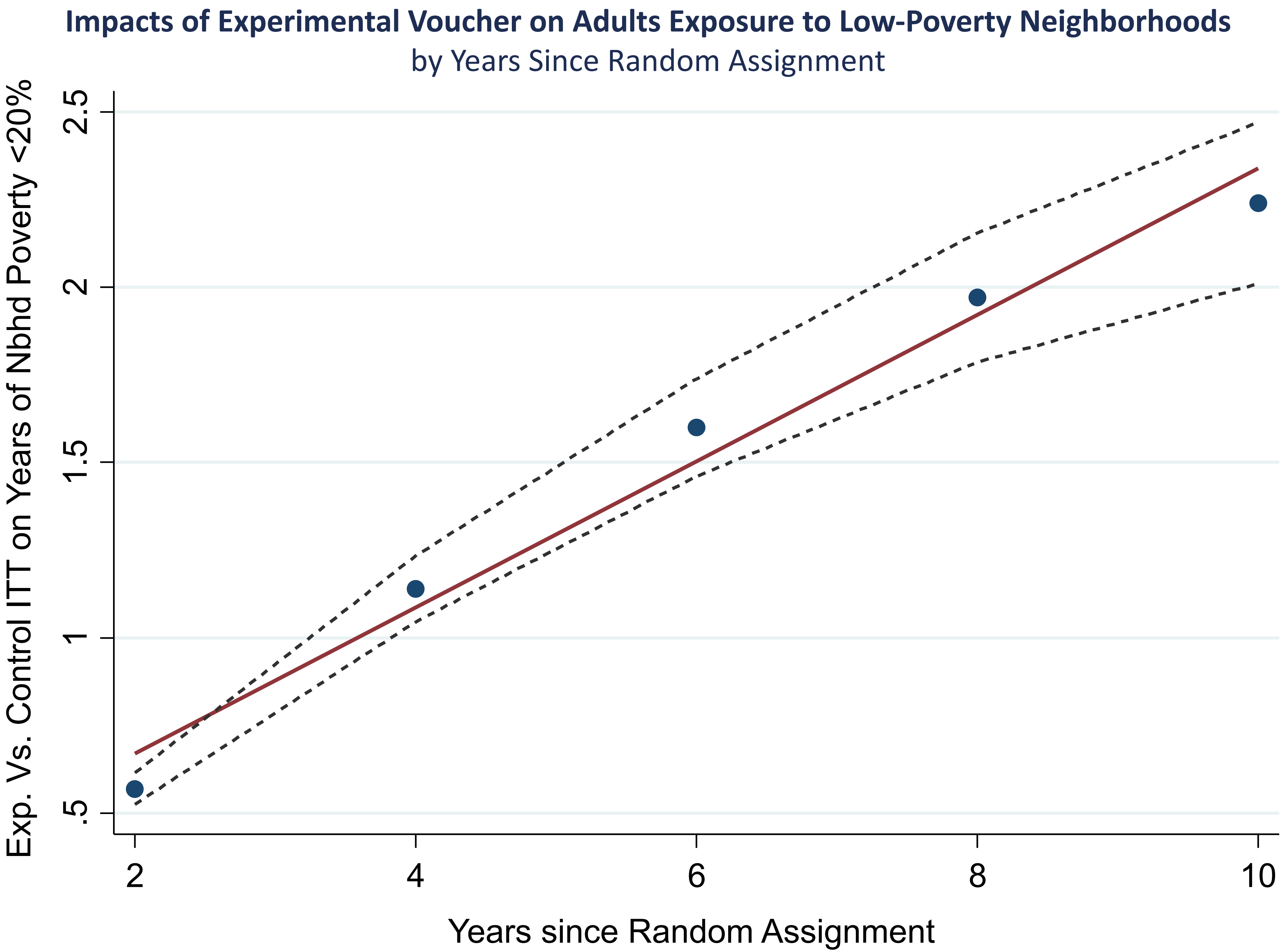
- Conduct permutation test for all five outcomes we analyzed above
- Calculate fraction of placebos in which p value for *all five* outcomes in any one of the 12 subgroups is below true p values for <13 group
  - Yields a p value for null hypothesis that there is no treatment effect on any of the five outcomes adjusted for multiple testing
  - Adjusted $p < 0.01$ based on 1000 replications

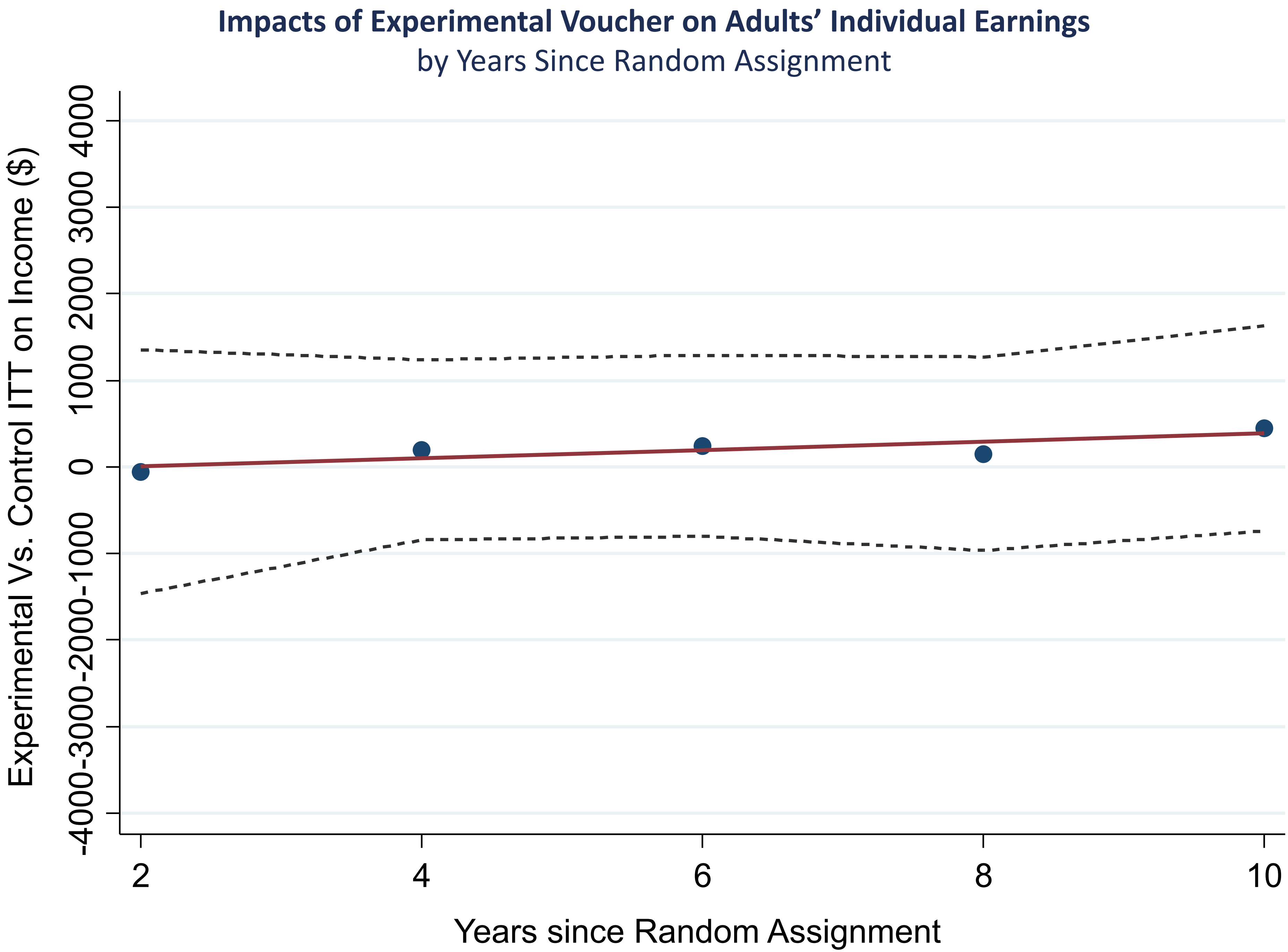
# Treatment Effects on Adults

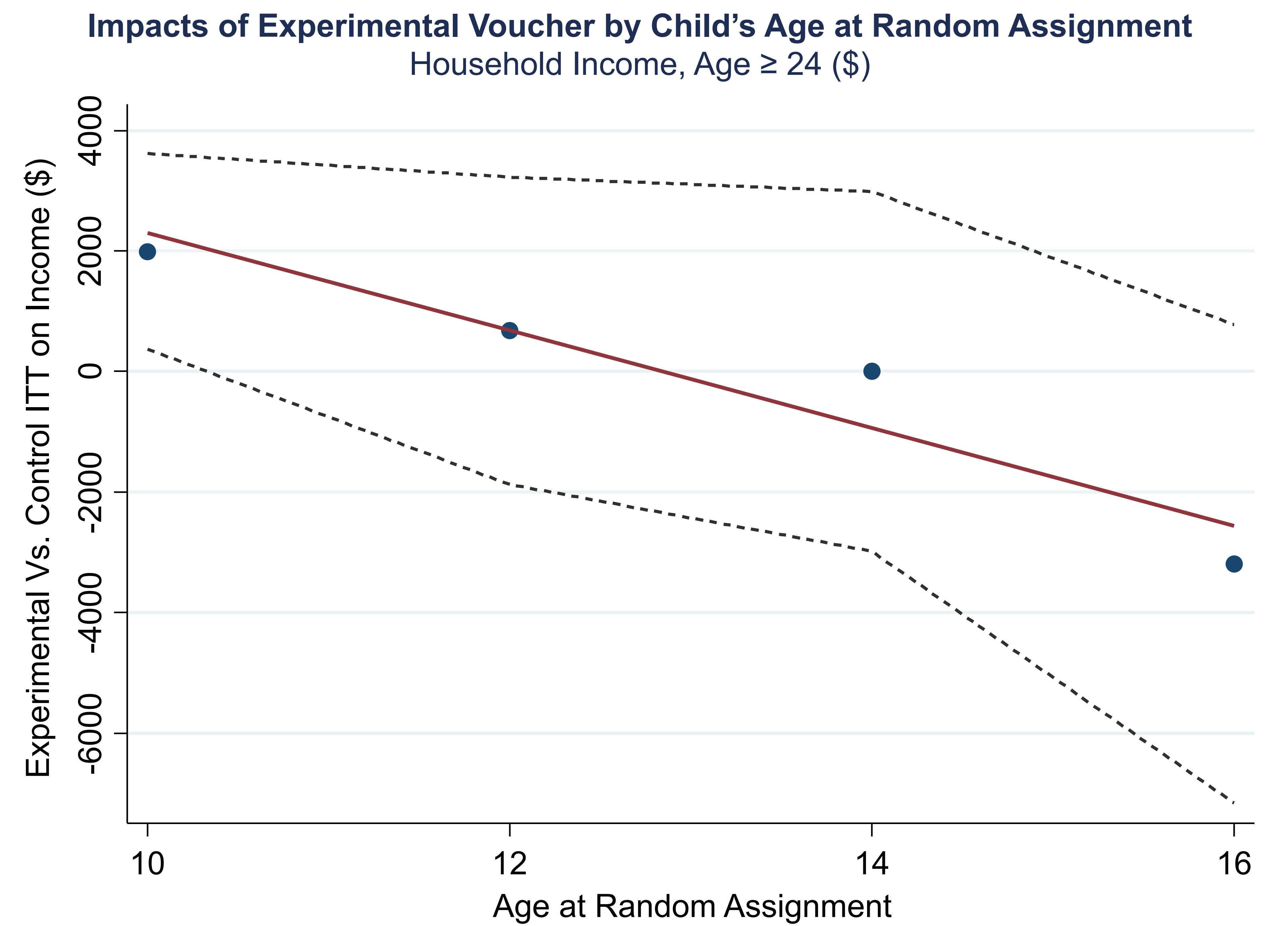
- Previous work finds no effects on adults' economic outcomes
  [Kling et al. 2007, Sanbonmatsu et al. 2011]

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

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


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

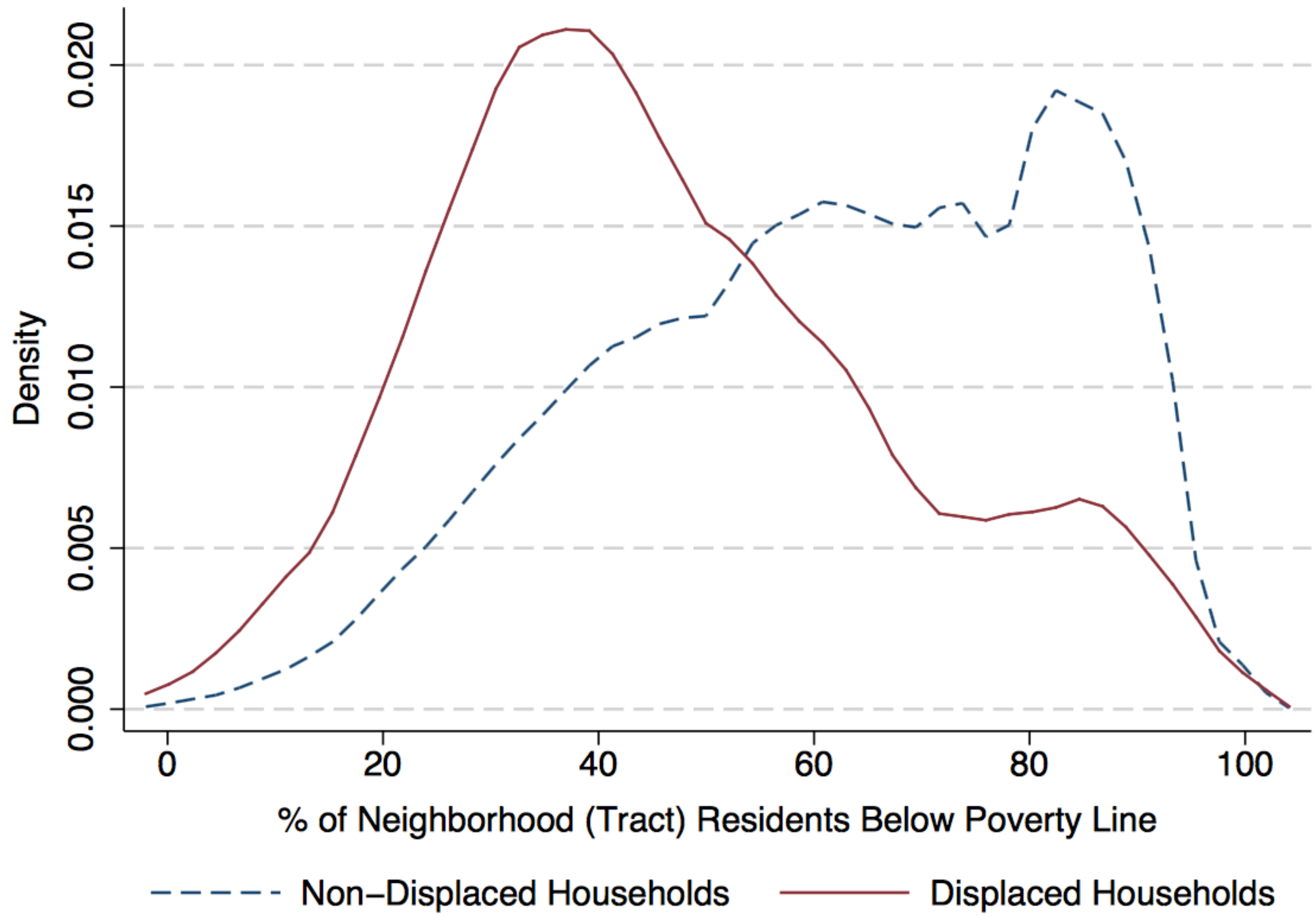

Impacts of Experimental Voucher on Adults' Individual Earnings
by Years Since Random Assignment
Experimental Vs. Control ITT on Income ($)
-4000
-3000
-2000
-1000
0
1000
2000
3000
4000
2
4
6
8
10
Years since Random Assignment


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

# Chyn (2016)

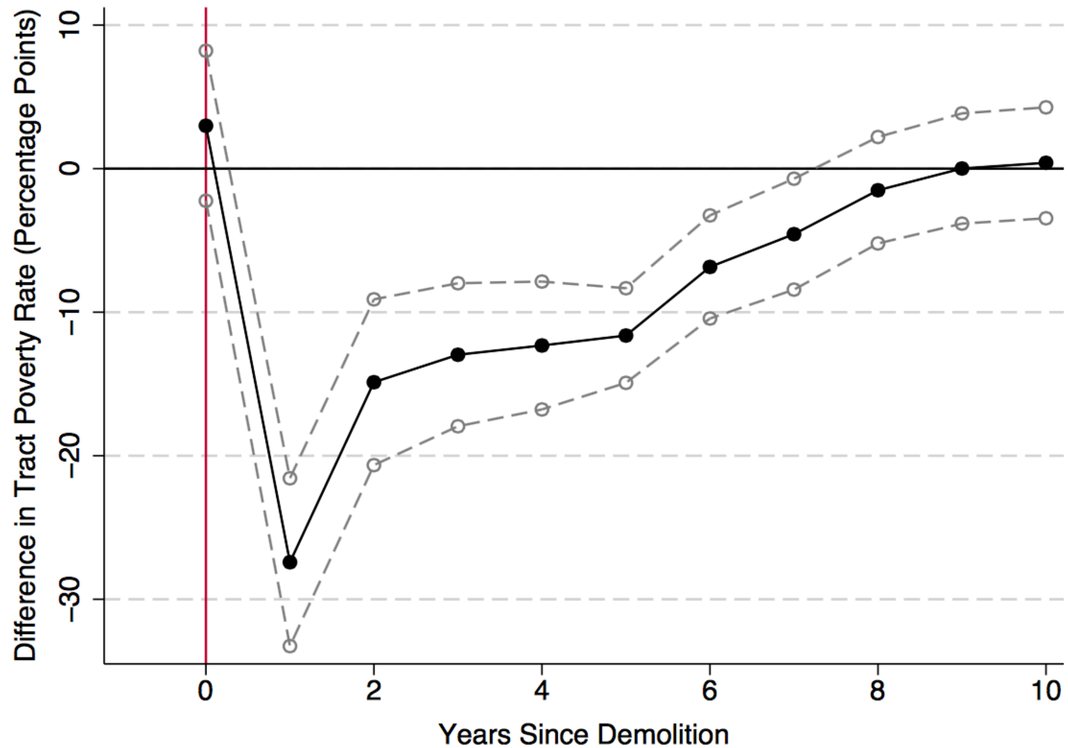
- Chyn (2016): “Moved to Opportunity: The Long-Run Effect of Public Housing Demolition on Labor Market Outcomes of Children”
  - Hope IV demolitions
  - Previous work documents impacts on test scores (Jacob 2004: “Public Housing, Housing Vouchers, and Student Achievement: Evidence from Public Housing Demolitions in Chicago”, The American Economic Review)
- Link to data on earnings outcomes using administrative records
  - Compare to Section 8 outcomes

Figure 1: Density of Neighborhood Poverty for Displaced (Treated) and Non-displaced (Control) Households




Notes: This figure displays the density of the Census tract-level poverty rate for households ($N = 2,767$) with at least one child (age 7 to 18 at baseline) affected by demolition. Poverty rates for each household are duration-weighted averages over all locations that a household lived since being displaced (treated) by housing demolition. Household location is tracked to 2009. The duration-weighted poverty rate for households that were displaced by demolition is shown in the solid red line, while households from non-demolished buildings are shown in the dashed blue line.

Figure 2: Difference in Neighborhood Poverty For Displaced and Non-displaced Households by Post-Demolition Year



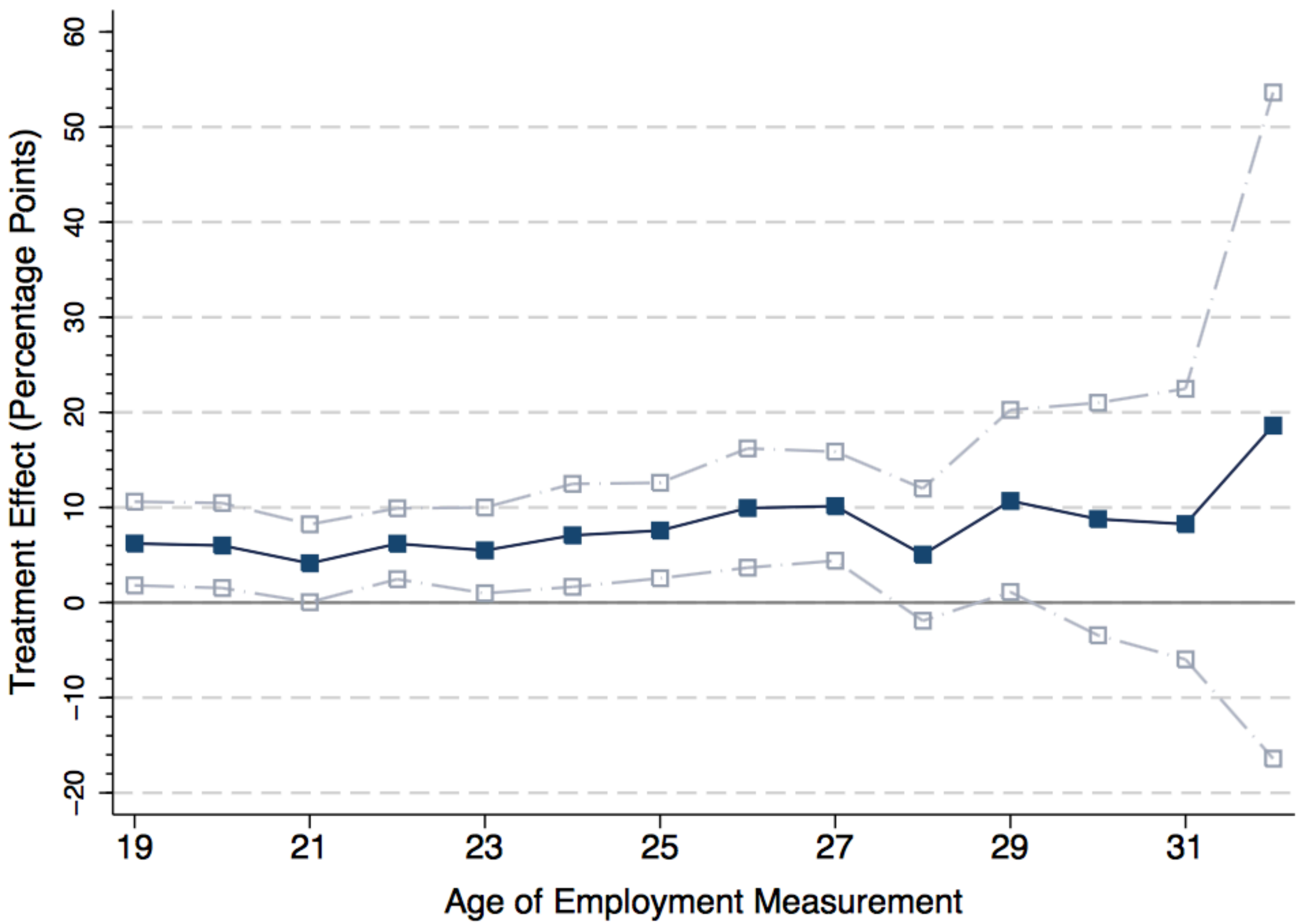

Notes: This figure illustrates the change over time in the difference in neighborhood poverty rate between displaced (treated) and non-displaced (control) households with children (age 7 to 18 at baseline). Specifically, I plot (in solid black) the set of coefficients $\pi_y$ for $y \in \{0, \cdots, 10\}$ from the following specification:

$$pbpov_{htp} = \sum_{y=0}^{y=10} \pi_y \; treat_h \; \mathbf{1}(t - t^* = y) + \sum_{y=0}^{y=10} \delta_y \mathbf{1}(t - t^* = y) + \psi_p + \epsilon_{ht}$$

where $h$ indexes a household; $t$ represents years; and $p$ indexes projects. The dependent variable is the percentage of residents living below the poverty line in a Census tract and $\psi_p$ is a set of project fixed effects. The variable $t^*$ represents the year of demolition for a particular household. Recall that public housing demolitions occur from 1995-1998 in my sample. The variable $treat_h$ is an indicator for treatment (displaced) status. The data used with this specification is a panel for a particular household where the first observation is the poverty rate based on the household's address at the time of demolition ($t^*$). Hence, the set of coefficients $\pi_y$ represent the difference in poverty rate between displaced (treated) and non-displaced (control) households in a particular post demolition period ($y$). There are 2,767 households in the sample. The dashed gray lines in the figure also outline the 95-percent confidence interval for the year-specific point estimates.

Figure 3: Labor-Market Treatment Effects for All Children by Age of Measurement

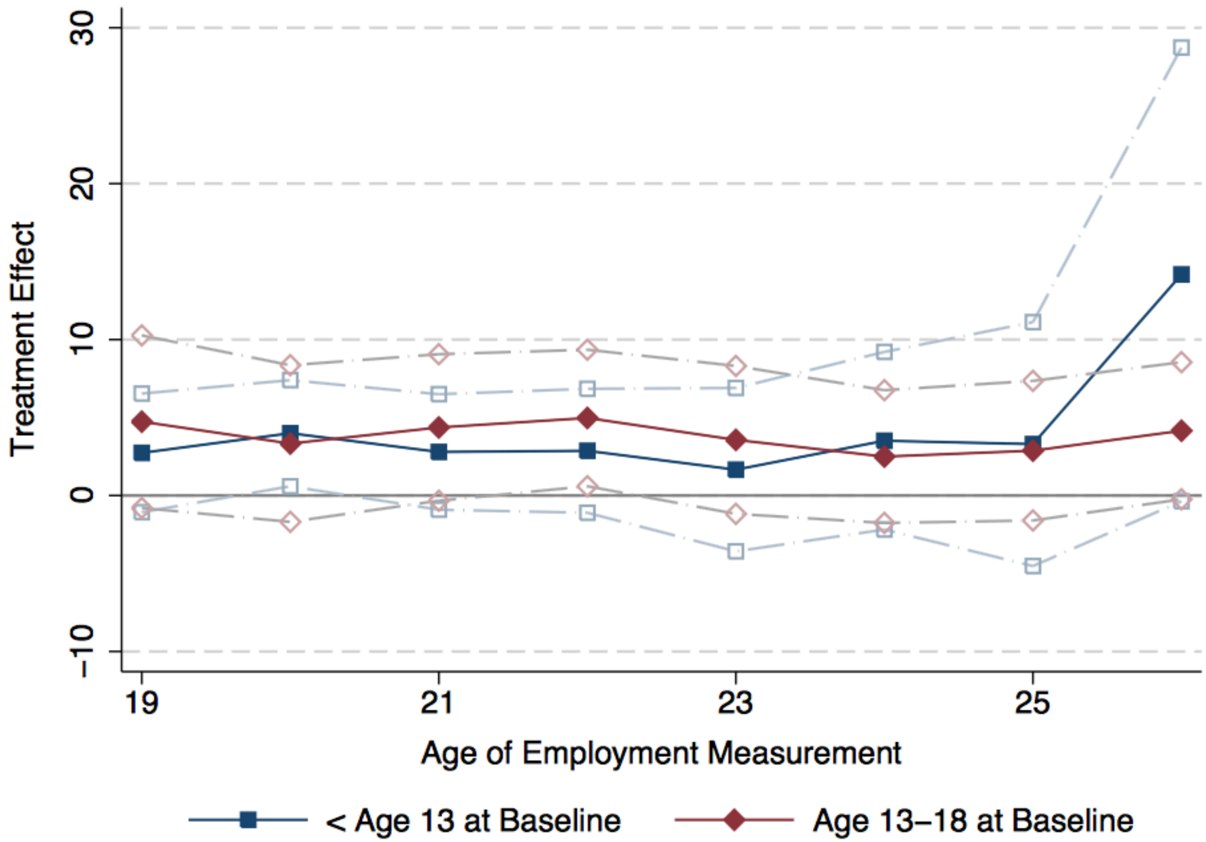
(a) Dependent Variable: Employed (=1)



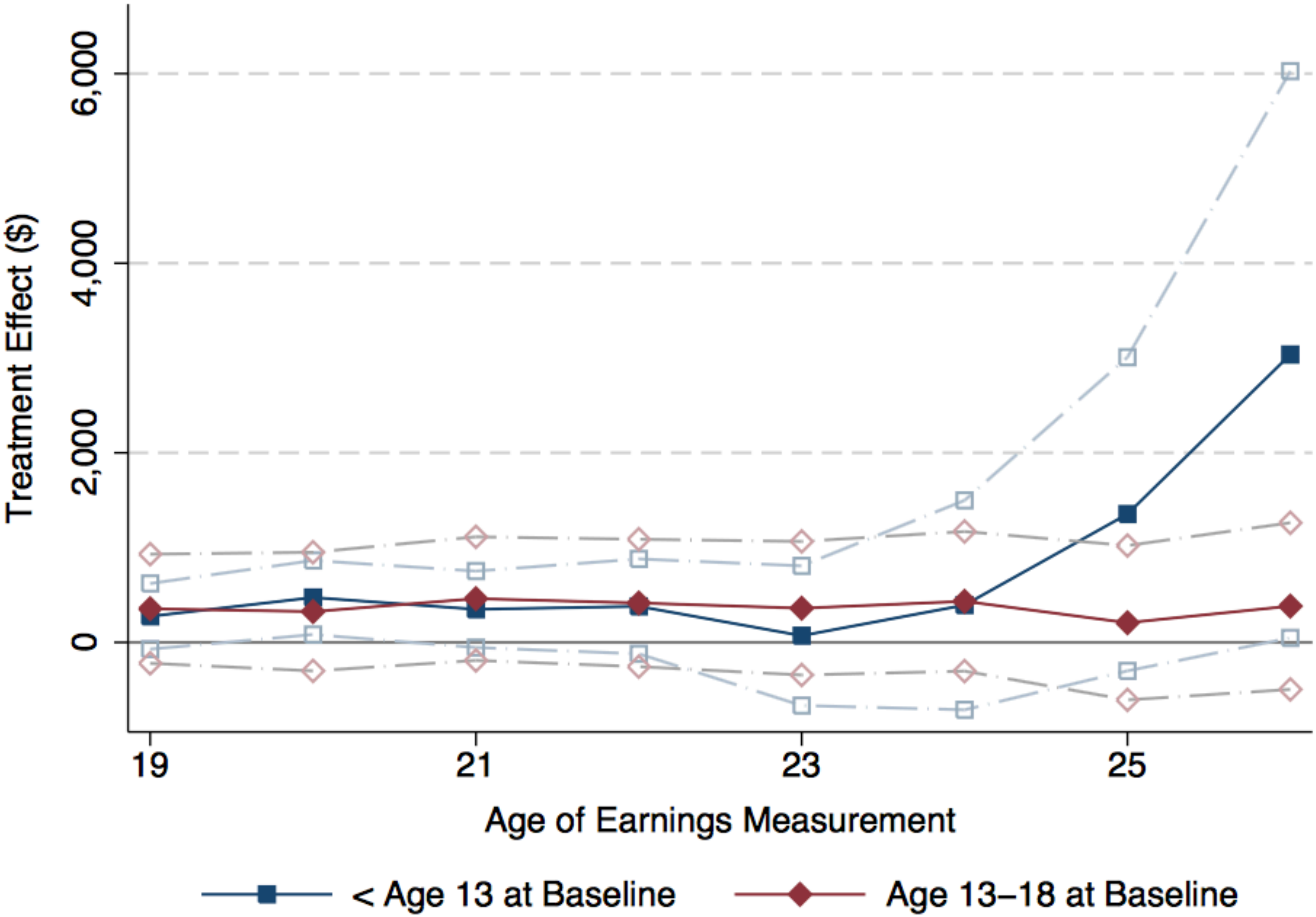
(b) Dependent Variable: Annual Earnings ($)

Figure 4: Younger vs Older Children: Labor-Market Treatment Effects by Age of Measurement

(a) Dependent Variable: Employed (=1)



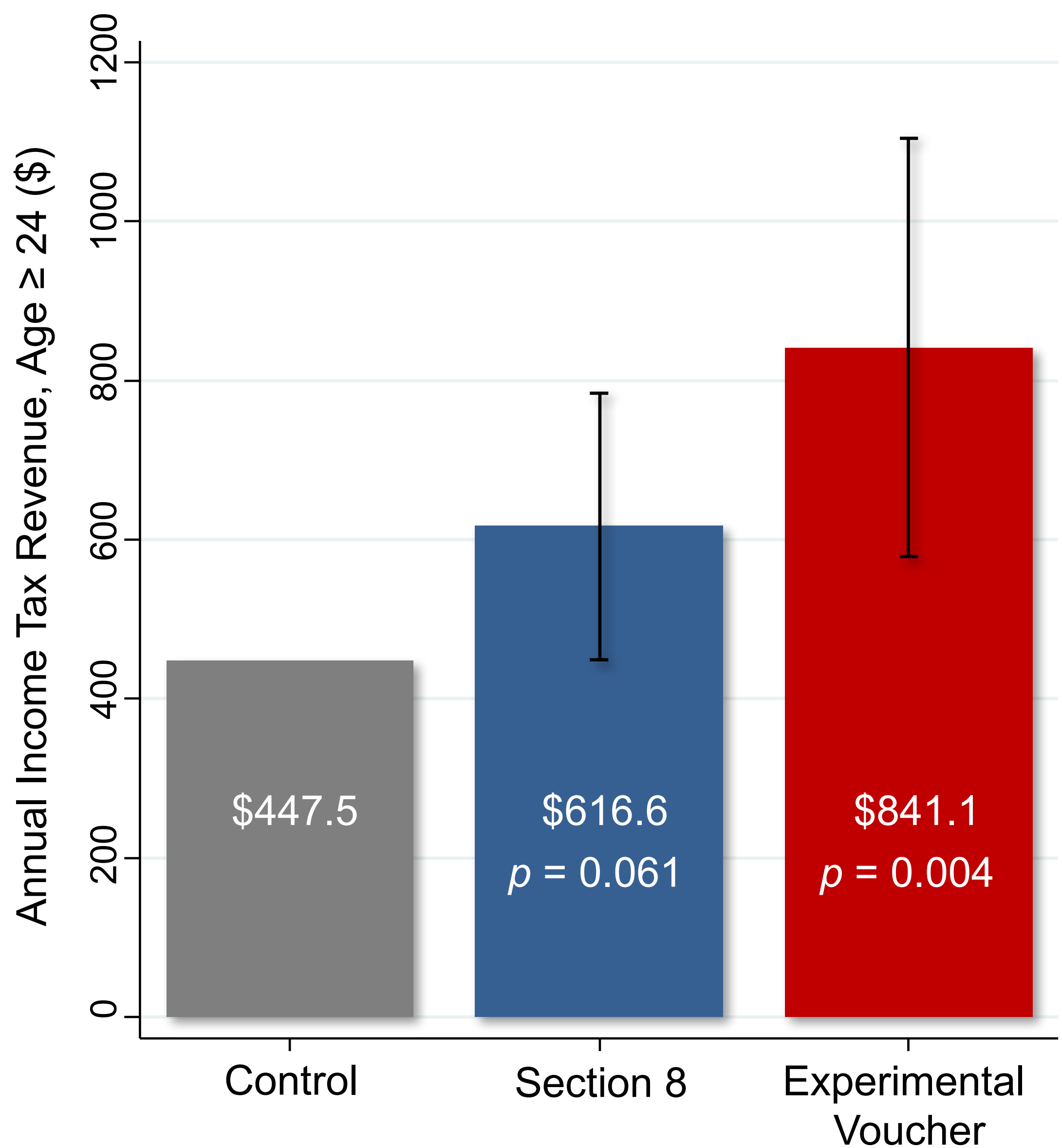
(b) Dependent Variable: Annual Earnings ($)



# Key Lessons

- Place Matters (Childhood environment matters)
  - Effects proportional to exposure time
  - Every year matters
- Open questions
  - Change where people are vs. change places?
  - “Choice” vs. “Place”-based
- Cost-effectiveness
  - More cost-effective relative to other redistributive programs?

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



# Appendix: Time Trends in Mobility

- How has mobility changed over time?

# The Fading American Dream
## Trends in Absolute Income Mobility Since 1940

Raj Chetty, Stanford Economics
David Grusky, Stanford Sociology
Maximilian Hell, Stanford Sociology
Nathan Hendren, Harvard Economics
Robert Manduca, Harvard Sociology
Jimmy Narang, UC-Berkeley Economics

February 2017

# This Paper

- We develop a method of estimating absolute mobility for the 1940-84 birth cohorts that can be implemented using existing data

- We estimate mobility by decomposing joint distribution of income into two components:

  1. Marginal income distributions for parents and children, estimated using CPS and Census cross-sections

  2. Joint distribution of parent and child ranks (copula)

     – For recent cohorts, obtain copula from tax records, building on prior work showing stable *relative* mobility [Chetty et al. 2014]

     – For early cohorts, derive bounds to show that estimates of absolute mobility are *insensitive* to copula

# Methodology

- Baseline income measure: pre-tax family income at age 30, deflated using CPI-U-RS

- Estimate absolute mobility by combining three sets of inputs for each birth cohort *c*:

  1. Children's marginal income distributions $Q_c^k(r^k)$
  2. Parents' marginal income distributions $Q_c^p(r^p)$
  3. Copula: joint distribution of parent and child ranks $C_c(r^k, r^p)$

- Calculate absolute mobility for birth cohort *c* as:

$$A_c = \int 1\{Q_c^k(r^k) \geq Q_c^p(r^p)\} C_c(r^k, r^p) dr^k dr^p$$

# Children's Income Distributions

- Estimate income distributions at age 30 for children in each birth cohort from 1940-84 using CPS data from 1970-2014
  - Sample: all non-institutionalized individuals born in the U.S.
  - Income defined as sum of spouses' personal pre-tax incomes

# Parents' Income Distributions

- Constructing parents' income distributions by child's birth cohort is more complicated because of lack of panel data
  - Overcome this problem by pooling data from multiple Census cross-sections

# Parents' Income Distributions

- Example: income distribution of parents of children in 1970 birth cohort

- Combine data from three Censuses (1% IPUMS):

  1. In 1970 Census, select parents aged 25-35 with children born in that year

  2. In 1980 Census, select parents aged 25-35 with 10 year old children (parents who had children before age 25 in 1970)

  3. In 1960 Census, select all individuals aged 25-35

     - Give this group weight equal to the fraction of individuals who have 1 year old children *after* age 35 in 1970 Census

     - Assumption: income distribution of those who have kids after age 35 is representative of income distribution of general population

# Copula: Joint Distribution of Ranks

- For children born in 1980s, estimate copula using population tax data
  [Chetty, Hendren, Kline, Saez, Turner 2015]

- Income definition in tax records: pre-tax family income (AGI+SSDI)
  - For non-filers, use W-2 wage earnings + SSDI + UI income
  - If no 1040 and no W-2, code income as 0

- Incomes of children born in 1980s measured at age ~30 in 2012

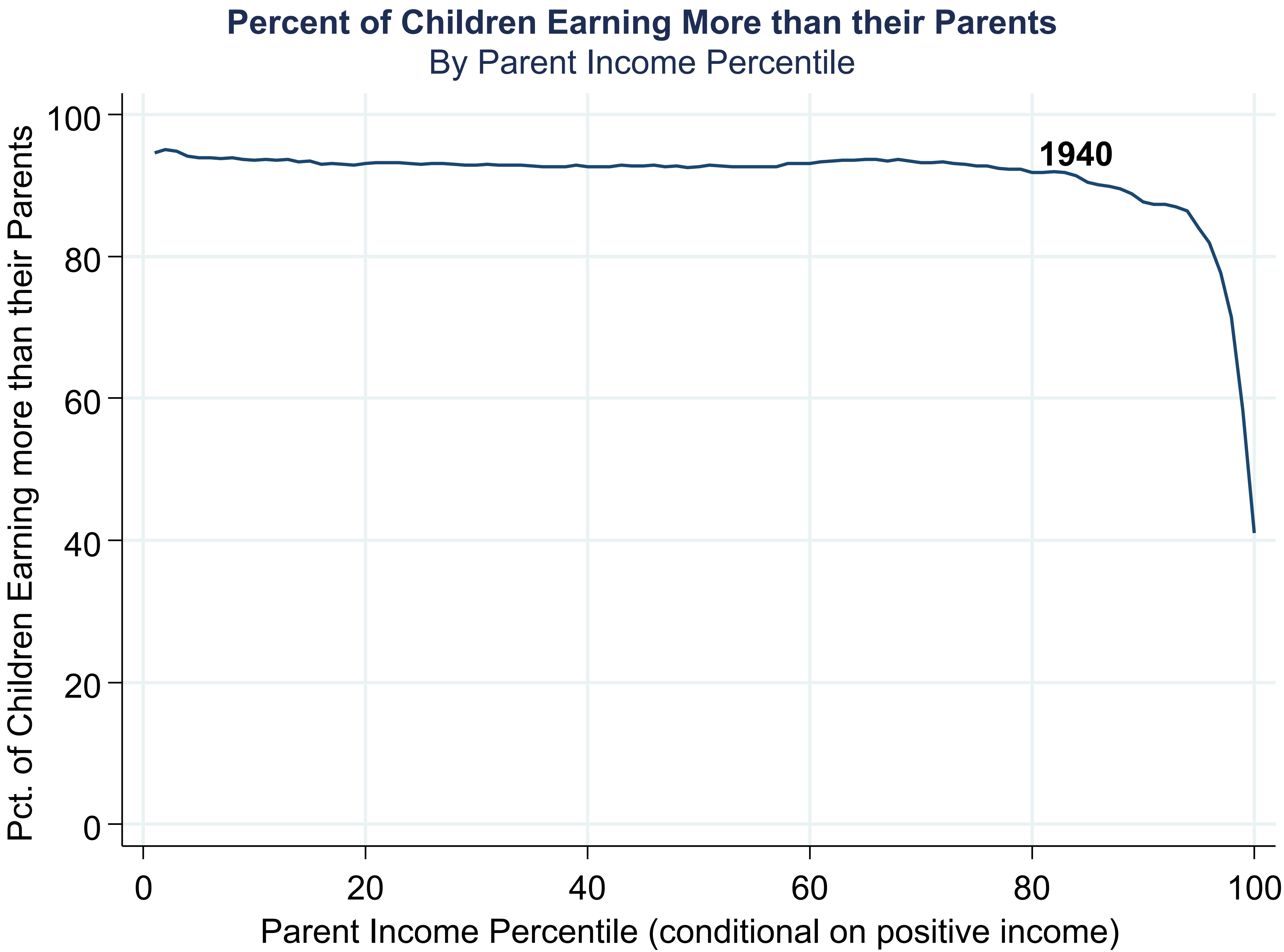
- Incomes of parents measured in 1996-2000 between ages 30-60
  - Copula (distribution of ranks) is stable after age 30
    [Chetty et al. 2014]

# Copula: Joint Distribution of Ranks

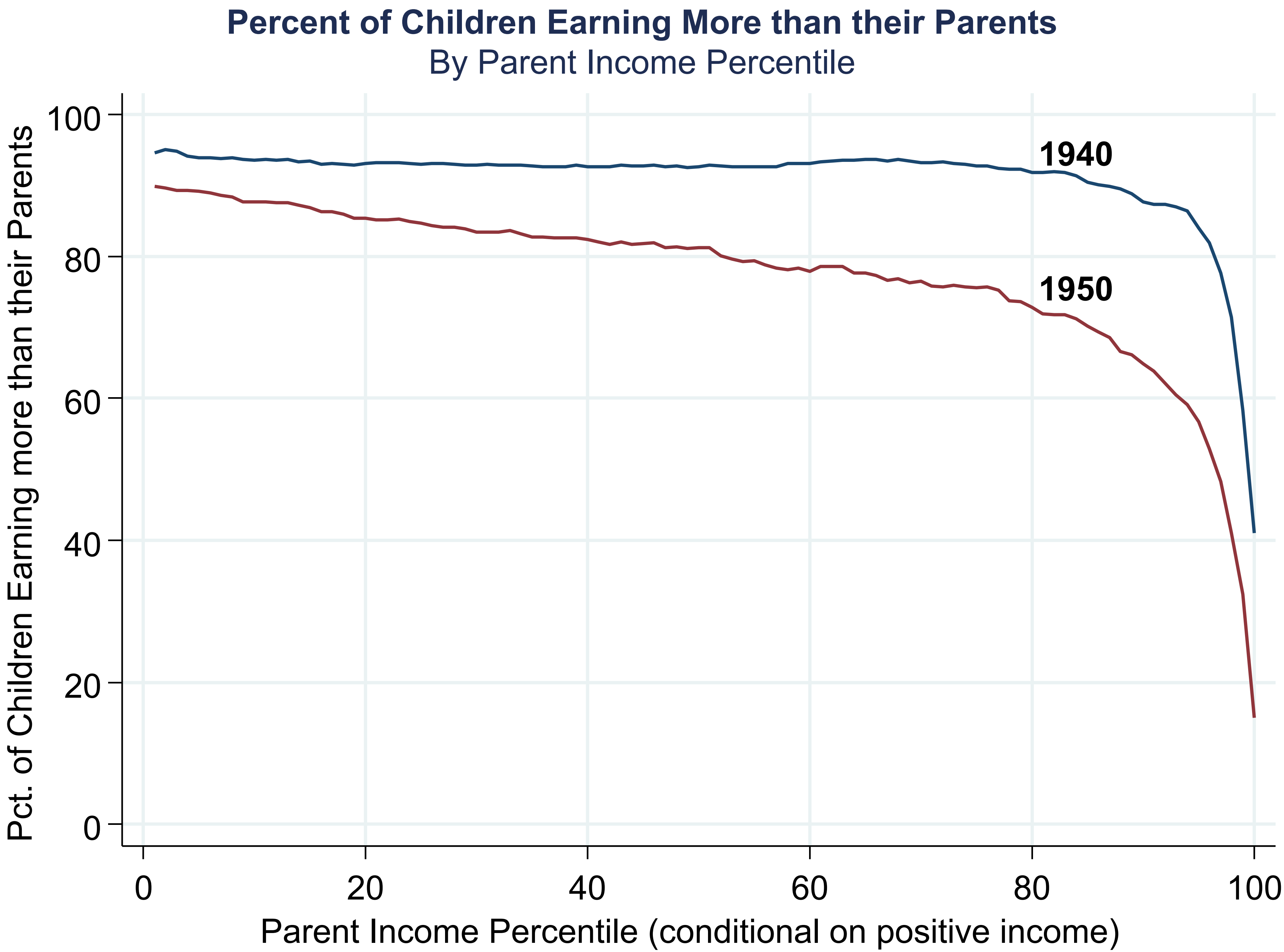
- Estimate copula non-parametrically as a 100 x 100 percentile transition matrix for 1980-82 birth cohorts
  - Rank children based on their incomes relative to other children in same birth cohort
  - Rank parents of these children based on their incomes relative to other parents
  - Compute joint probabilities of each rank pair

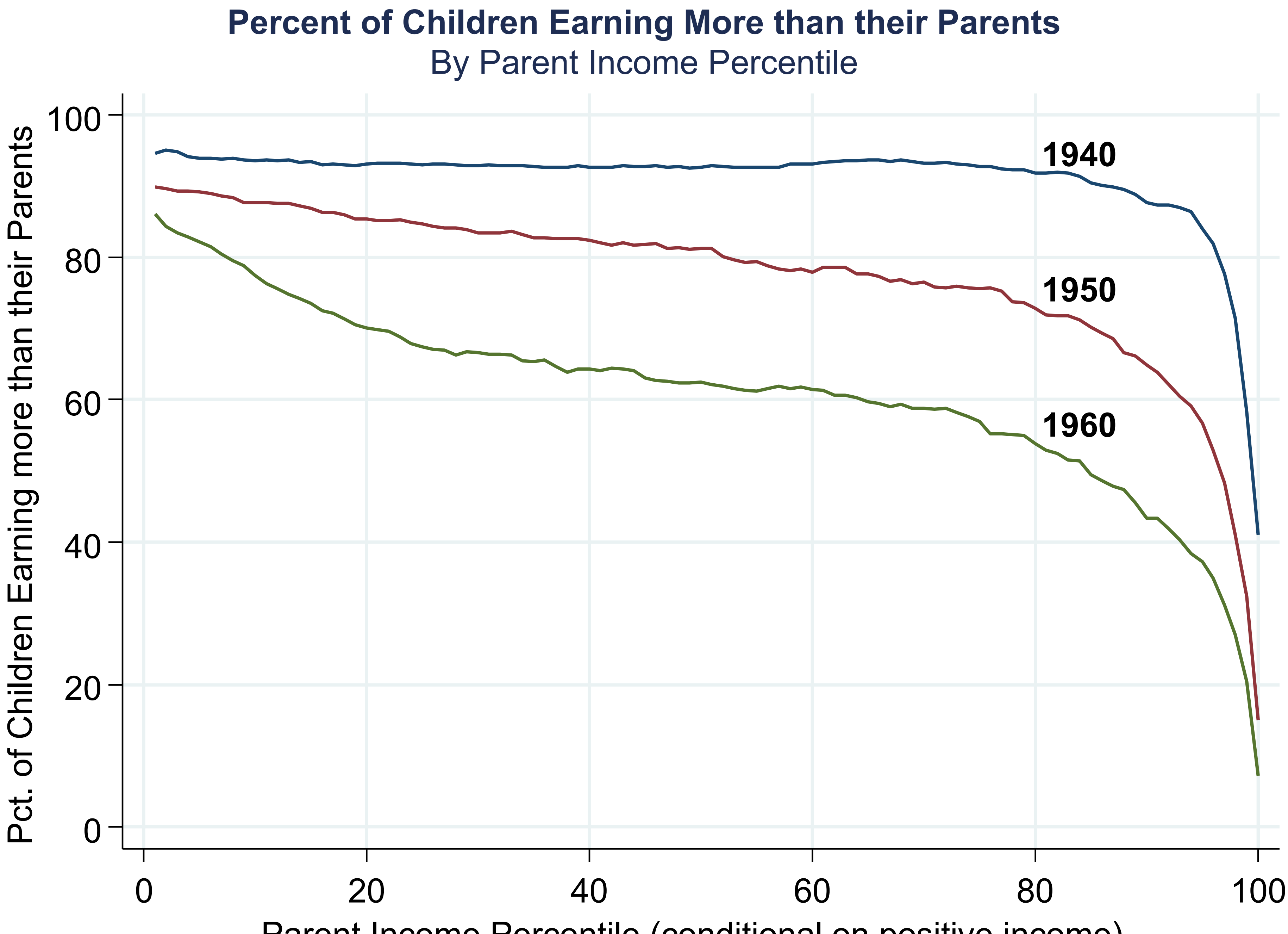
# Copula Stability

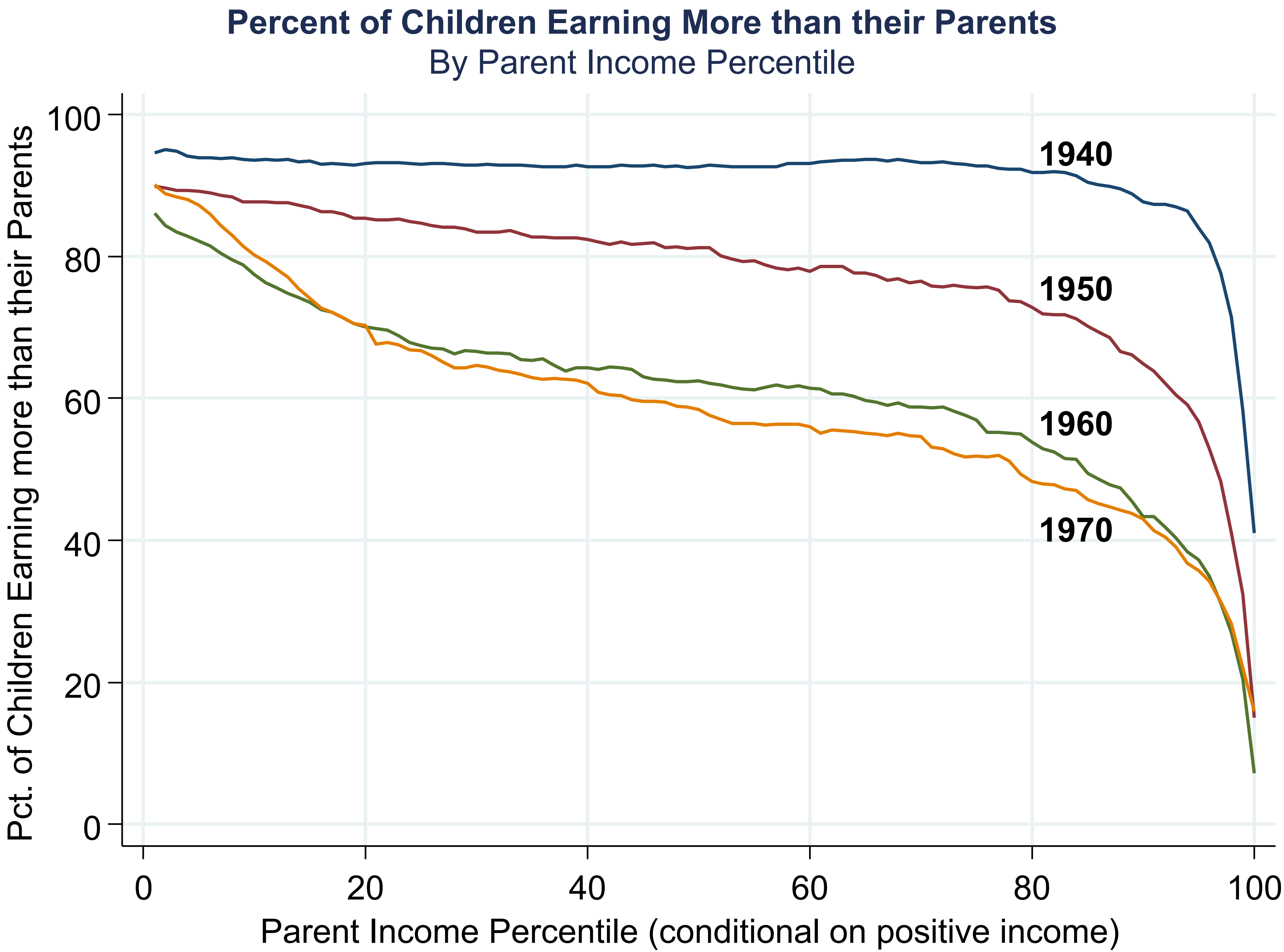
- Chetty et al. (2014) show that copula is very stable back to 1971 birth cohort using Statistics of Income 0.1% sample
    - Constant *relative* mobility (in percentile ranks, not absolute dollars)
- Baseline: assume copula stability for *all* cohorts going back to 1940
    - Then derive bounds for absolute mobility with alternative copulas



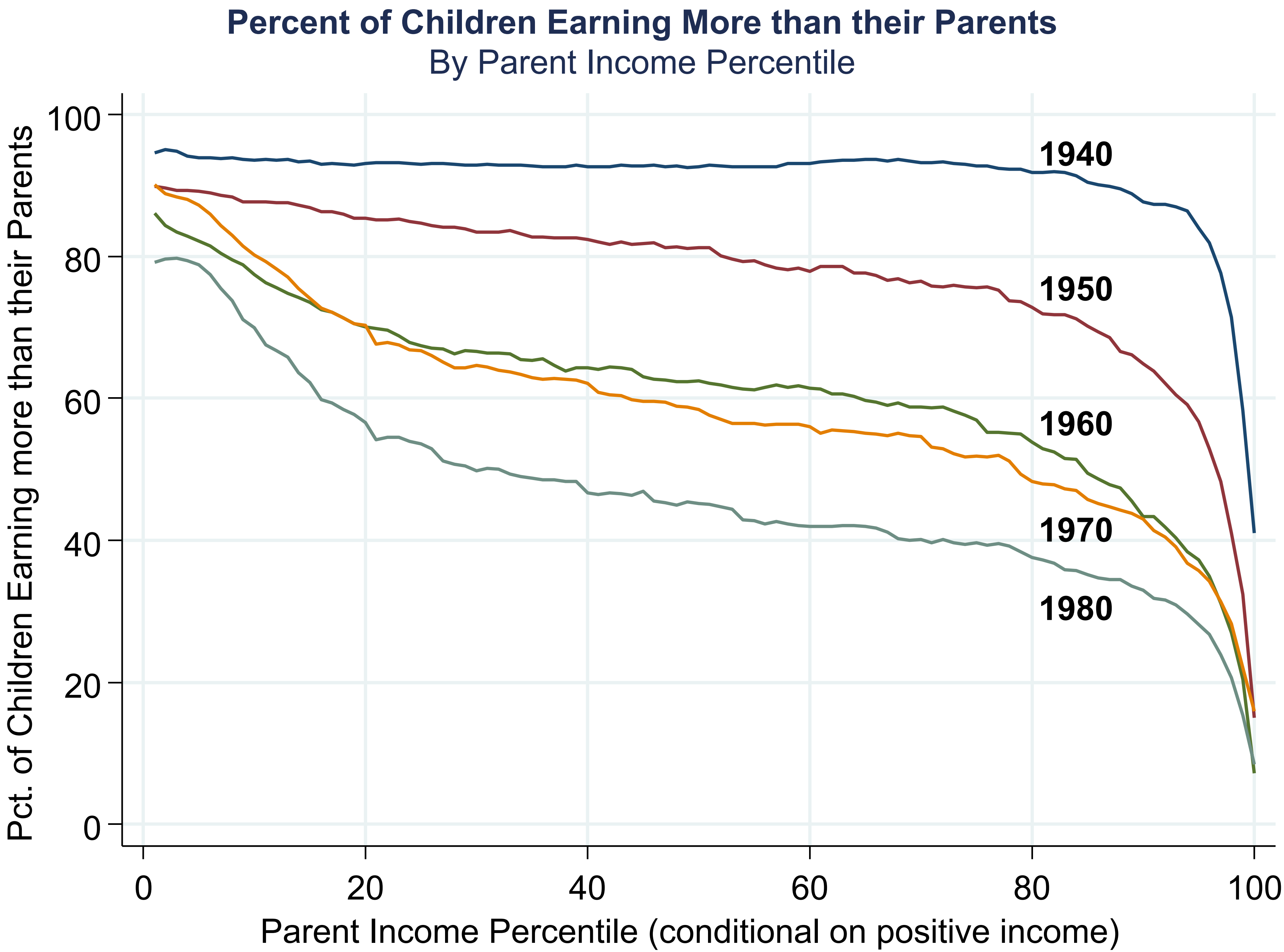
Percent of Children Earning More than their Parents
By Parent Income Percentile
Pct. of Children Earning more than their Parents
Parent Income Percentile (conditional on positive income)
1940
0
20
40
60
80
100

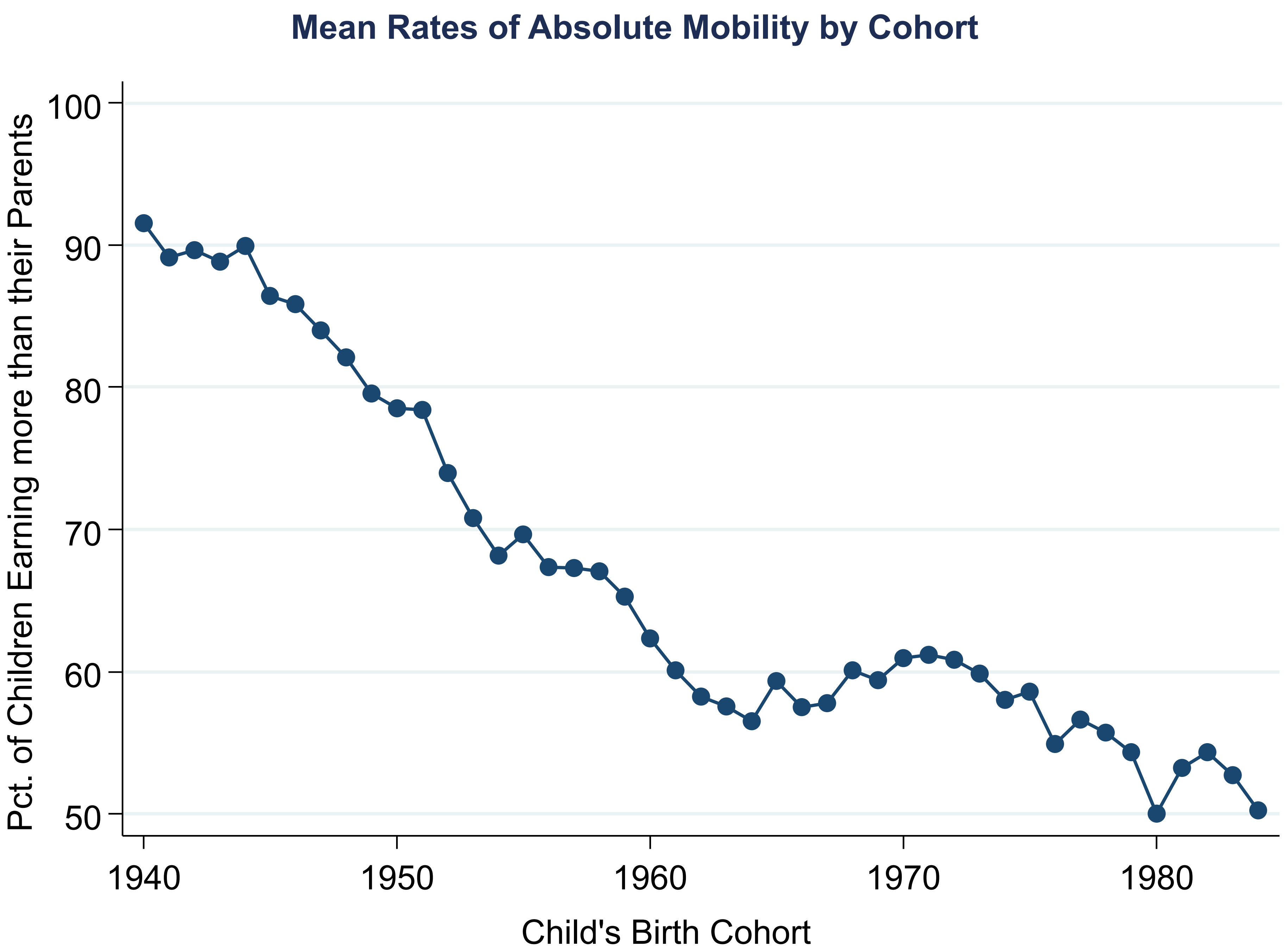

Percent of Children Earning More than their Parents
By Parent Income Percentile
Pct. of Children Earning more than their Parents
Parent Income Percentile (conditional on positive income)
1940
1950
0
20
40
60
80
100
0
20
40
60
80
100


Percent of Children Earning More than their Parents
By Parent Income Percentile
Pct. of Children Earning more than their Parents
Parent Income Percentile (conditional on positive income)
1940
1950
1960
0
20
40
60
80
100



Percent of Children Earning More than their Parents
By Parent Income Percentile
Pct. of Children Earning more than their Parents
100
80
60
40
20
0
1940
1950
1960
1970
0
20
40
60
80
100
Parent Income Percentile (conditional on positive income)


Percent of Children Earning More than their Parents
By Parent Income Percentile
Pct. of Children Earning more than their Parents
Parent Income Percentile (conditional on positive income)
1940
1950
1960
1970
1980
0
20
40
60
80
100



Mean Rates of Absolute Mobility by Cohort
Pct. of Children Earning more than their Parents
100
90
80
70
60
50
1940
1950
1960
1970
1980
Child's Birth Cohort

# Sensitivity to Copula: Bounds on Absolute Mobility

- Baseline estimates rely on assumption that copula remains stable back to 1940 cohort

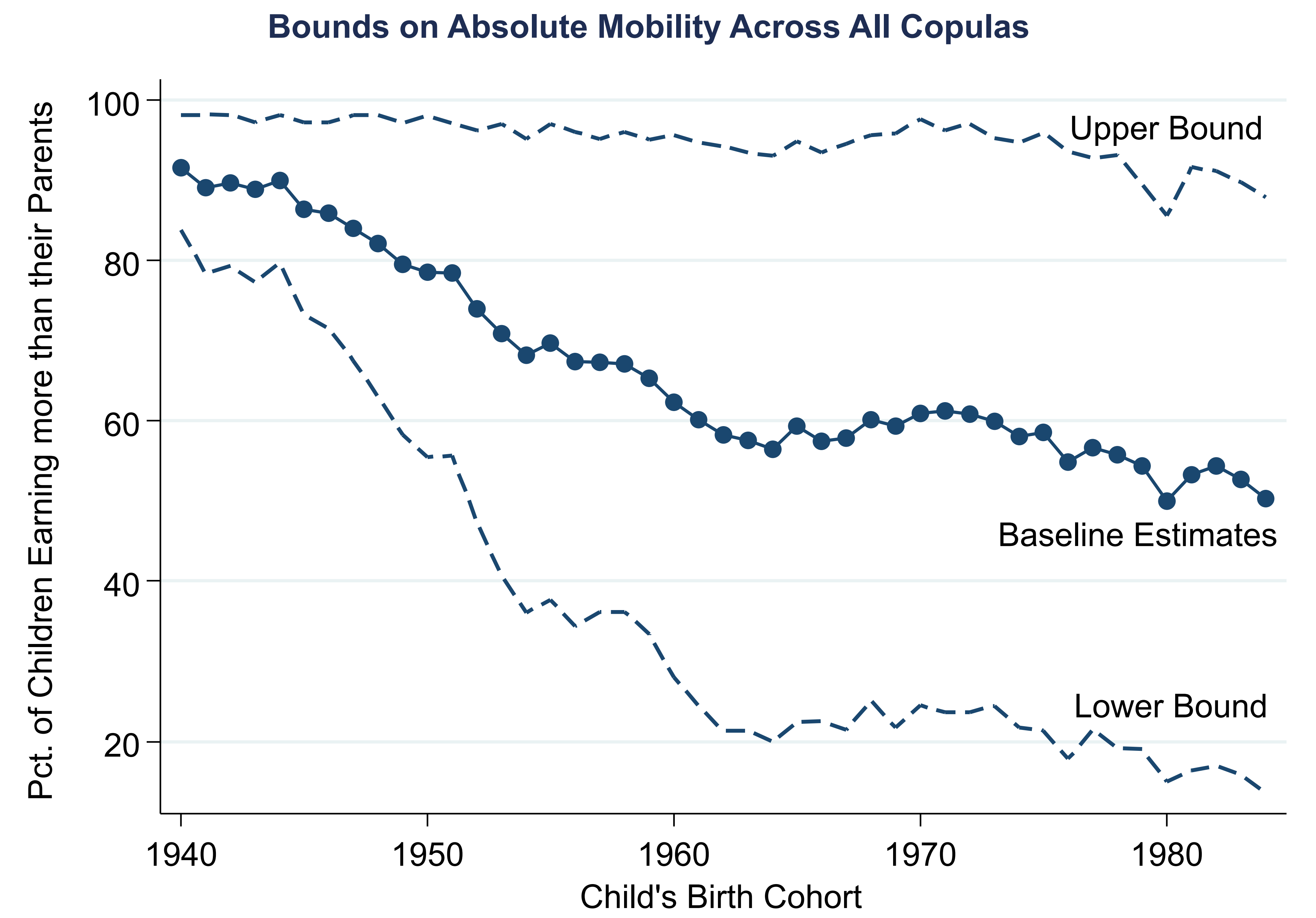
- Now relax this assumption and derive bounds on absolute mobility under alternative copulas by birth cohort

  - Consider all copulas under which children's ranks increase with parent ranks (first-order stochastic dominance)

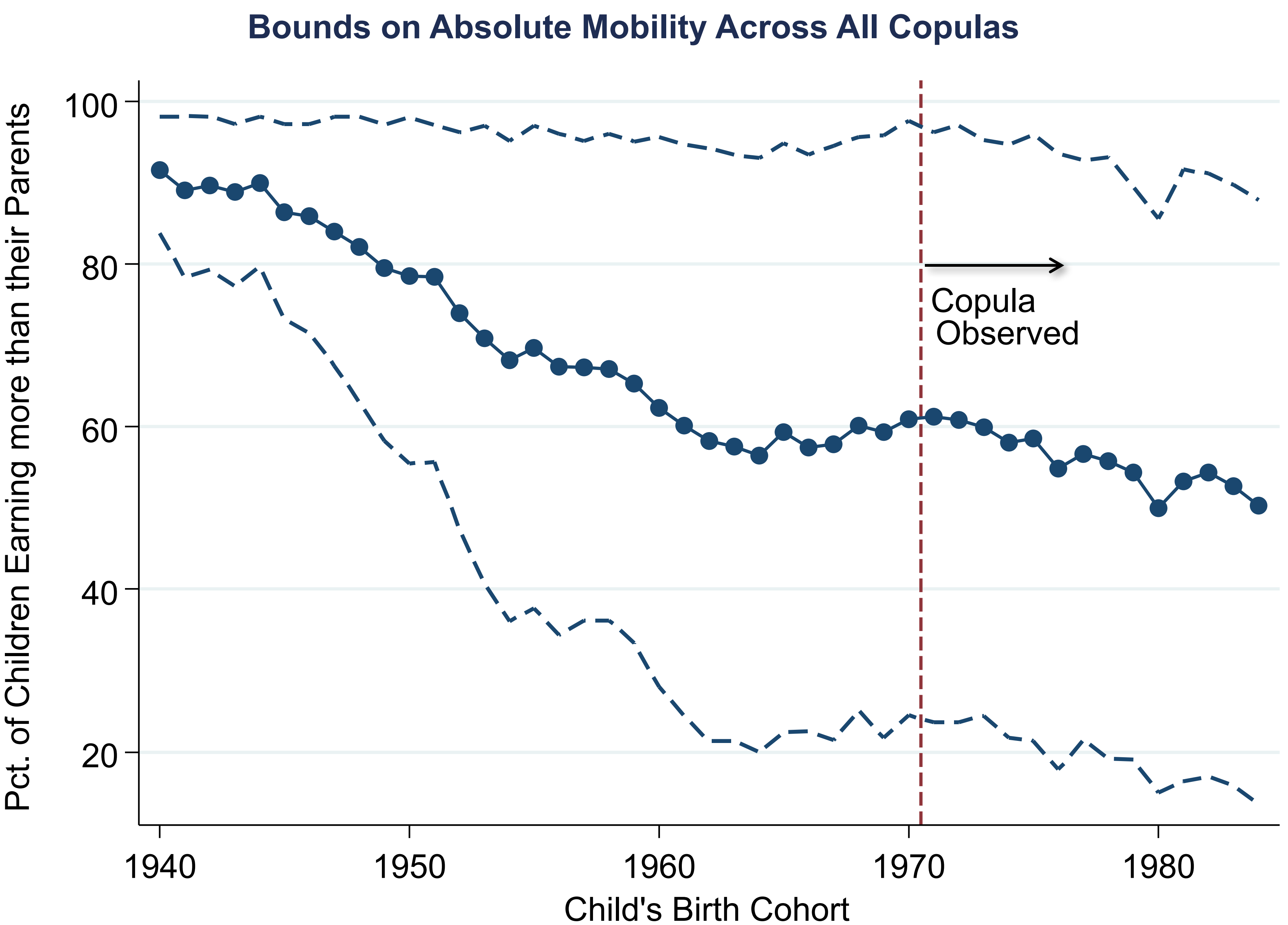
  - Rules out negative intergenerational persistence

- High-dimensional (10,000-variable) maximization problem, but objective function and constraints are all linear

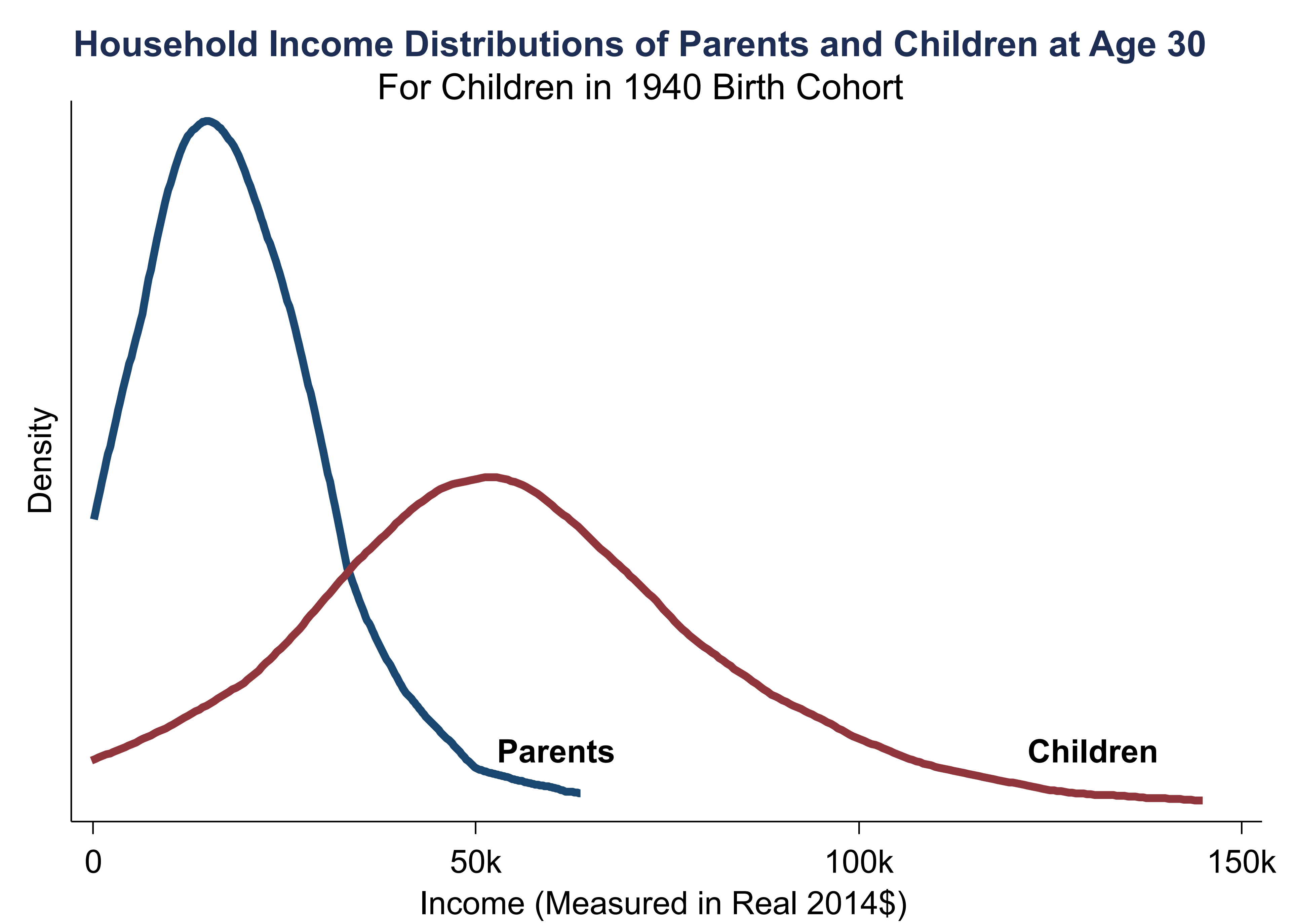
  - Can be solved efficiently using linear programming

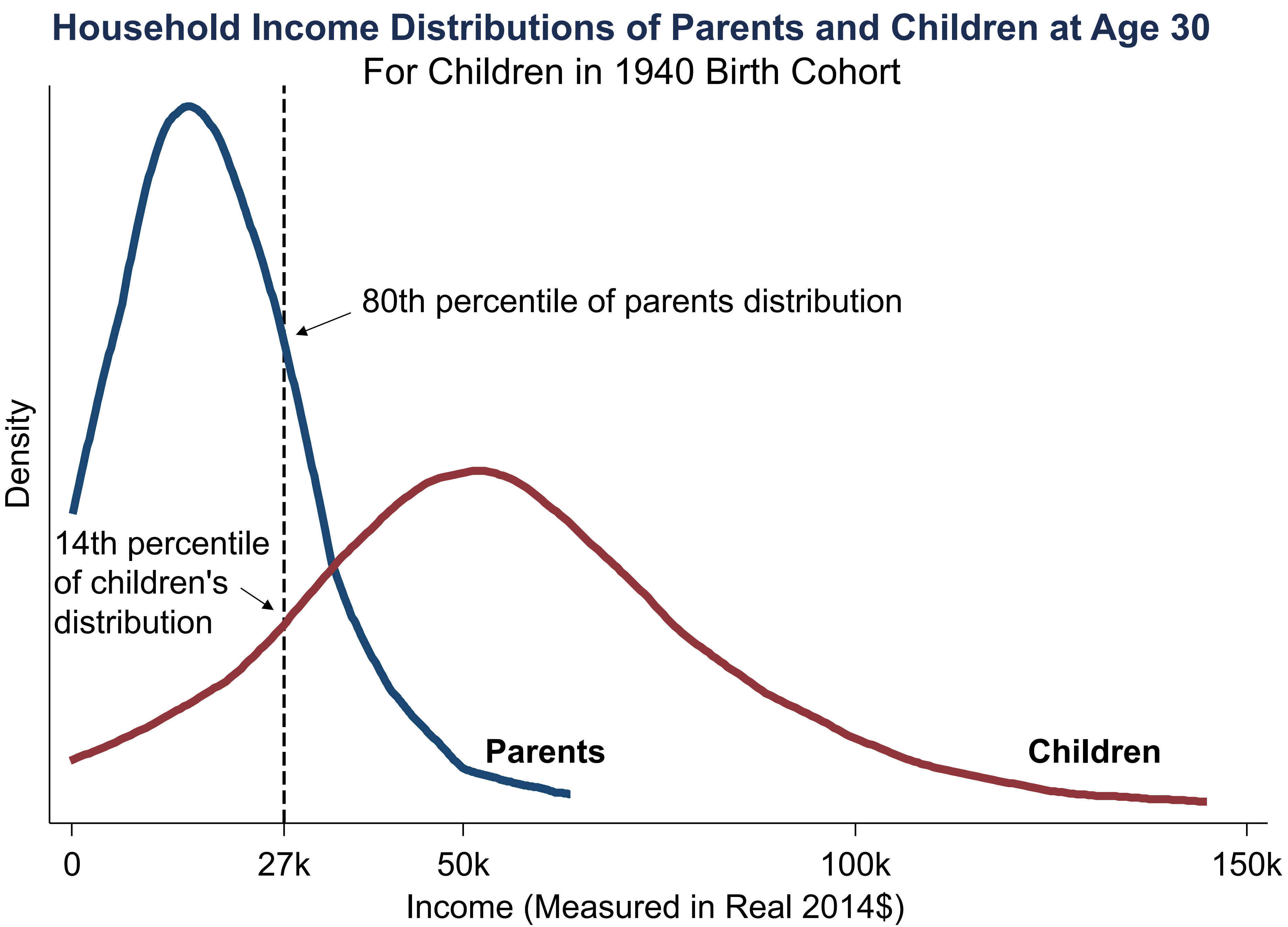


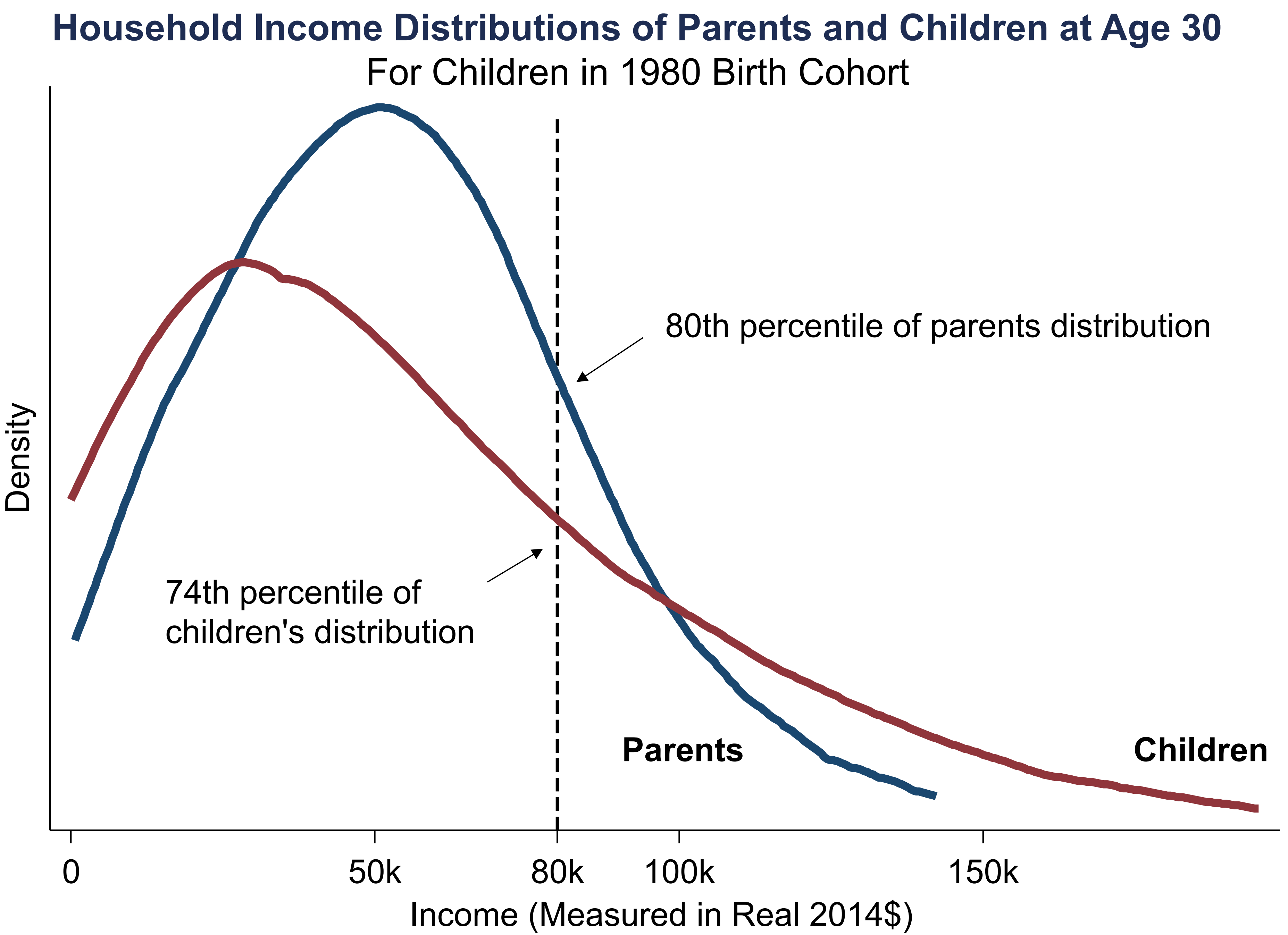
Bounds on Absolute Mobility Across All Copulas
Upper Bound
Baseline Estimates
Lower Bound
Pct. of Children Earning more than their Parents
Child's Birth Cohort
100
80
60
40
20
1940
1950
1960
1970
1980



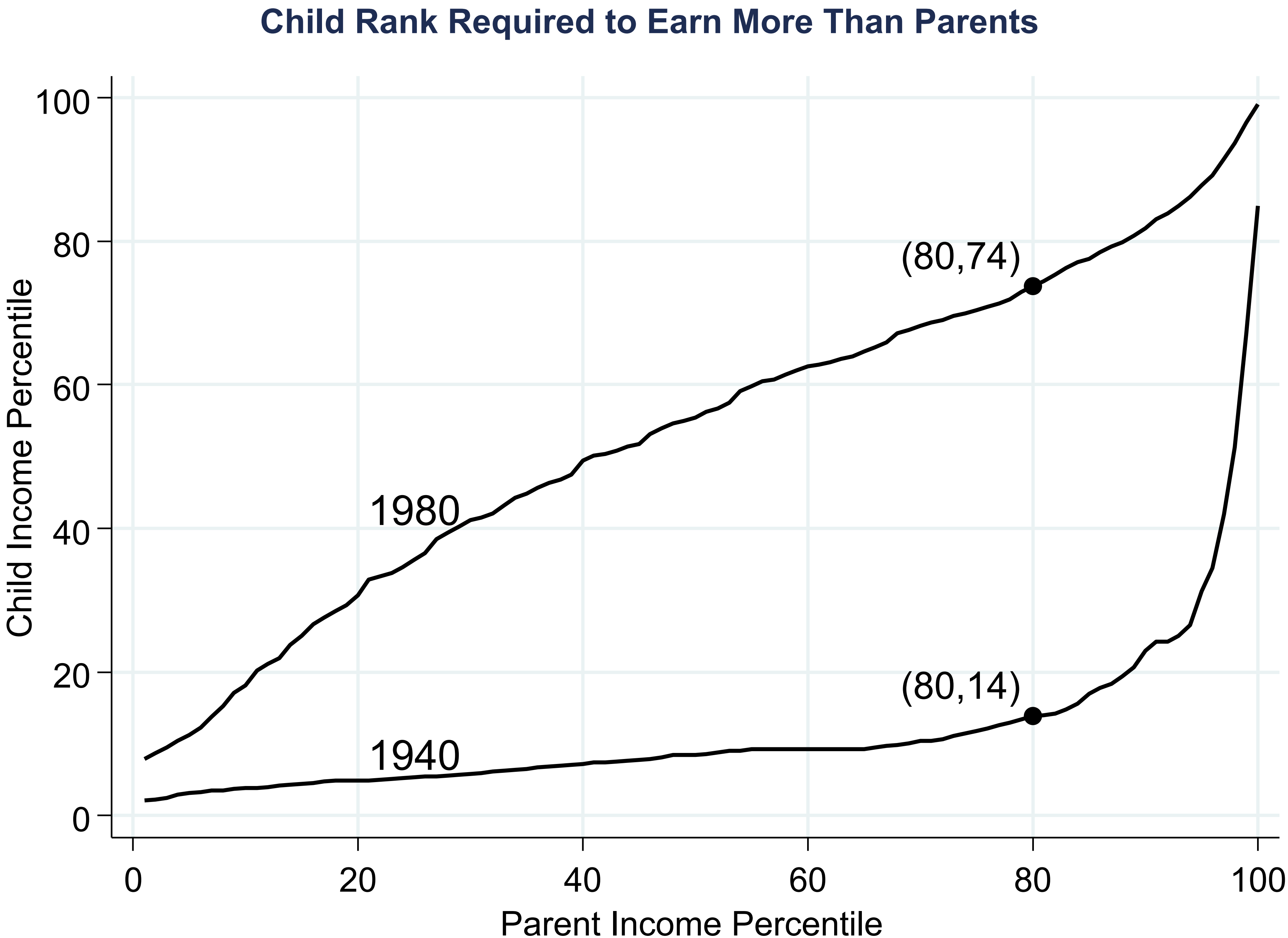
Bounds on Absolute Mobility Across All Copulas
100
80
60
40
20
Pct. of Children Earning more than their Parents
Copula
Observed
1940
1950
1960
1970
1980
Child's Birth Cohort


Household Income Distributions of Parents and Children at Age 30
For Children in 1940 Birth Cohort
Density
Parents
Children
0
50k
100k
150k
Income (Measured in Real 2014$)

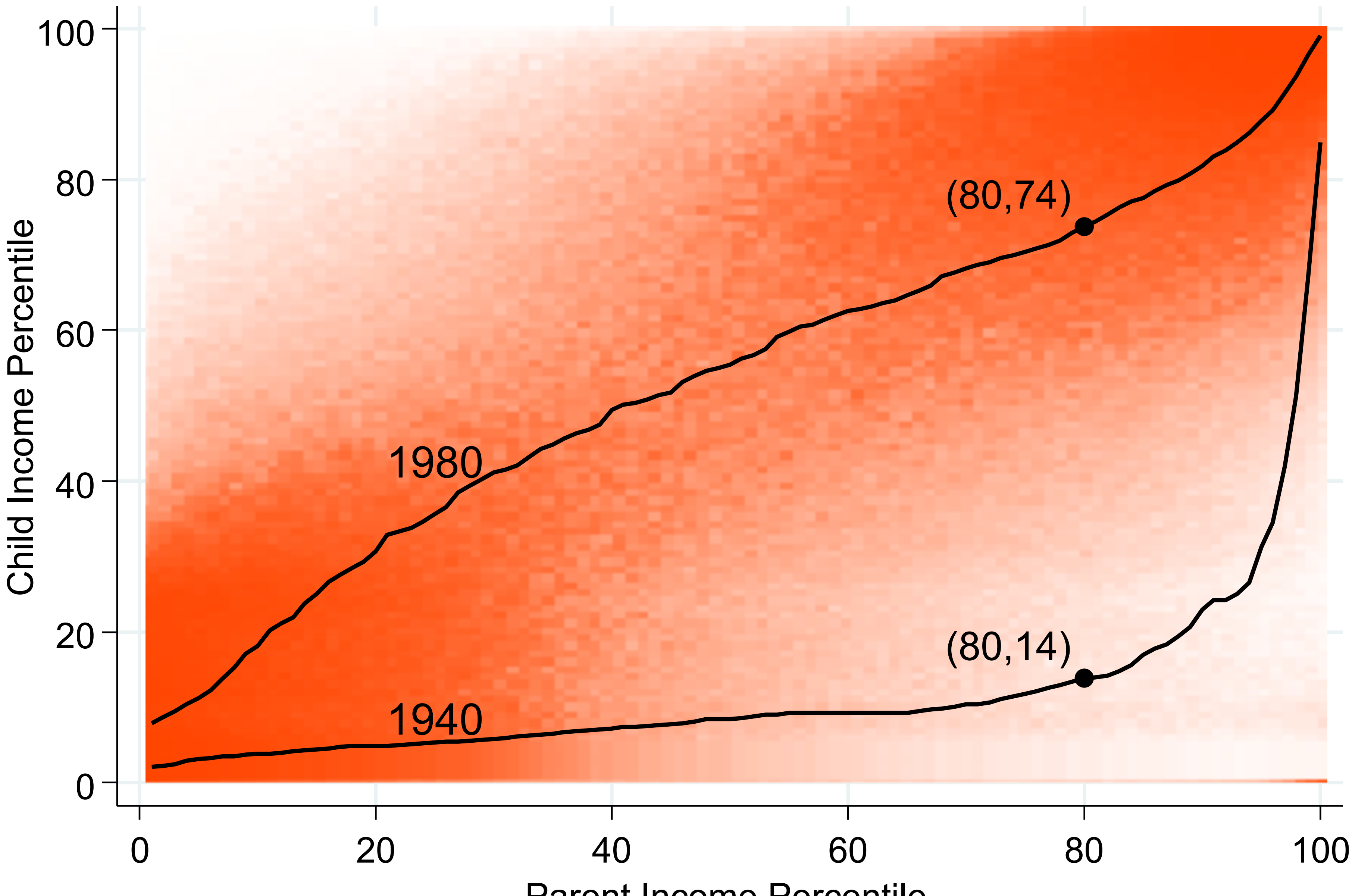

Household Income Distributions of Parents and Children at Age 30
For Children in 1940 Birth Cohort
Density
80th percentile of parents distribution
14th percentile
of children's
distribution
Parents
Children
0
27k
50k
100k
150k
Income (Measured in Real 2014$)



Household Income Distributions of Parents and Children at Age 30
For Children in 1980 Birth Cohort
Density
80th percentile of parents distribution
74th percentile of
children's distribution
Parents
Children
0
50k
80k
100k
150k
Income (Measured in Real 2014$)


Child Rank Required to Earn More Than Parents
Child Income Percentile
Parent Income Percentile
1980
1940
(80,74)
(80,14)
0
20
40
60
80
100

## Child Rank Required to Earn More Than Parents with Copula for 1980 Cohort




Note: Darker colors represent higher density in copula