Place and Kids

Nathaniel Hendren

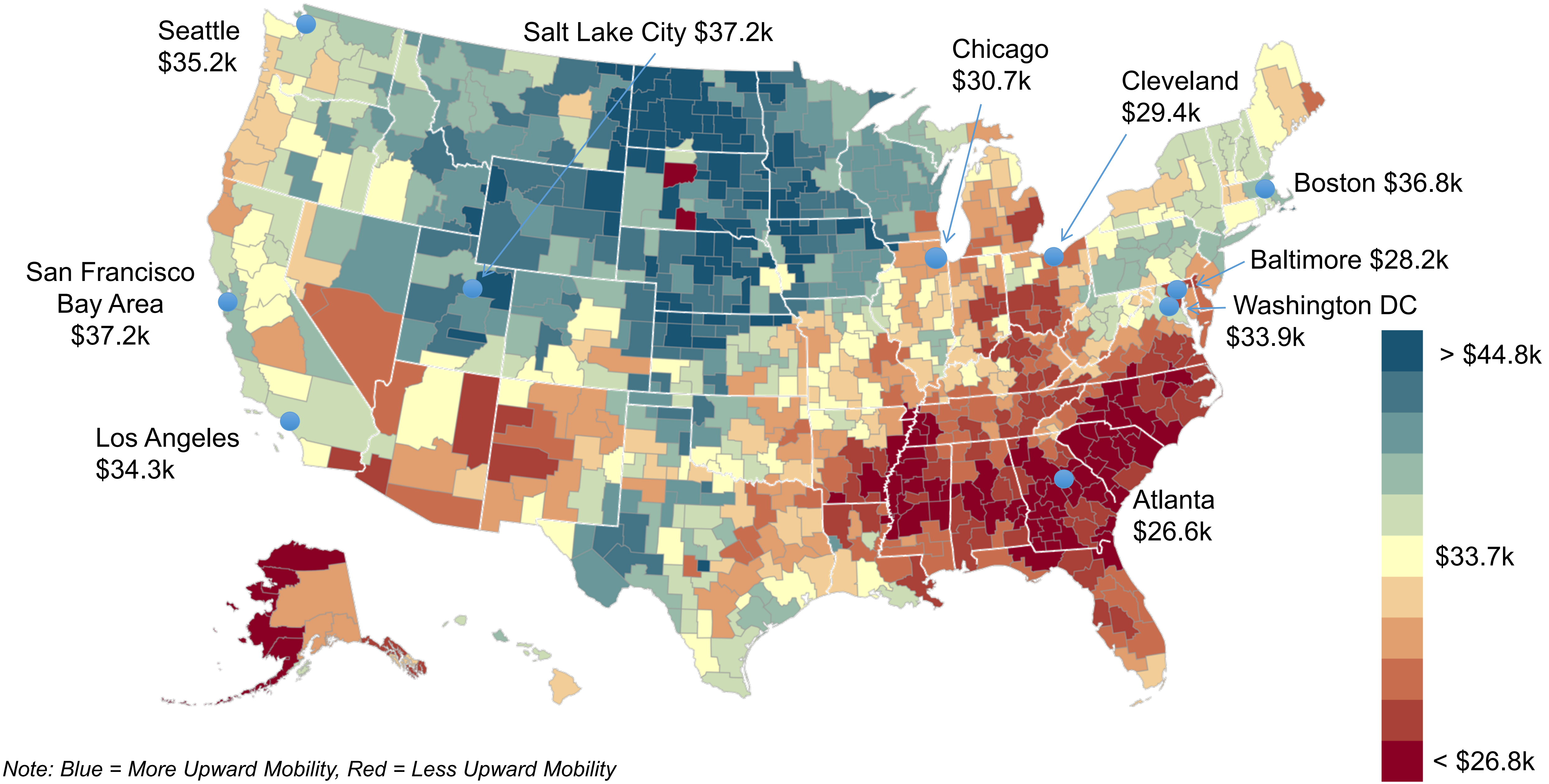
Spring 2023

The Public Economics of “Place”

- **Last Lecture:** Impact of Place on adults and models of sorting across place
- **This lecture:** What about impacts on kids?

The Geography of Upward Mobility in the United States

Average Household Income for Children with Parents Earning $27,000 (25th percentile)



Note: Blue = More Upward Mobility, Red = Less Upward Mobility

“People versus Place”

- Is the variation in economic outcomes ”people vs. places”?
  - A.k.a. Selection versus causal effect
- Growing approach: Use people who move across places to infer causal effect of place
  - Healthcare utilization – Finkelstein, Gentzkow, Williams (QJE 2016)
  - Mortality - Finkelstein, Gentzkow, Williams (AER 2021)
  - Intergenerational Mobility – Chetty and Hendren (QJE 2018)

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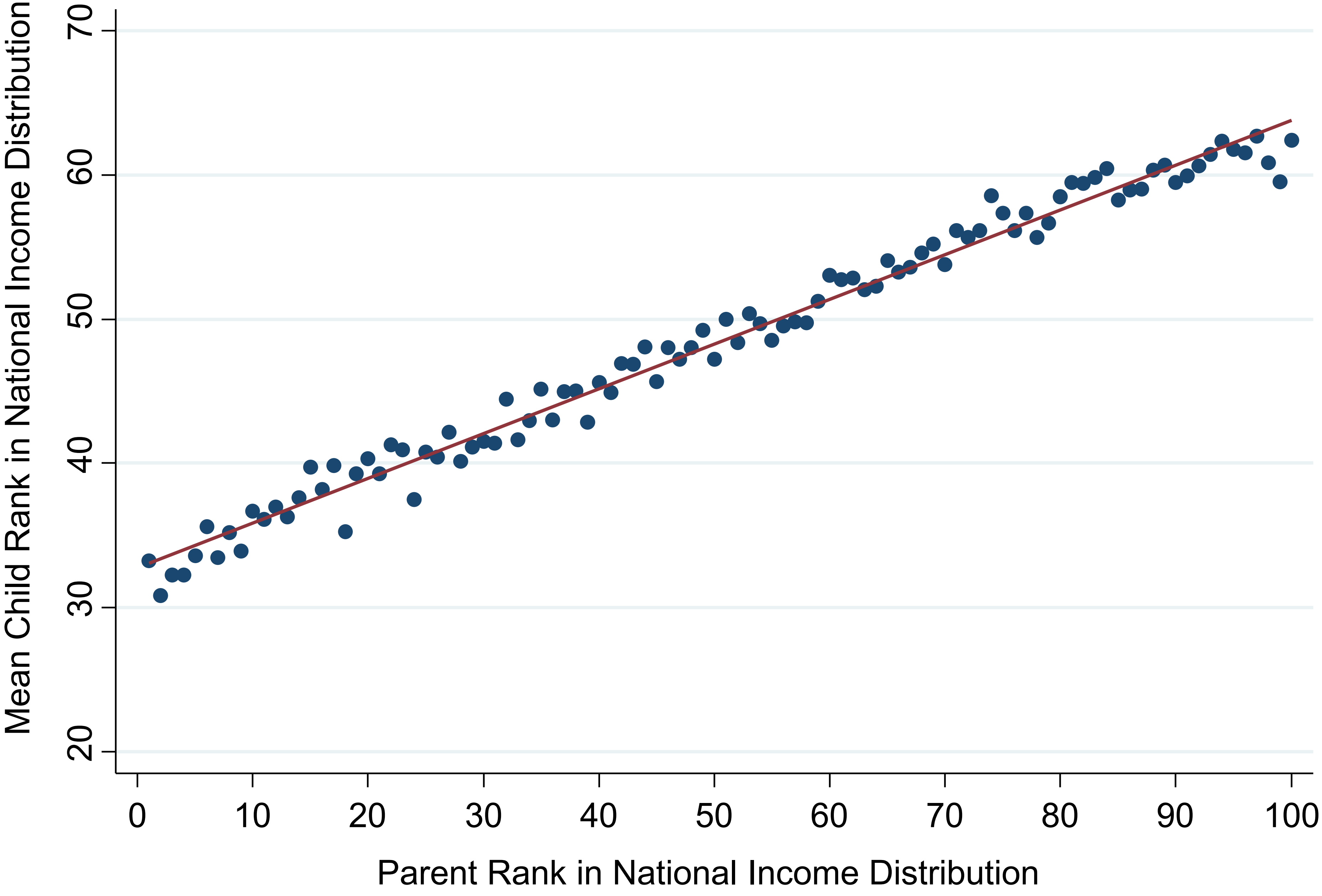
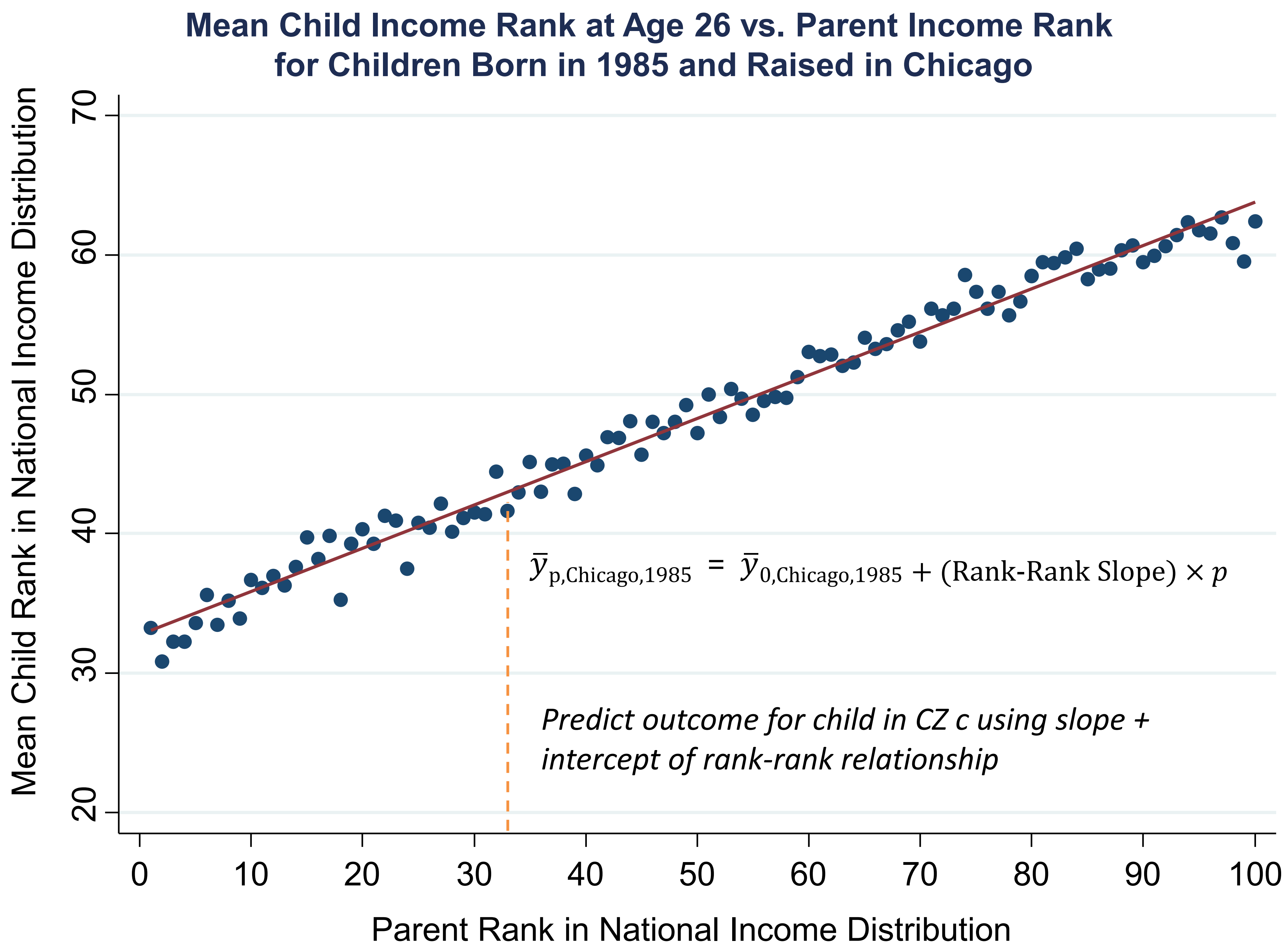
    - Mortality - Finkelstein, Gentzkow, Williams (AER 2021)
    - **Intergenerational Mobility – Chetty and Hendren (QJE 2018)**
        - Use US tax records from 1996-2012 to study causal effect of childhood exposure to different areas of the US

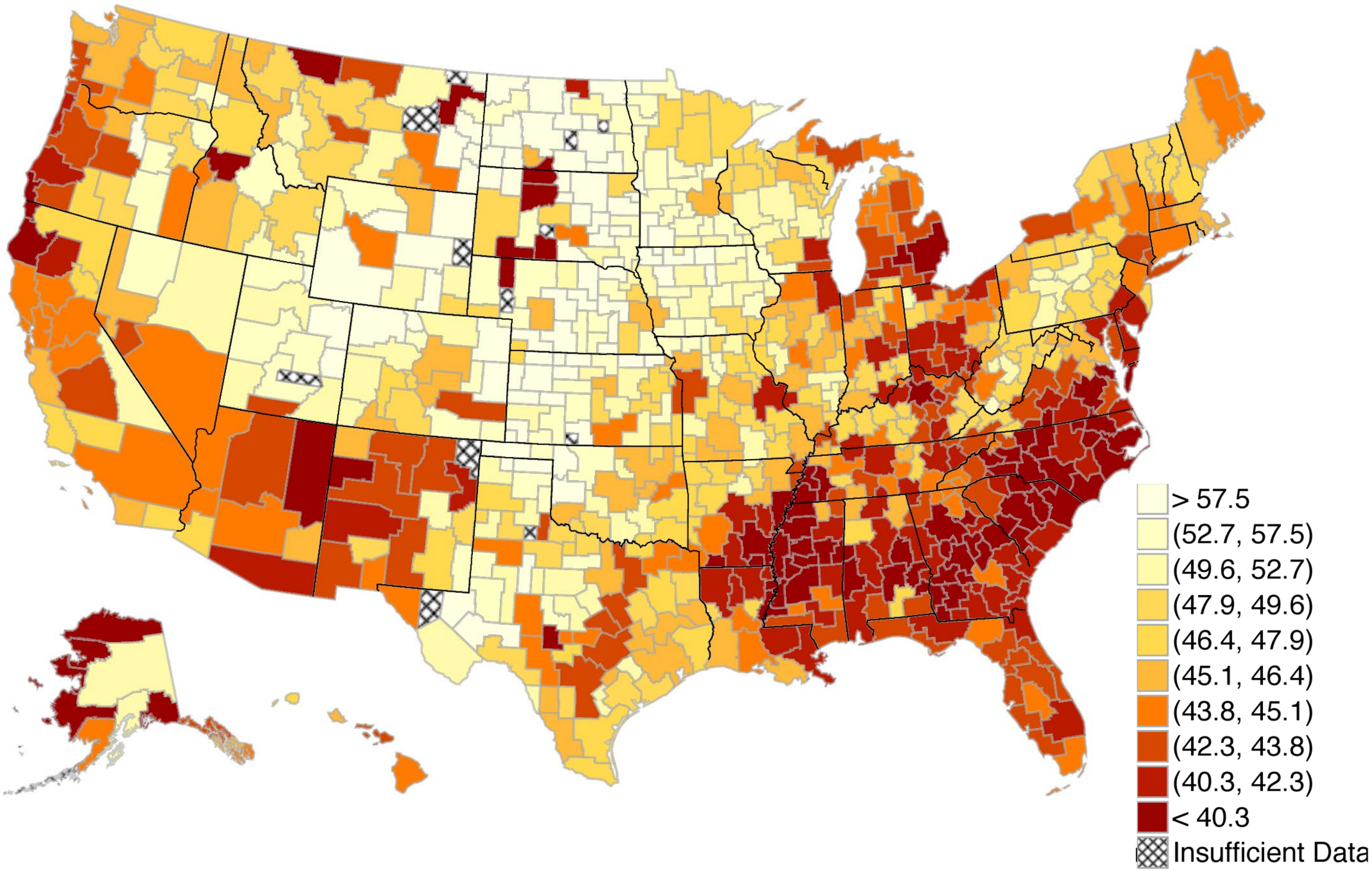
Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago




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

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



Is this variation "Causal"?

Childhood Exposure Effects

- Does growing up in a “more red” CZ cause a child to grow up to have lower incomes?

- 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 (θ_i) that produces better child outcomes

- Estimating (1) in observational data yields a coefficient

$$b_m = \beta_m + \delta_m$$

where $\delta_m = \dfrac{Cov\left(\theta_i, \bar{y}_{pds}\right)}{var\left(\bar{y}_{pds}\right)}$ 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 (DD on timing and geography)

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

  - I'll be curious if you find the following arguments convincing ☺

Estimating Exposure Effects in Observational Data

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

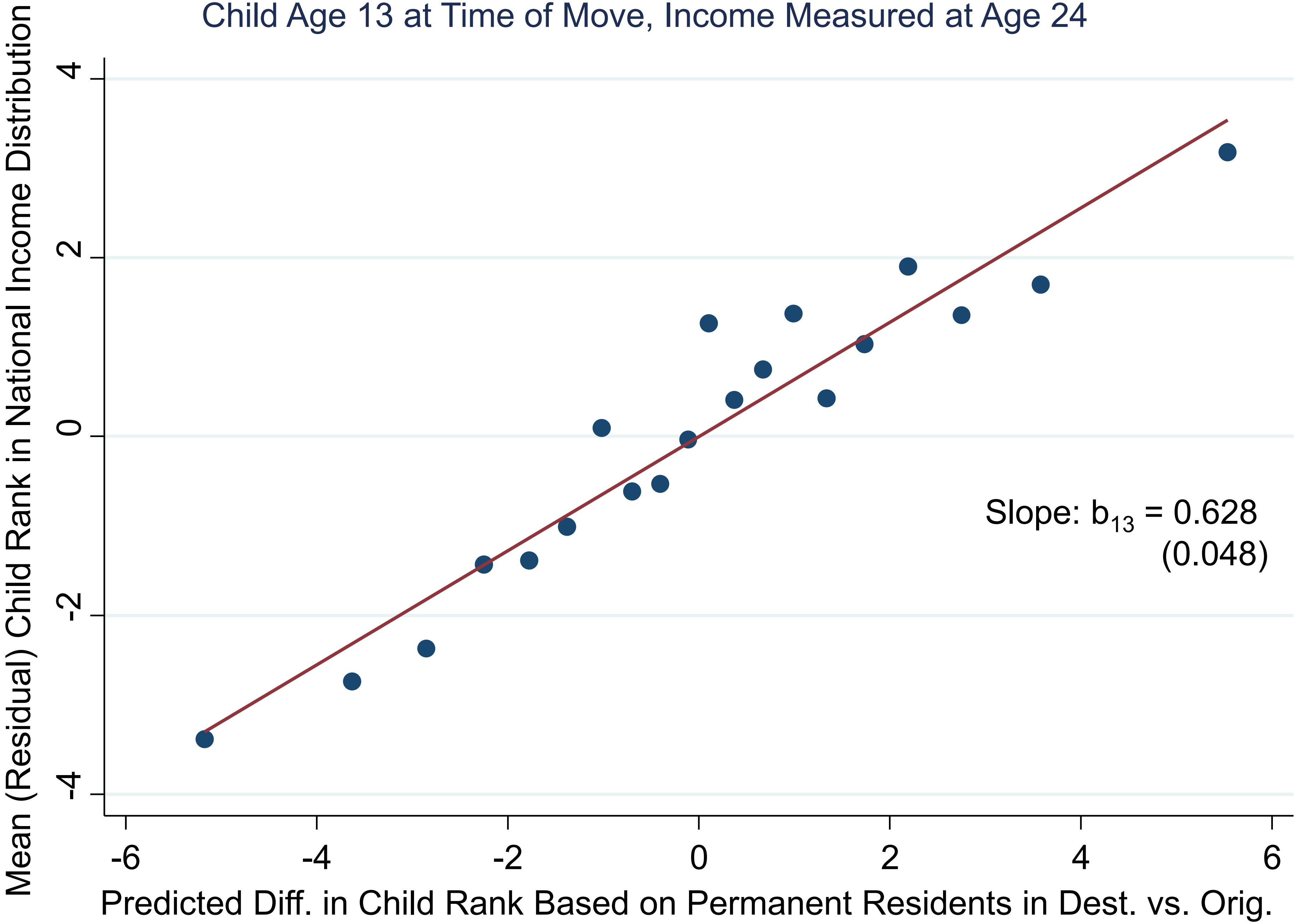
- Regress child's income rank at a given age (e.g. age 24, 26, or 30) y_i on predicted outcome of permanent residents in destination:

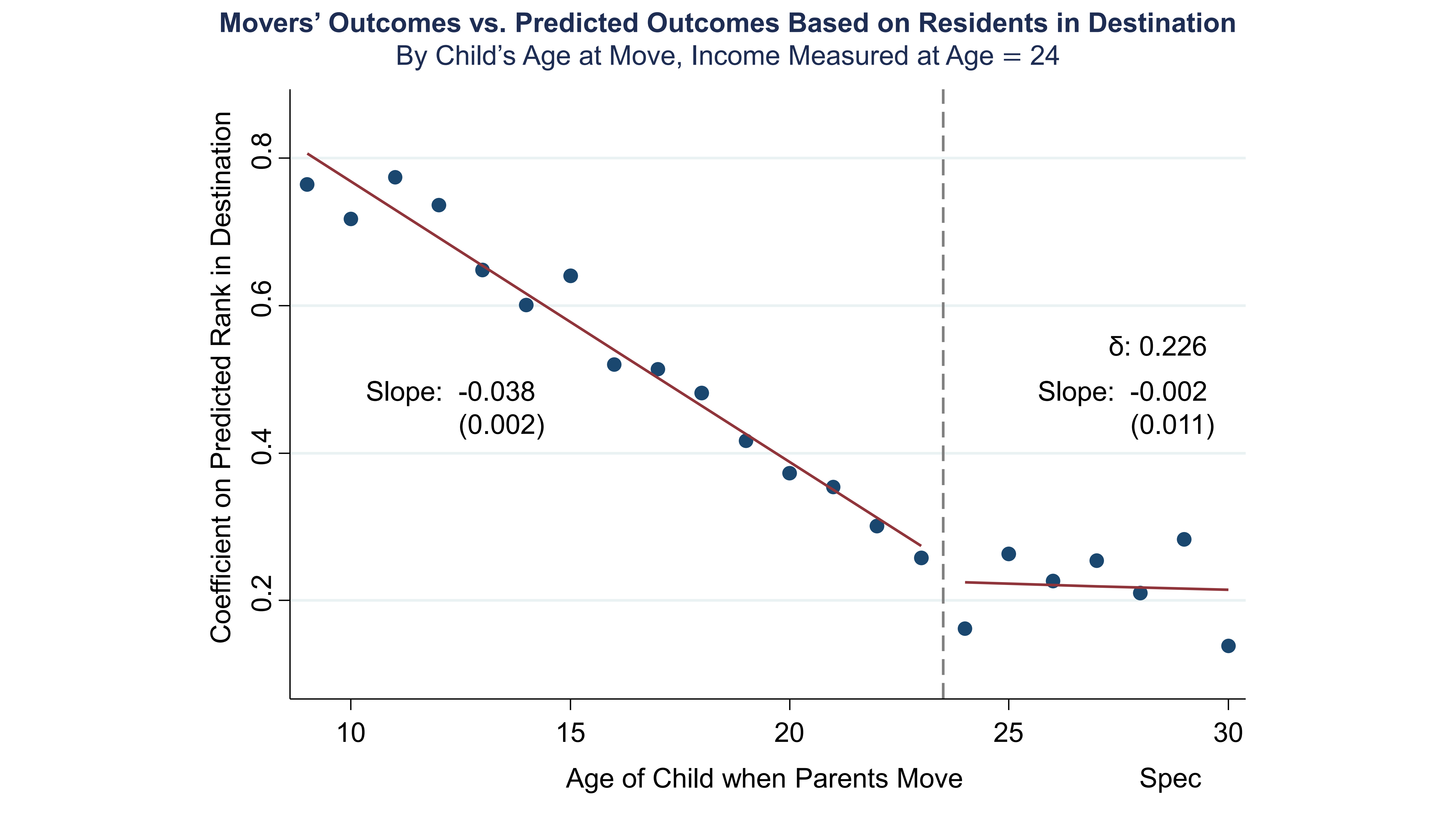
$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

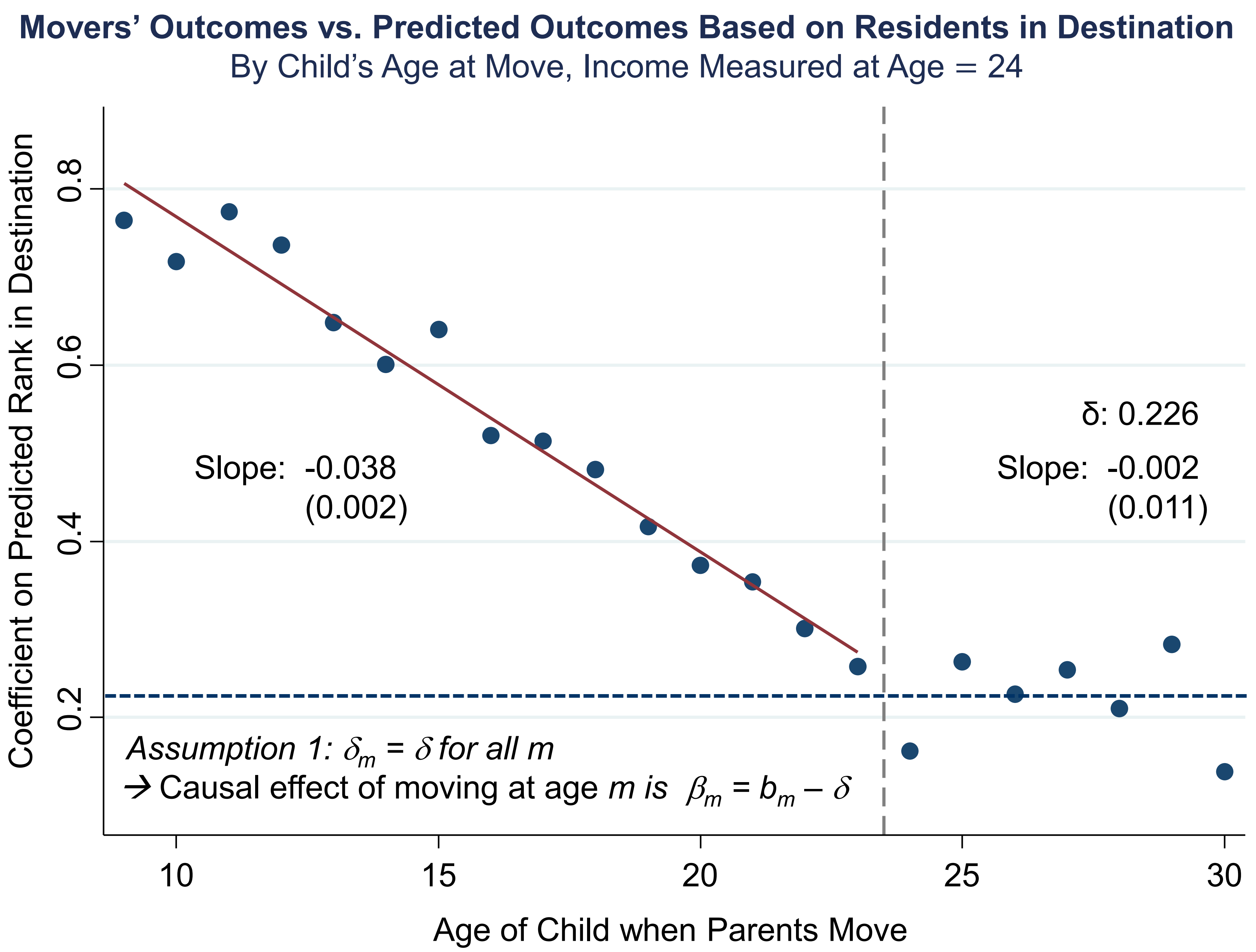
- Include parent decile (q) by origin (o) by birth cohort (s) fixed effects to identify b_m purely from differences in *destinations*

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

Child Age 13 at Time of Move, Income Measured at Age 24




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

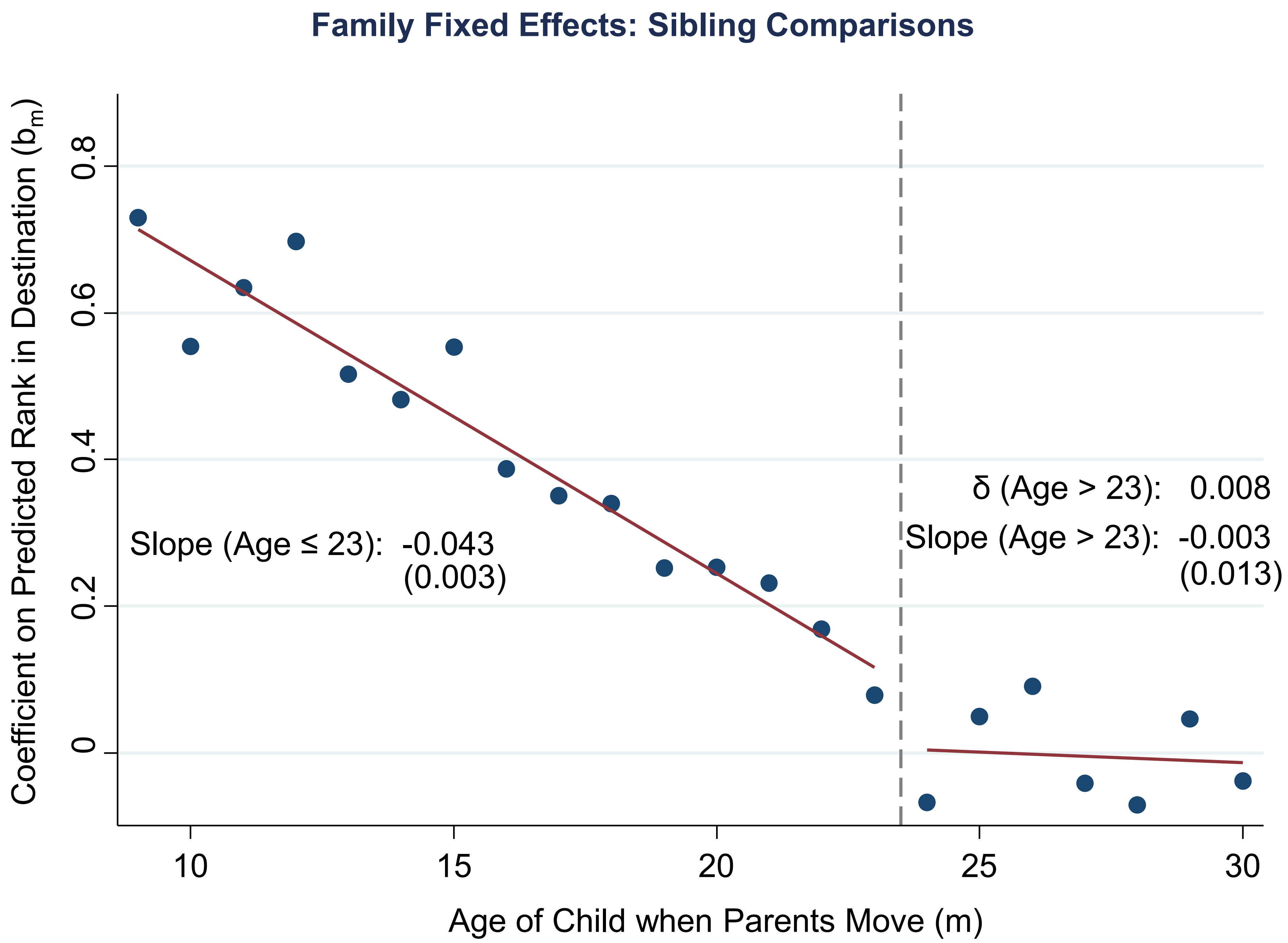
Identifying Causal Exposure Effect

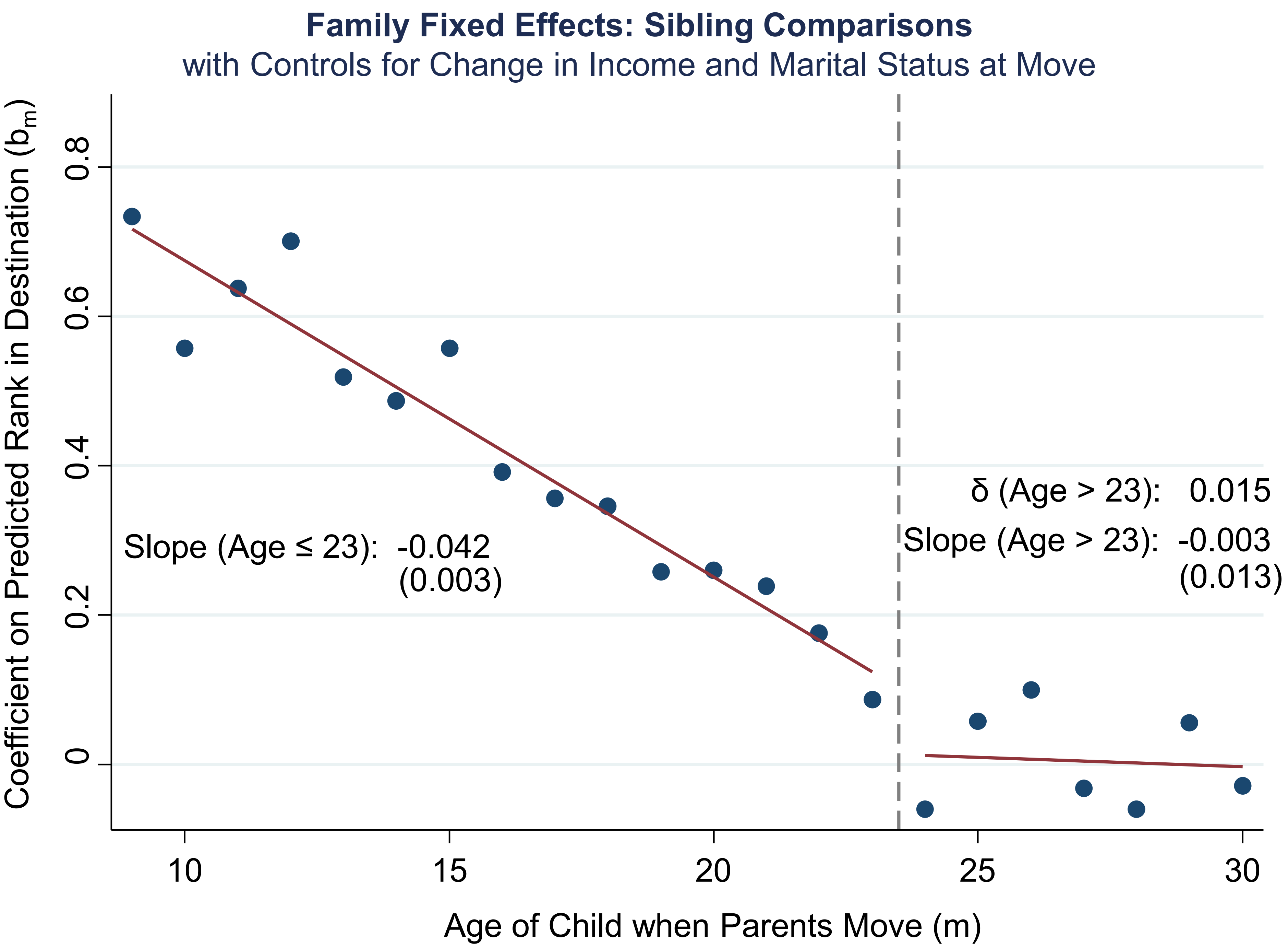
- Key identification assumption: *timing* of moves to better/worse areas uncorrelated with child's potential outcomes

- Two main concerns (Jencks and Mayer, 1990)

  1. Sorting of families to different areas
  2. Time-varying shocks driving movement to different areas

- Easy solution: control for family fixed effects and time-varying observables such as marital status and income changes


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


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

Time-Varying Unobservables

- Family fixed effects do not rule out time-varying unobservables that affect children in proportion to exposure time
  - Wealth shocks
  - “Parental capital” shocks correlated with where you move
- Paper presents results from “outcome-based placebo tests”
  - Exploit heterogeneity in place effects across subgroups to obtain overidentification tests of exposure effect model

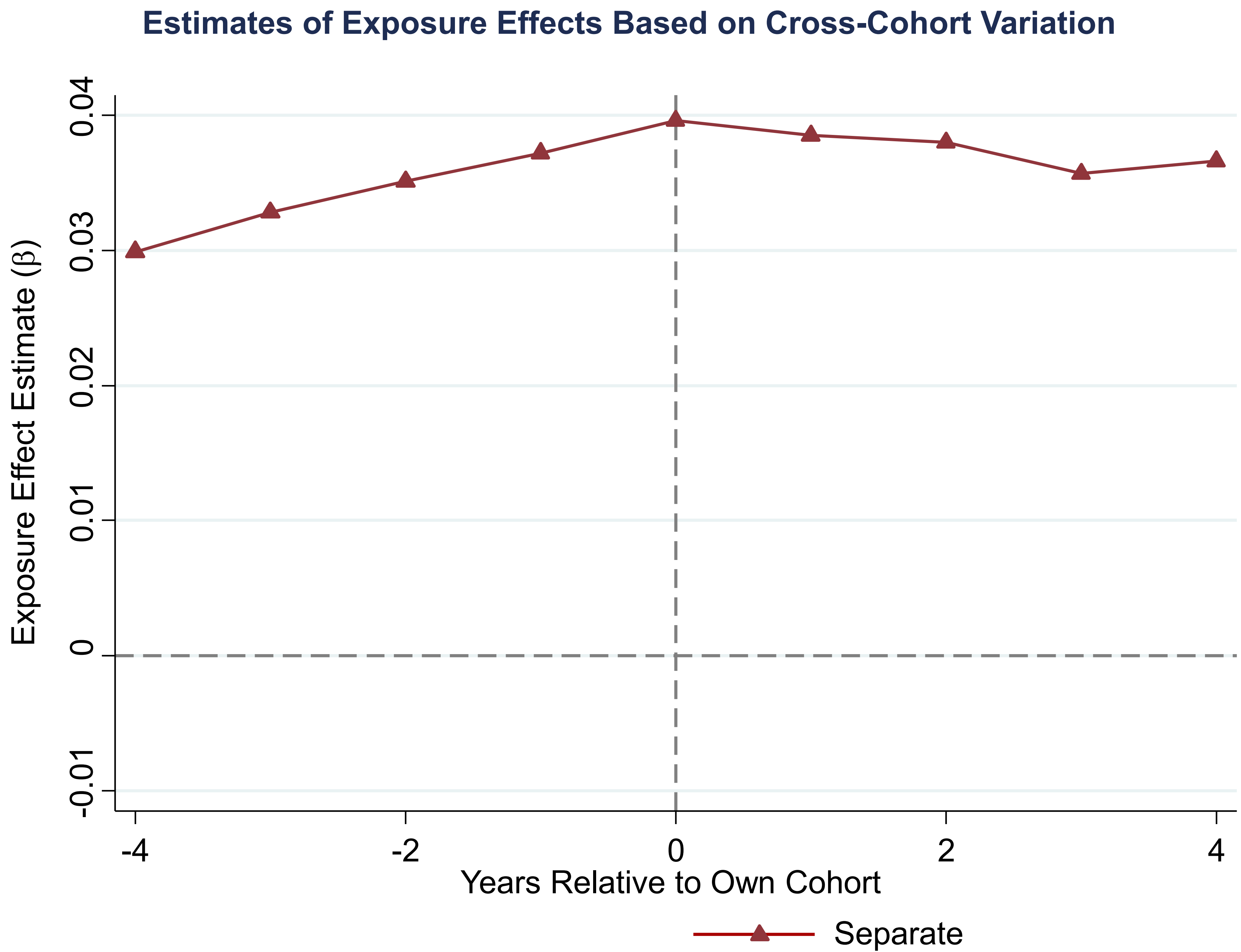
Outcome-Based Placebo Tests

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

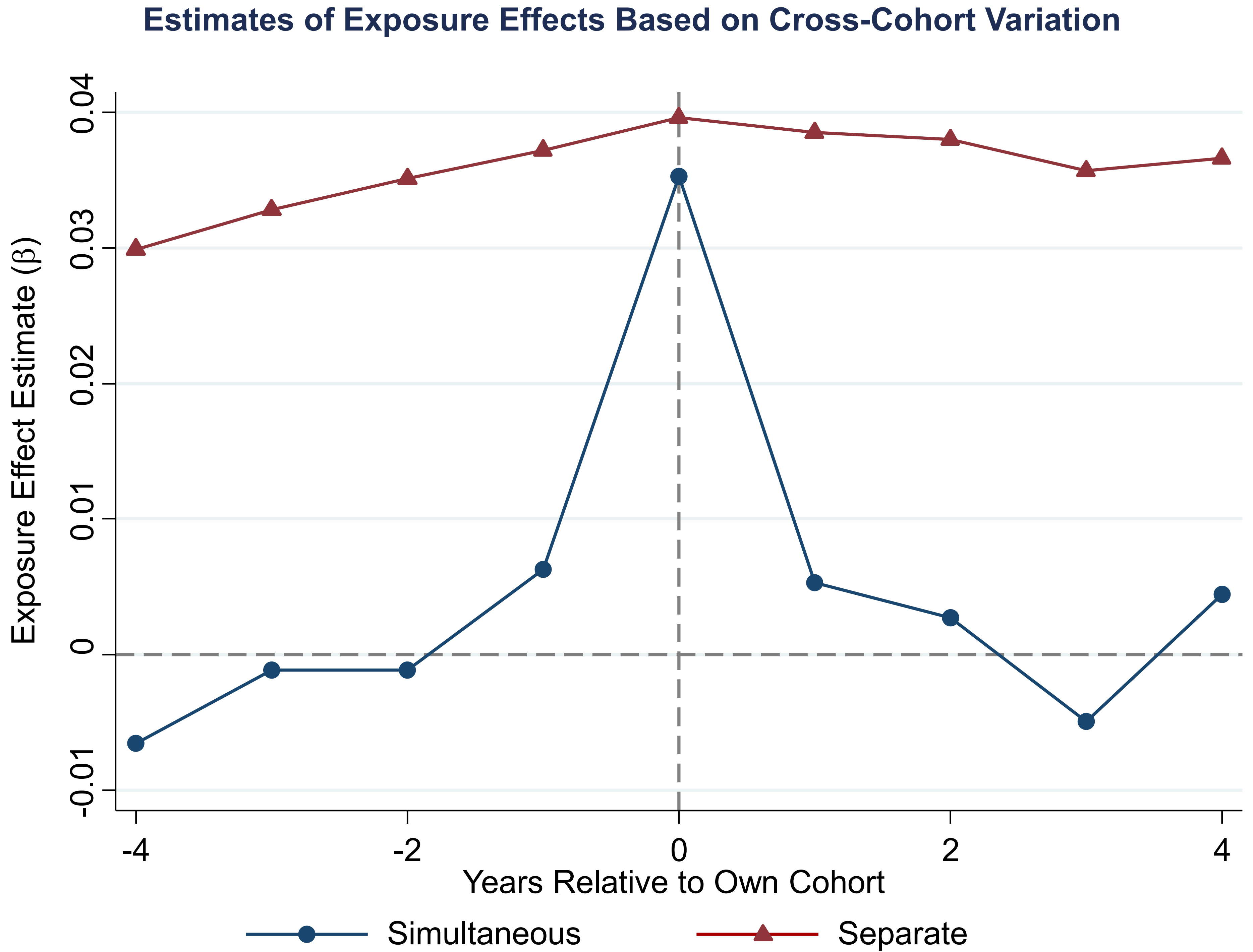
- Start with variation in place effects across birth cohorts
  - Some areas are getting better over time, others are getting worse
  - Causal effect of neighborhood on a child who moves in to an area should depend on properties of that area while he is growing up

Outcome-Based Placebo Tests

- Example: 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 θ_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
Exposure Effect Estimate (β)
0.04
0.03
0.02
0.01
0
-0.01
-4
-2
0
2
4
Years Relative to Own Cohort
Simultaneous
Separate

Identification of Exposure Effects: Summary

- Chetty and Hendren (2018) argument: families making their moves based on time-varying unobservables would not perfectly know the 15-year-later-realized high frequency variation in cohort-level outcomes
    - Would suggest you should see loading onto neighboring cohorts in predicting outcomes for own cohort
- Summing up: If you believe their results, roughly 2/3 of the variation in intergenerational mobility is the causal effect of childhood exposure
- Chetty and Hendren (2018B) constructs causal estimates for each county and provides rankings for each county in the US
    - Bayesian shrinkage methods increasingly used in many contexts
    - Discuss methods at the end if time

RCT Evidence: 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

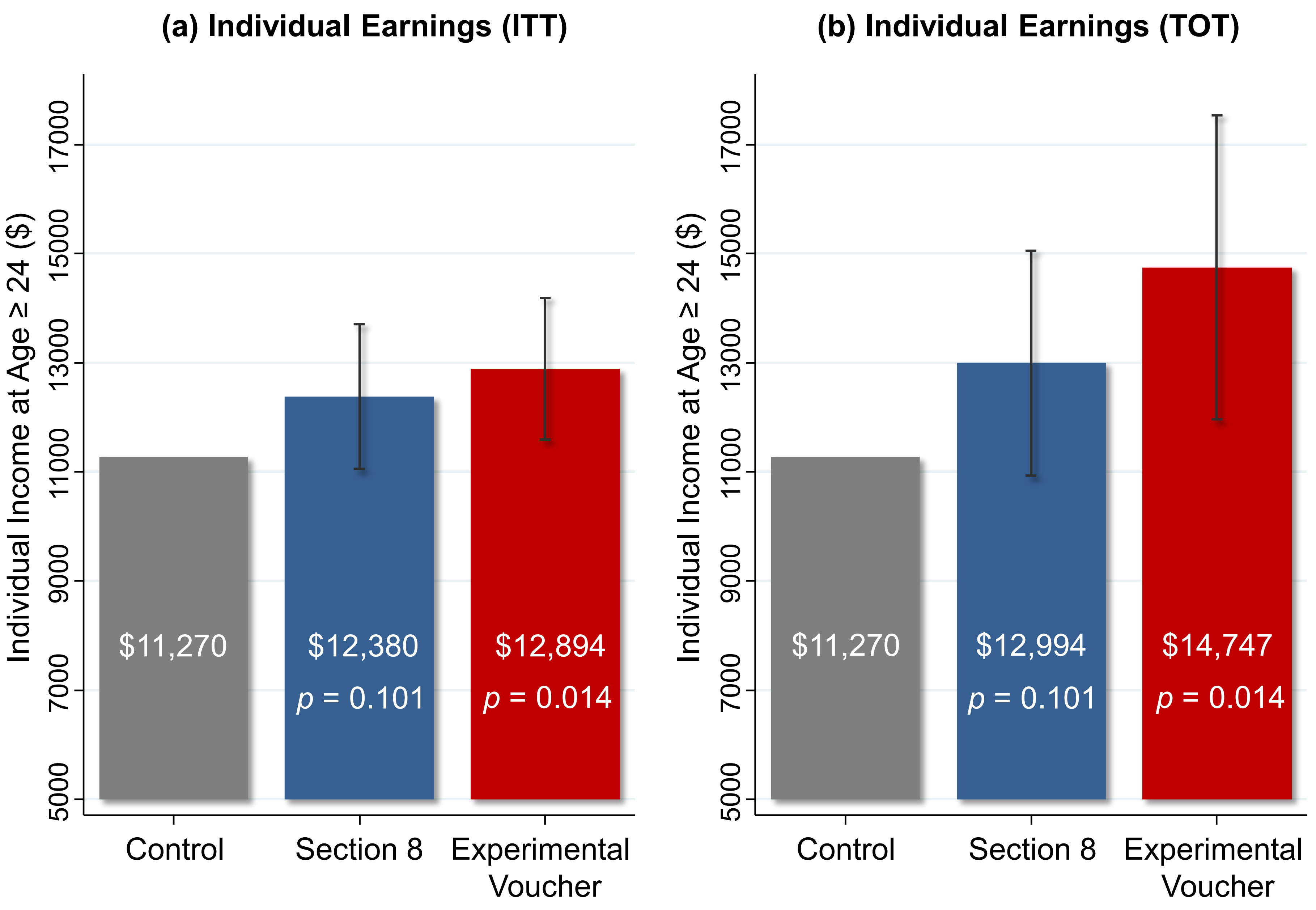
MTO Experiment: Exposure Effects?

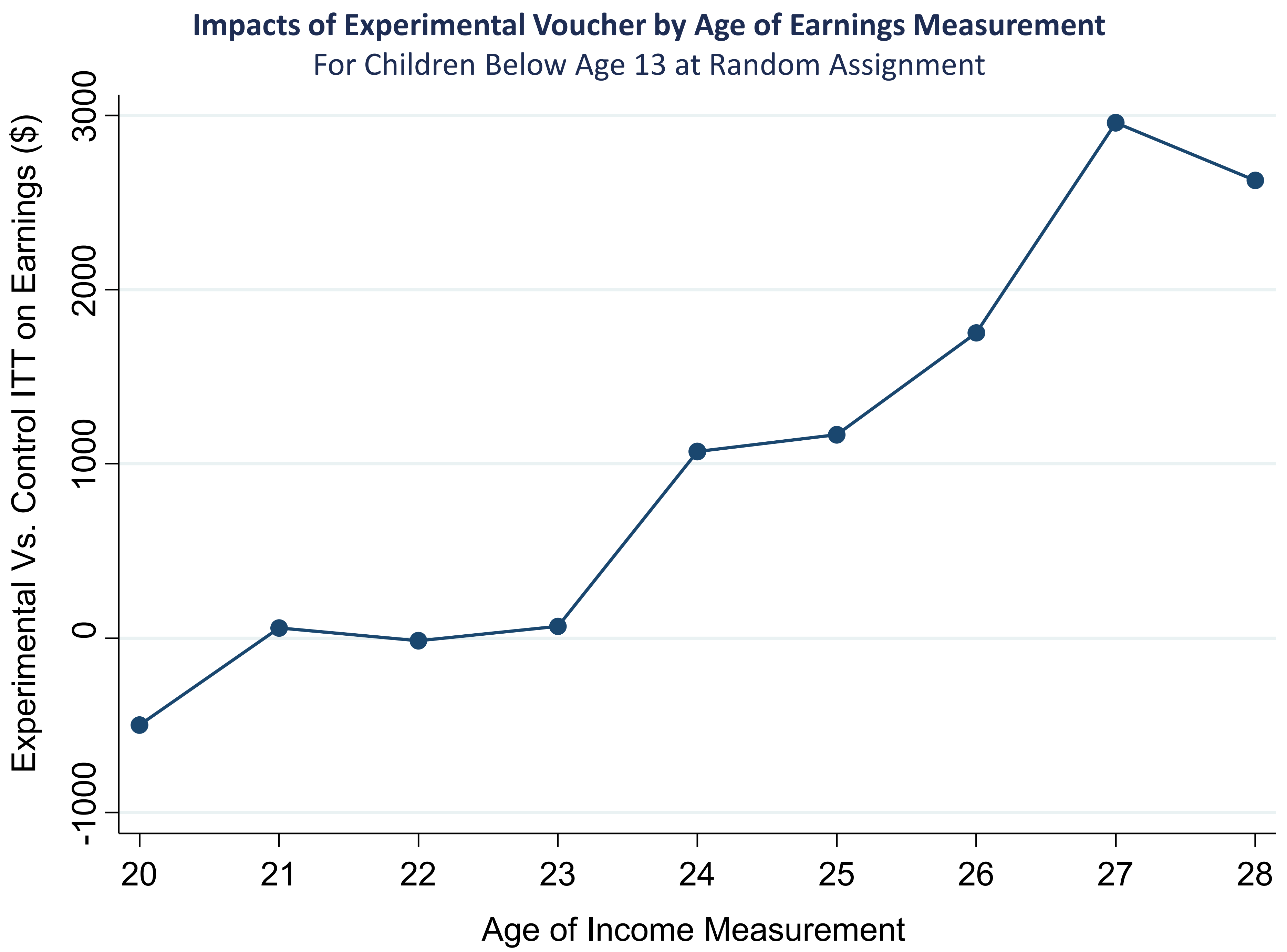
- Prior research on MTO:
  - Little impact of moving to a better area on earnings and other economic outcomes
    - Rejects “Spatial Mismatch Hypothesis” of Kain (1968)
  - But work has focused on adults and older youth at point of move
    [e.g., Kling, Liebman, and Katz 2007]
- What about the young kids?

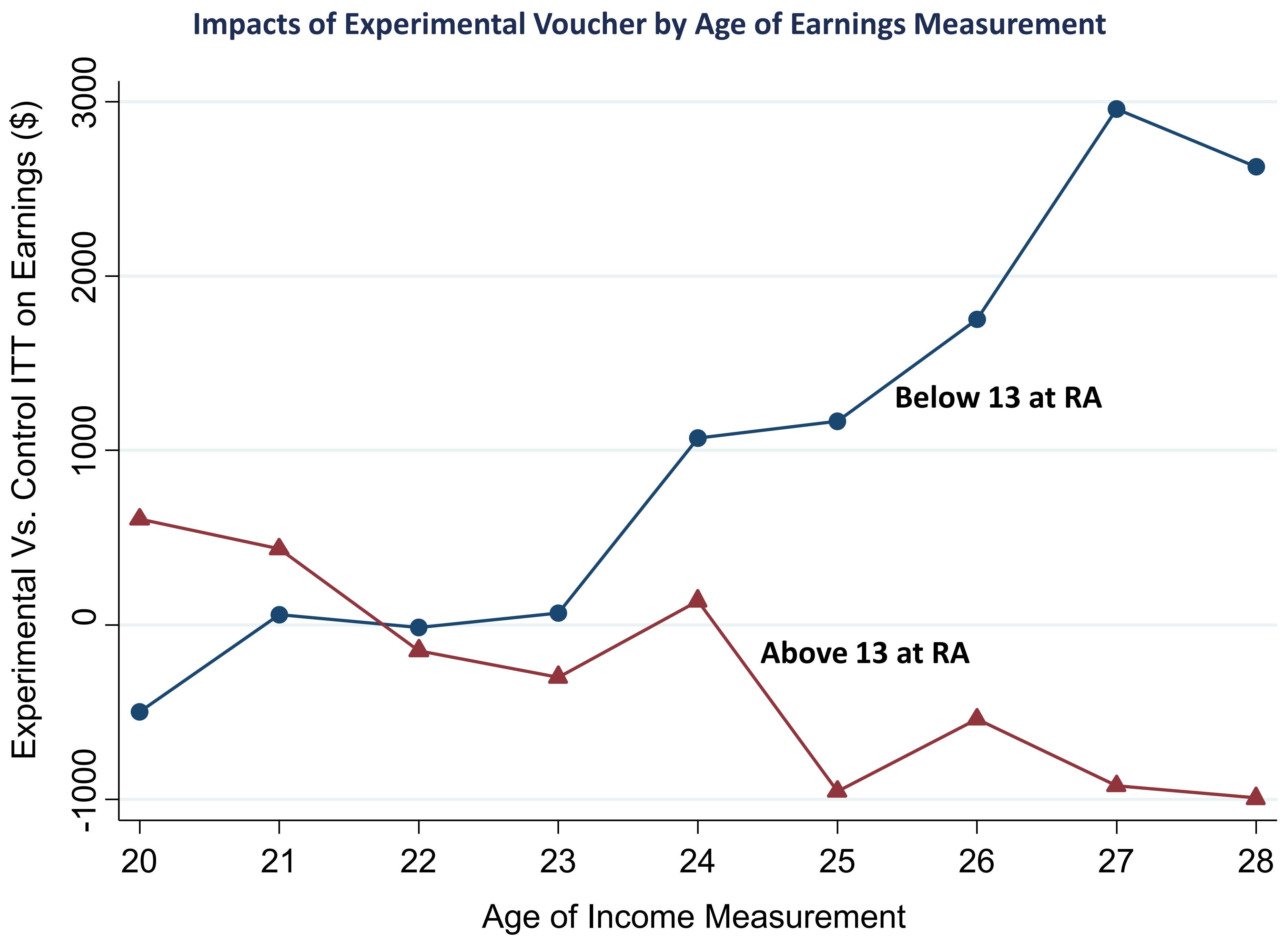
Chetty, Hendren, Katz. “The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment”

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

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 ($)
3000
2000
1000
0
-1000
20
21
22
23
24
25
26
27
28
Age of Income Measurement



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

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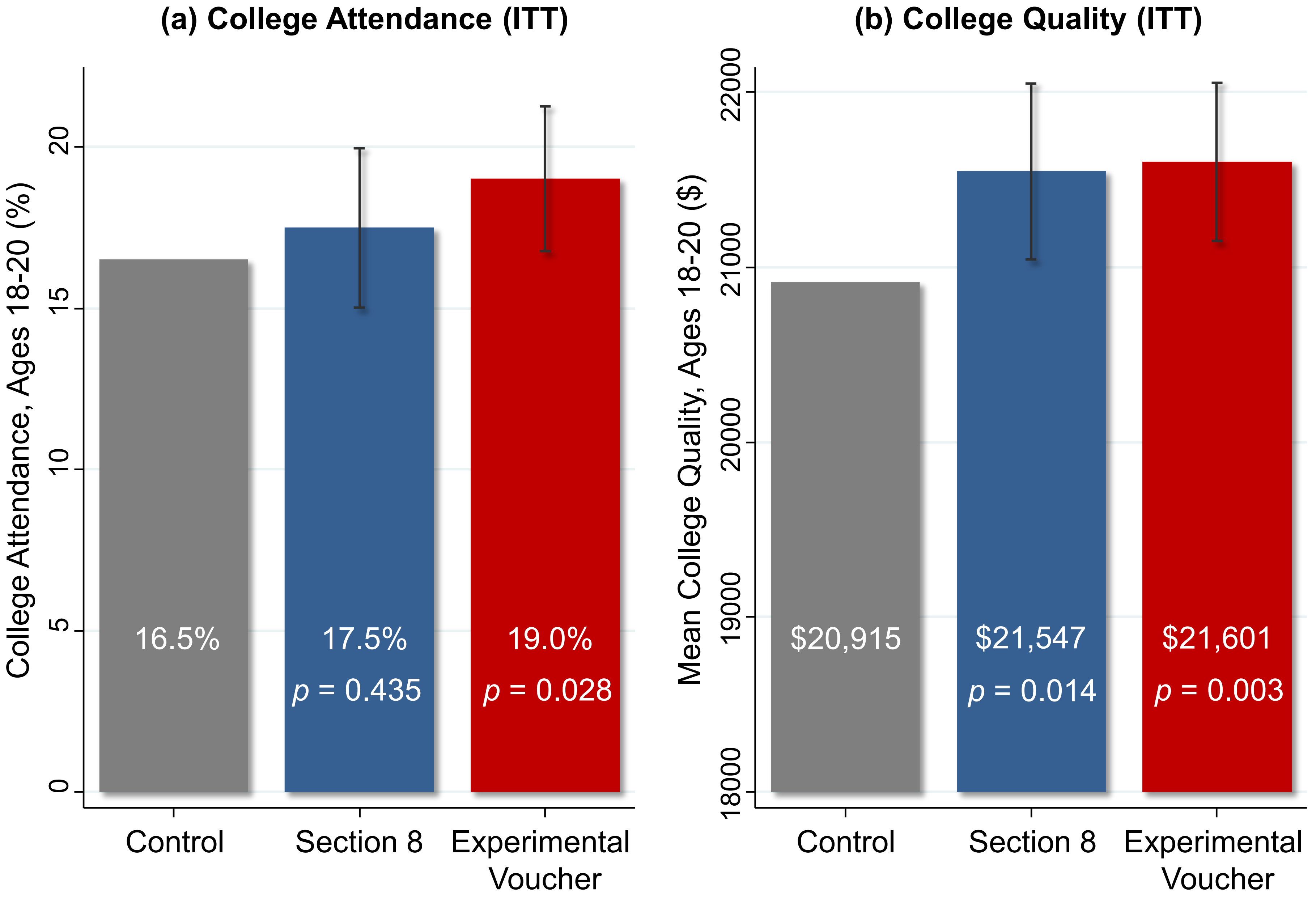

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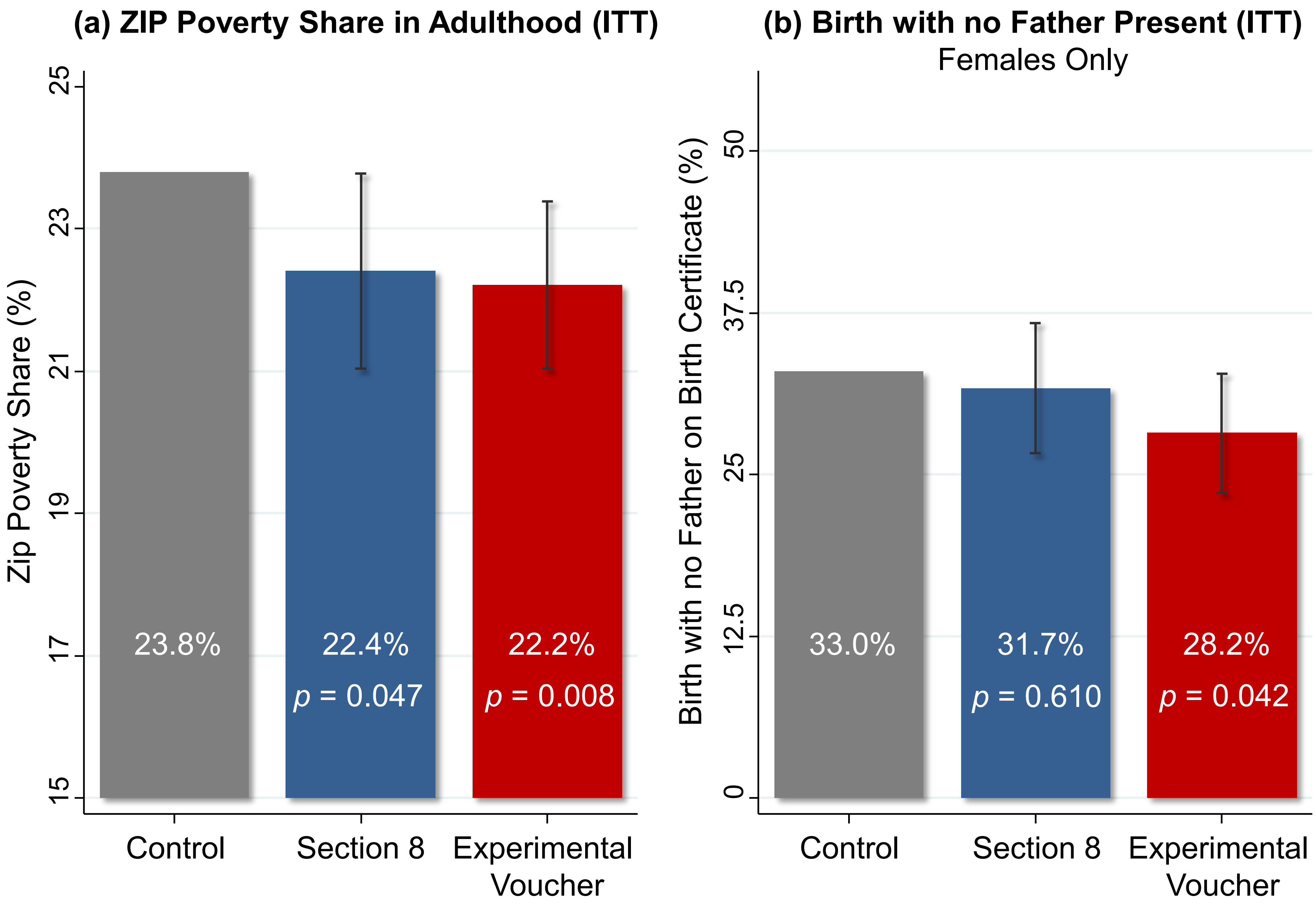
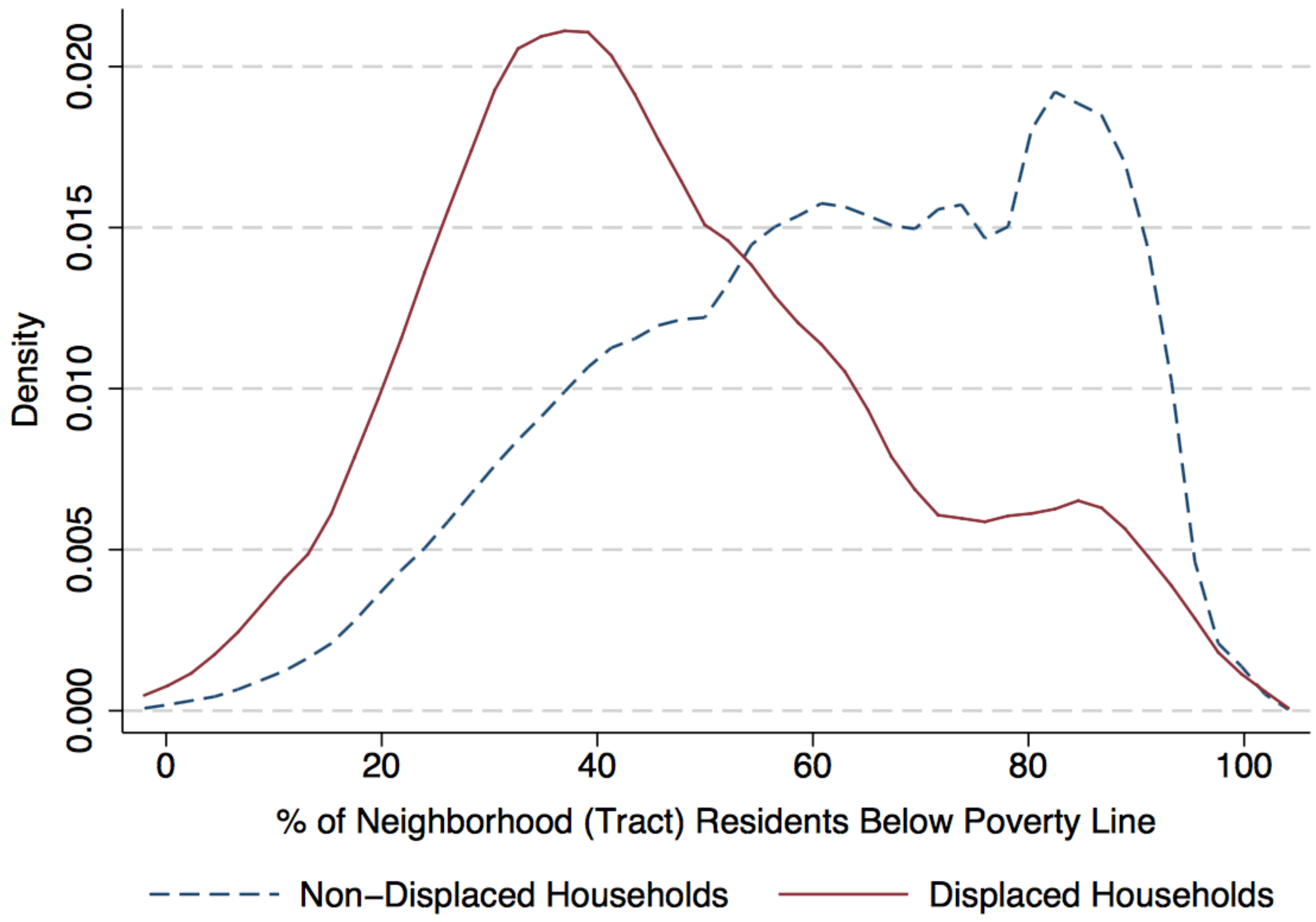


Chyn (2018): Public Housing Demolitions

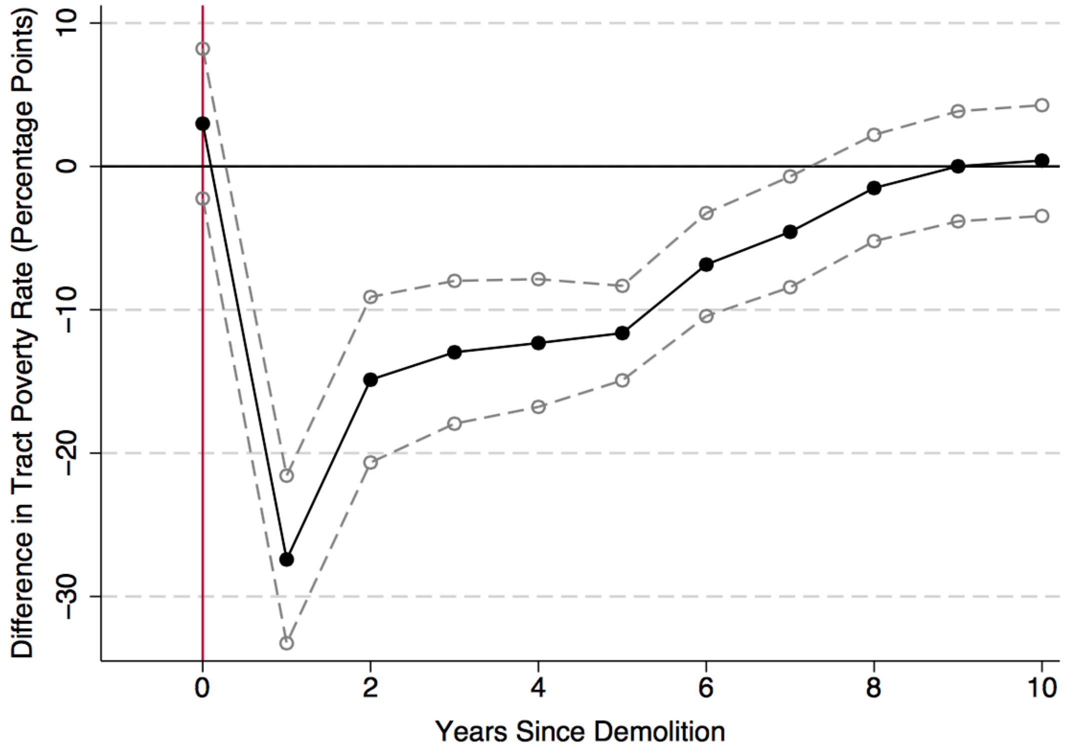
- Past 50+ years saw a dramatic rise and fall of public housing in the US
  - Watch the “Pruett Igoe Myth” on YouTube
- Eric Chyn’s JMP (AER 2018) studies the causal effect of public housing demolitions in Chicago on children’s long run outcomes
  - Exploits long sequencing of Hope VI demolitions
  - Compare neighboring buildings (demolished vs. not demolished)

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 π_y for $y \in \{0, \cdots, 10\}$ from the following specification:

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

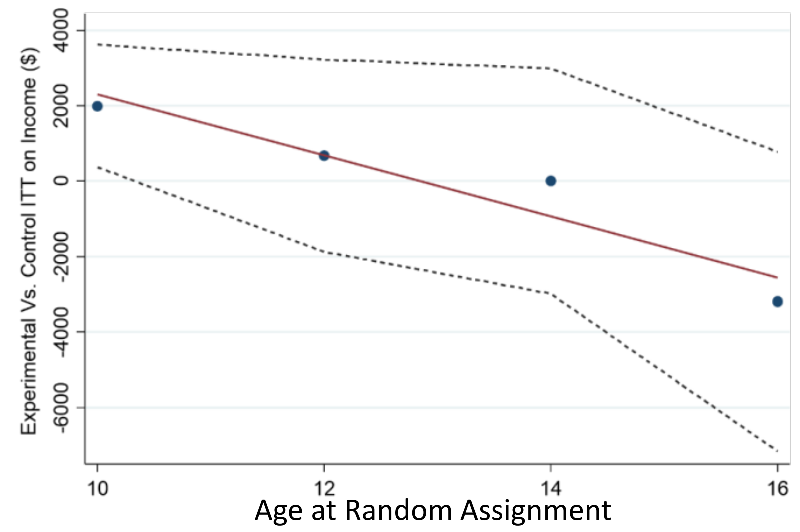
where h indexes a household; t represents years; and p indexes projects. The dependent variable is the percentage of residents living below the poverty line in a Census tract and ψ_p is a set of project fixed effects. The variable t^* represents the year of demolition for a particular household. Recall 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 π_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.

(b) Dependent Variable: Annual Earnings ($)

(b) Dependent Variable: Annual Earnings ($)

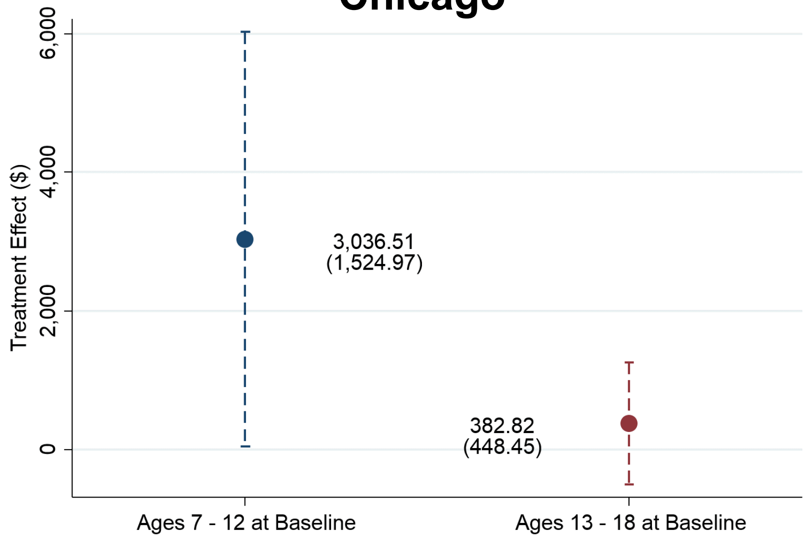
Childhood Exposure Effects Around the World

MTO Experiment
Baltimore, Boston, Chicago, LA, NYC



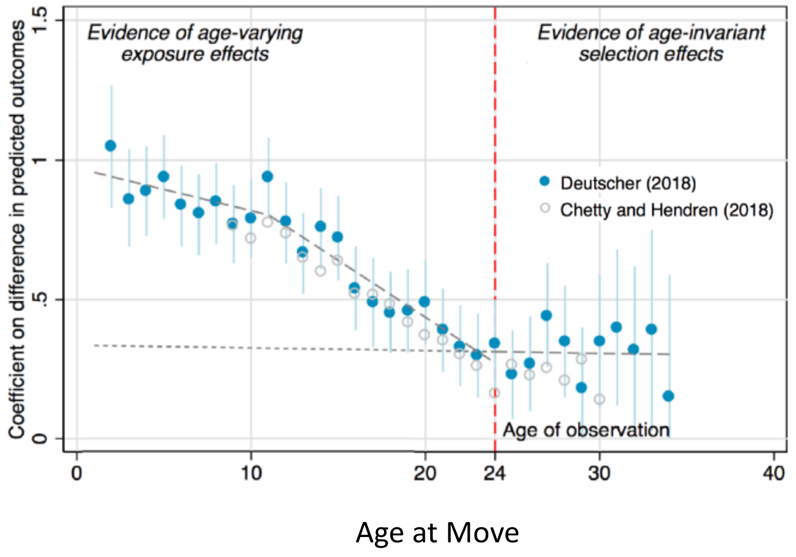
Source: Chetty, Hendren, Katz (AER 2016)

Public Housing Demolitions Chicago



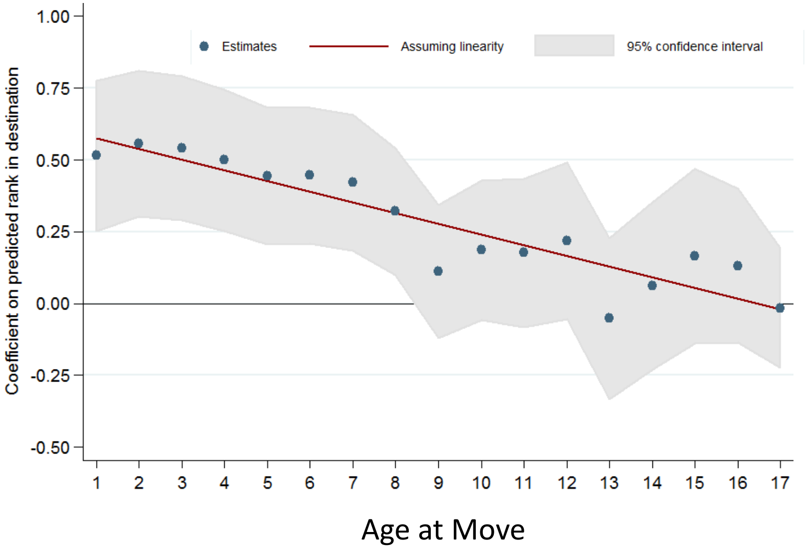
Source: Chyn (AER 2018)

Australia



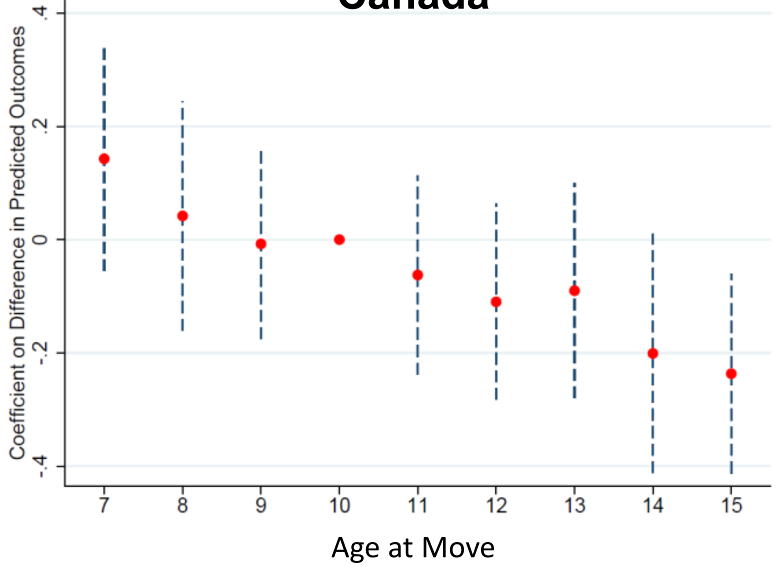
Source: Deutscher (AEJ Applied 2019)

Denmark



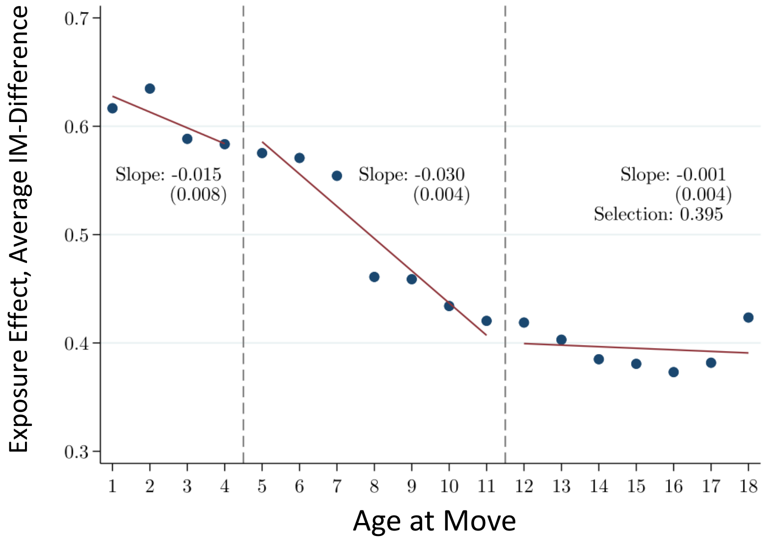
Source: Faurschou (2018)

Canada



Source: Laliberté (AEJ: Econ Policy 2021)

Africa



Source: Alesina, Hohmann, Michalopoulos, Papaioannou (Econometrica 2020)

Part 2: If Place Matters, What Should We Do About It?

Help Poor People, Not Poor Places

Aug. 12, 1999 12:01 am ET

SAVE PRINT TEXT

By Edward L. Glaeser, a professor of economics at Harvard University.

P resident Clinton's six-city "New Markets" tour earlier this summer signaled a renewed focus on the problems of the poor. But while the president's concern is appreciated by all of us who care about the islands of poverty in America's sea of affluence, his proposals are fundamentally flawed. They may still help some of the poor, but also risk repeating some of the worst mistakes of the Johnson era.

The trouble with the president's recommendations is that they violate the first economic rule of urban poverty policy: Programs should be person-based, not place-based.

Economists have long argued that place-based programs are a mistake. They strongly prefer person-based policies that create transfers, entitlements or relief from regulation on the basis of personal characteristics. Examples of person-based policies include the Earned Income Tax Credit and the GI Bill.

https://www.wsj.com/articles/SB934404174689915612

If Place Matters, What Should We Do About It?

- Incidence: Place based policy may not have the desired incidence
  - Rosen-Roback model shows that if people are sufficiently mobile, then place-based policies have incidence on landowners, not workers
  - See the rest of Owen Zidar's 14.472 MIT lecture slides

- Efficiency: Is place-based policy more vs. less efficient than giving (the same or similar) people cash?

- Same questions arise for other policies:
  - Healthcare/Medicaid
  - Food stamps
  - Disability Insurance

If Place Matters, What Should We Do About It?

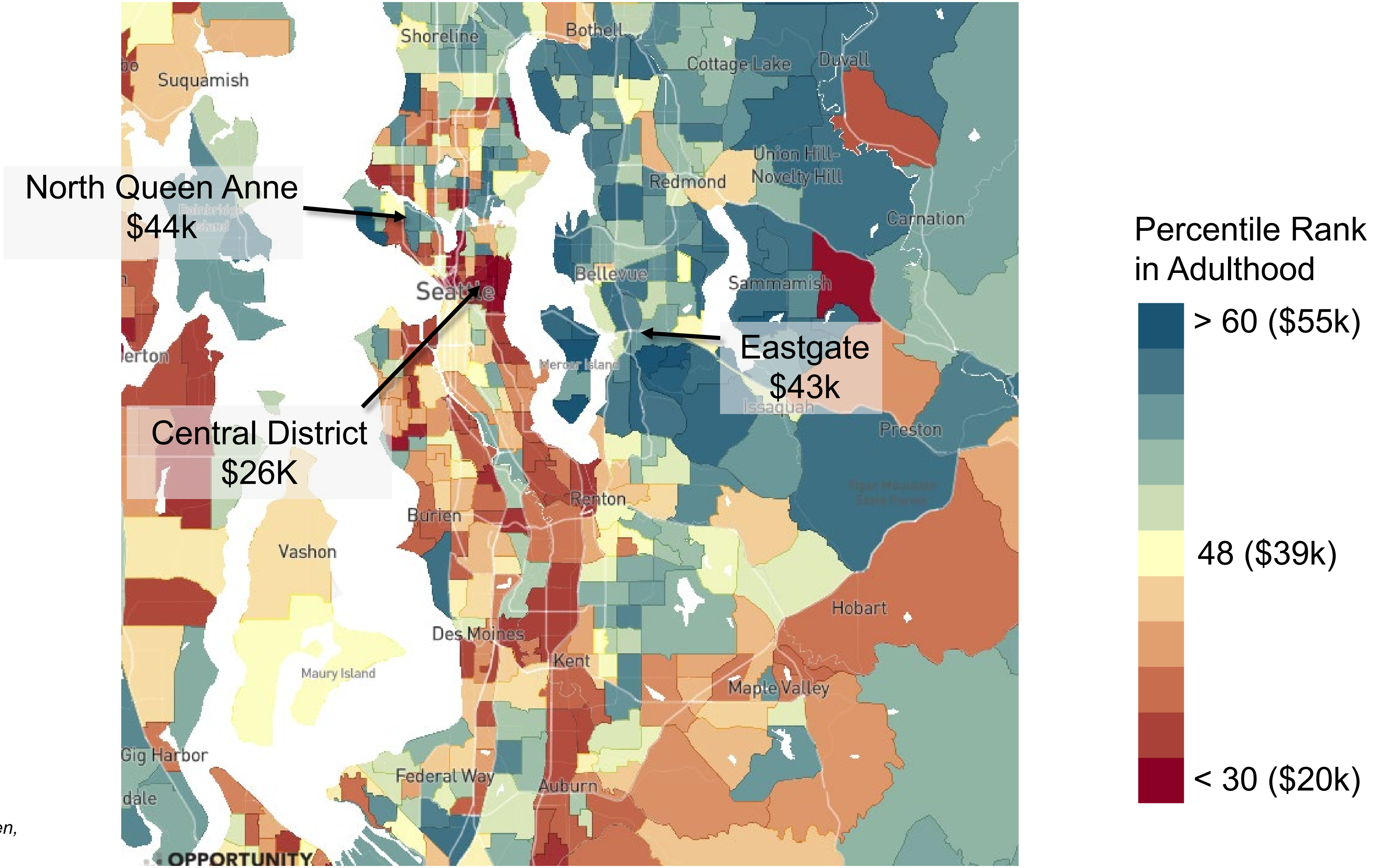
- Kaplow (1996, 2004, 2006, 2008, …) provides the general argument for why income tax based redistribution can be the most efficient
  - If location is like any other choice of a good, then tax schedule is generally efficient
  - Are there externalities or frictions in choice?

- Bergmann et al. (2019) study search “frictions” in choosing where to live

- Focused on housing vouchers and the broad fact that 80% of housing vouchers are used in high poverty neighborhoods

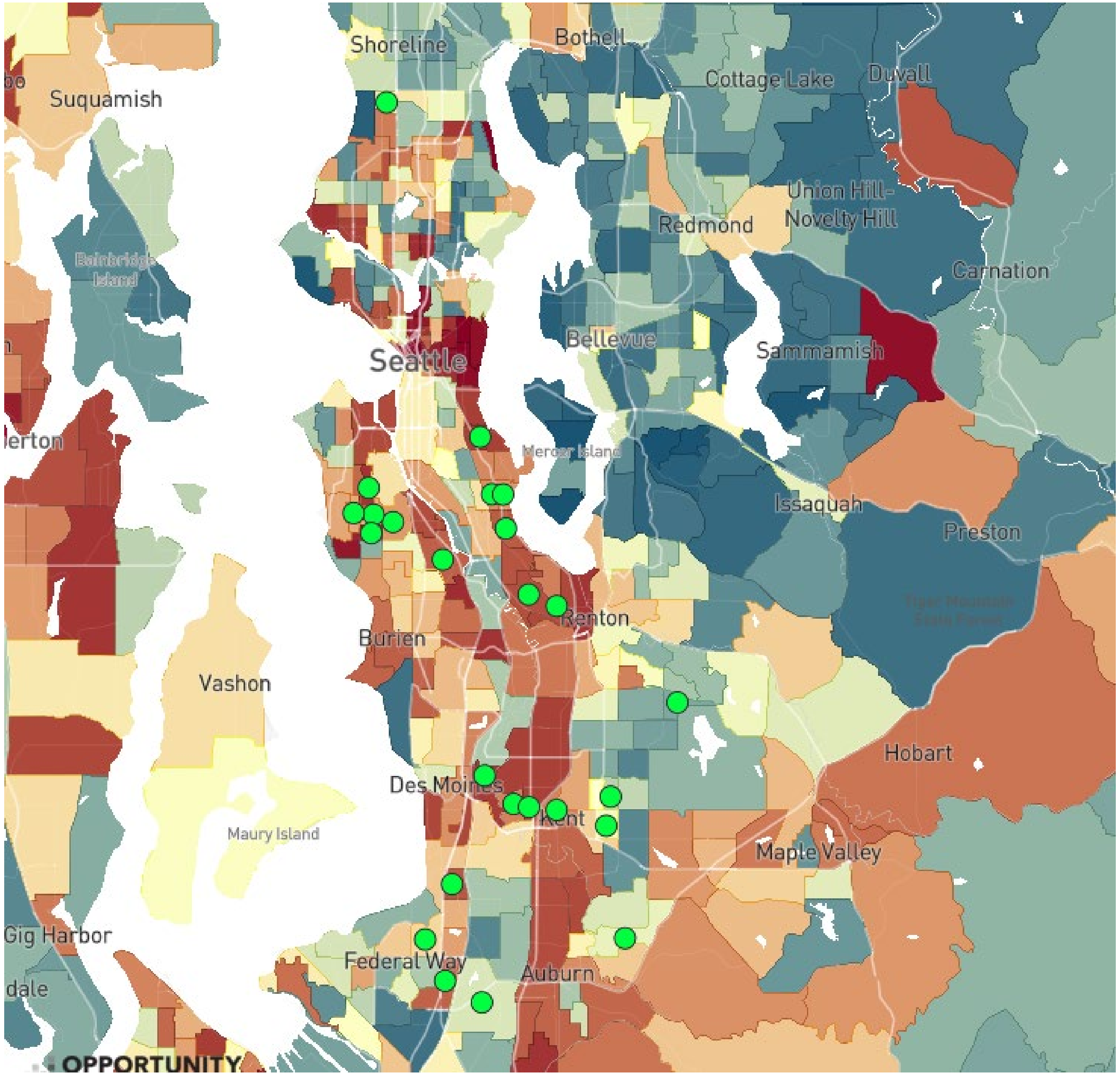
The Geography of Upward Mobility in Seattle

Average Income at Age 35 for Children with Parents Earning $27,000 (25th percentile)



Source: Chetty, Friedman, Hendren, Jones, Porter (2018)

Most Common Locations of Families Receiving Housing Vouchers



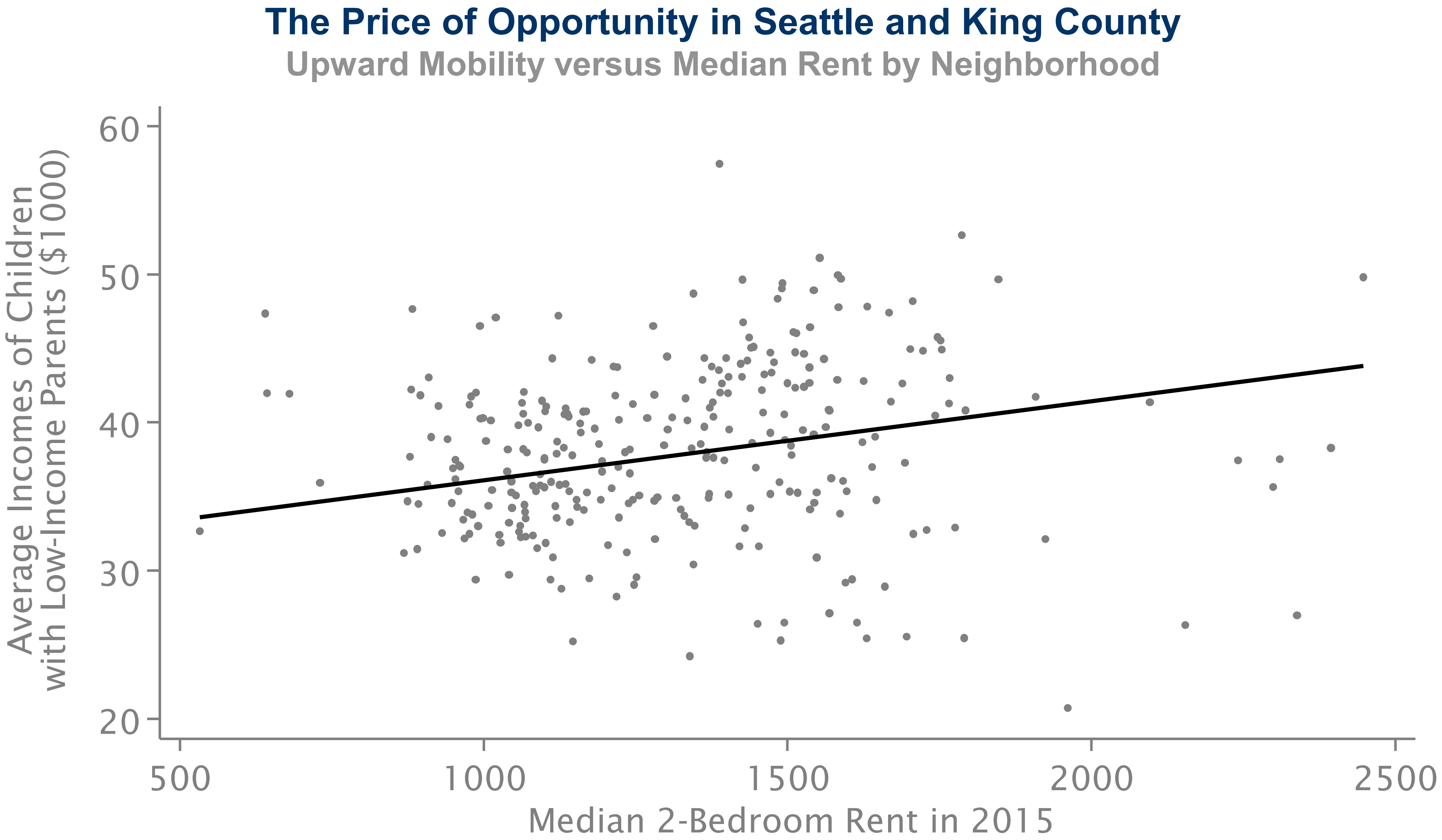
25 most common tracts where voucher holders lived before the CMTO experiment

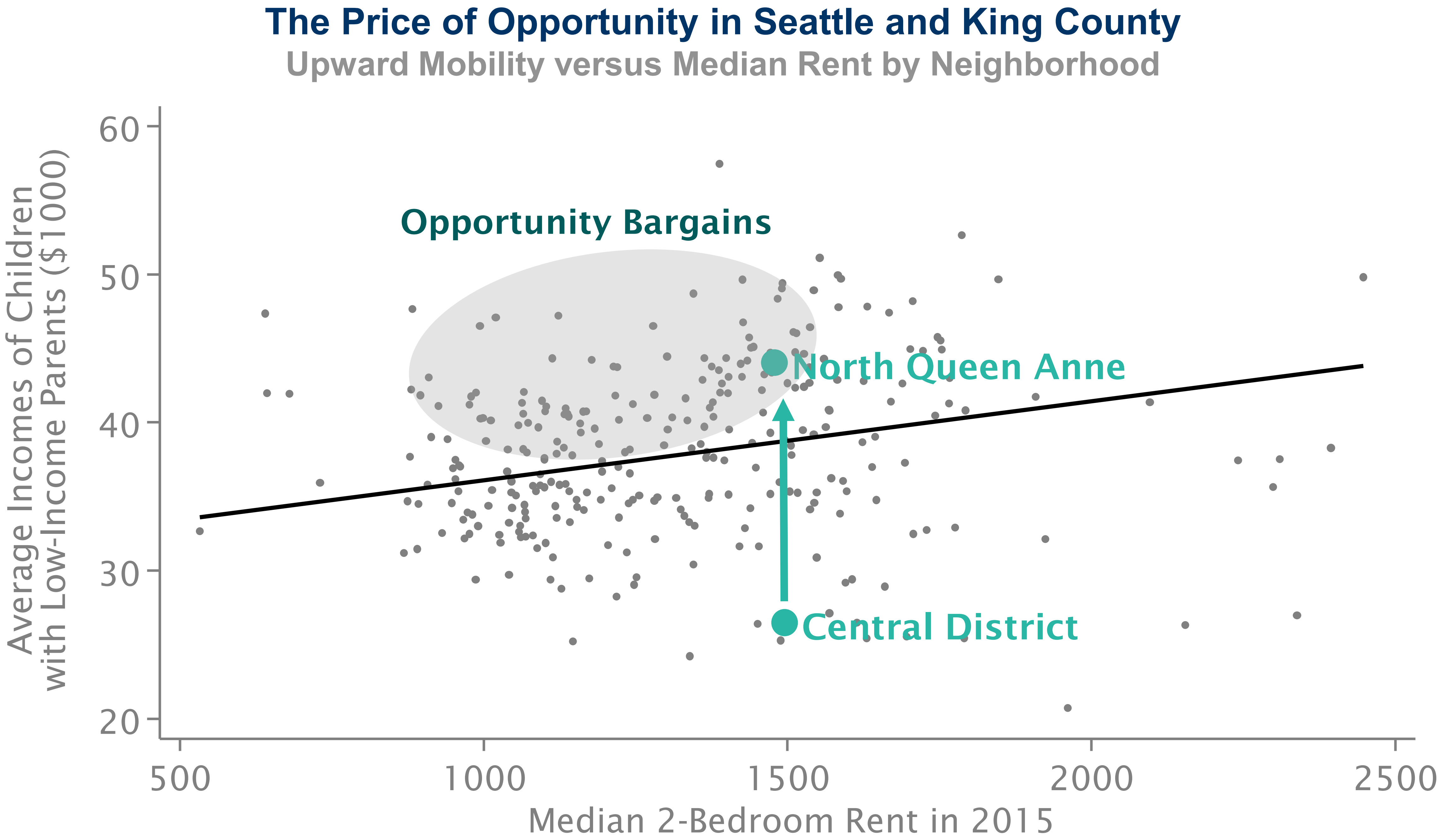
Percentile Rank in Adulthood

> 60 ($55k)

48 ($39k)

< 30 ($20k)


The Price of Opportunity in Seattle and King County
Upward Mobility versus Median Rent by Neighborhood
Average Incomes of Children with Low-Income Parents ($1000)
60
50
40
30
20
500
1000
1500
2000
2500
Median 2-Bedroom Rent in 2015


The Price of Opportunity in Seattle and King County
Upward Mobility versus Median Rent by Neighborhood
Opportunity Bargains
North Queen Anne
Central District
60
50
40
30
20
500
1000
1500
2000
2500
Average Incomes of Children
with Low-Income Parents ($1000)
Median 2-Bedroom Rent in 2015

Question: Why Don't Low-Income Families Move to Opportunity?

- Two classes of explanations:

  1. **Preferences**: families may prefer to stay in current neighborhoods because of other amenities (e.g., commute time, proximity to family)

  2. **Barriers**: families may be unable to find housing in high-opportunity areas because of lack of information, search frictions, or landlords' tastes

- If barriers are what is driving segregation, can we reduce them through changes in affordable housing policy?

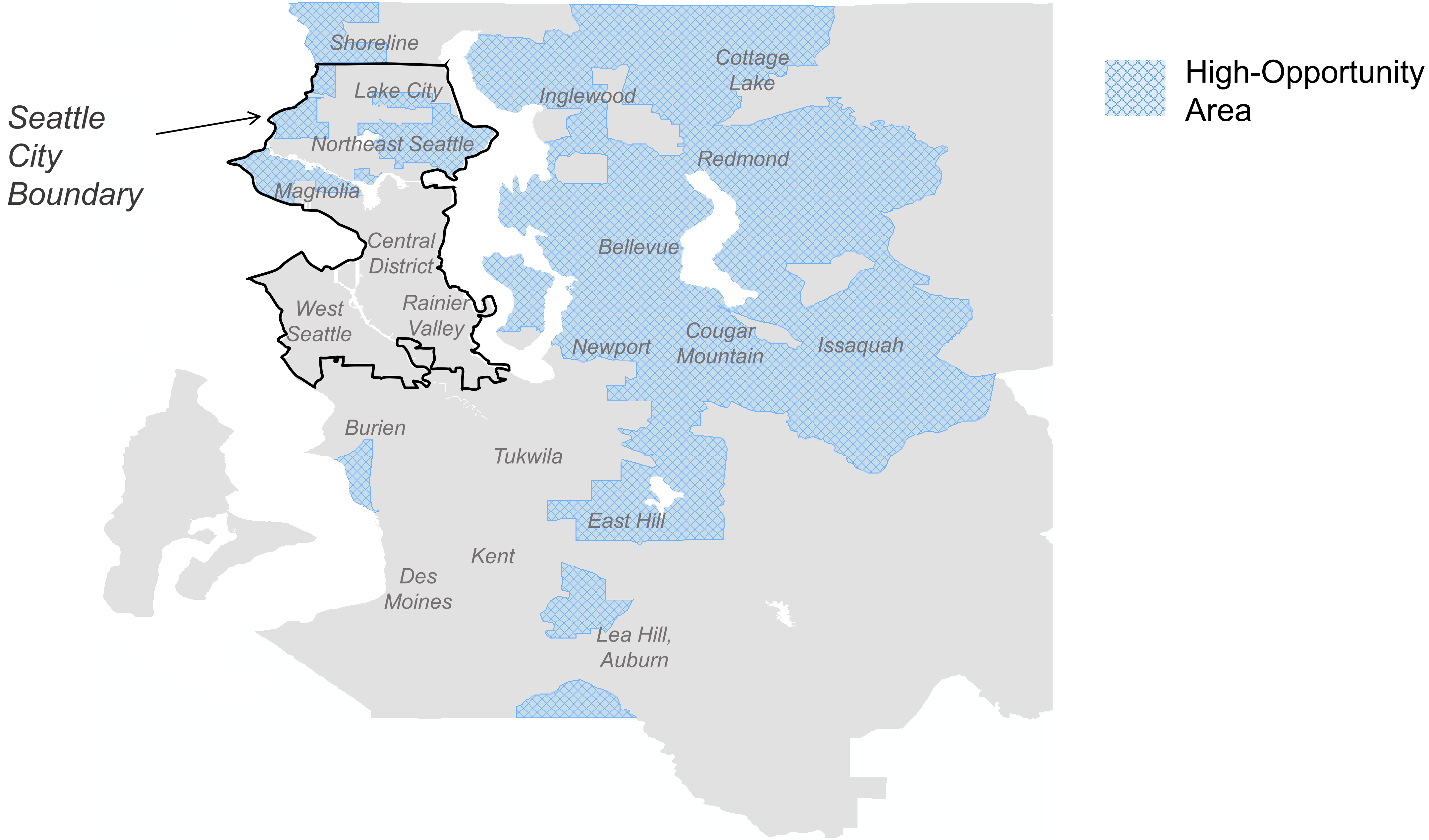
Creating Moves to Opportunity in Seattle and King County

Randomized trial to develop and test policy-scalable strategies to reduce barriers housing choice voucher recipients face in moving to high-opportunity areas in Seattle and King County

Definition of Opportunity Areas

- Intervention focuses on families with young children (1+ child below age 15)
- Therefore, use Opportunity Atlas to define “opportunity areas” as places where historically children from low income families have had the highest upward mobility
- Starting point: Census tracts in top third of distribution within Seattle (SHA) and King County (KCHA)
- Adjust definitions in collaboration with housing authorities to account for two issues:
  - Neighborhood change (using test score data to assess stability)
  - Creating contiguous areas

Designation of High-Opportunity Neighborhods



Treatment Interventions

CUSTOMIZED SEARCH ASSISTANCE

On average, non-profit staff spend **6.3 hours** with each household

DIRECT LANDLORD ENGAGEMENT

52% of rentals in high-opportunity areas made through links via non-profit staff

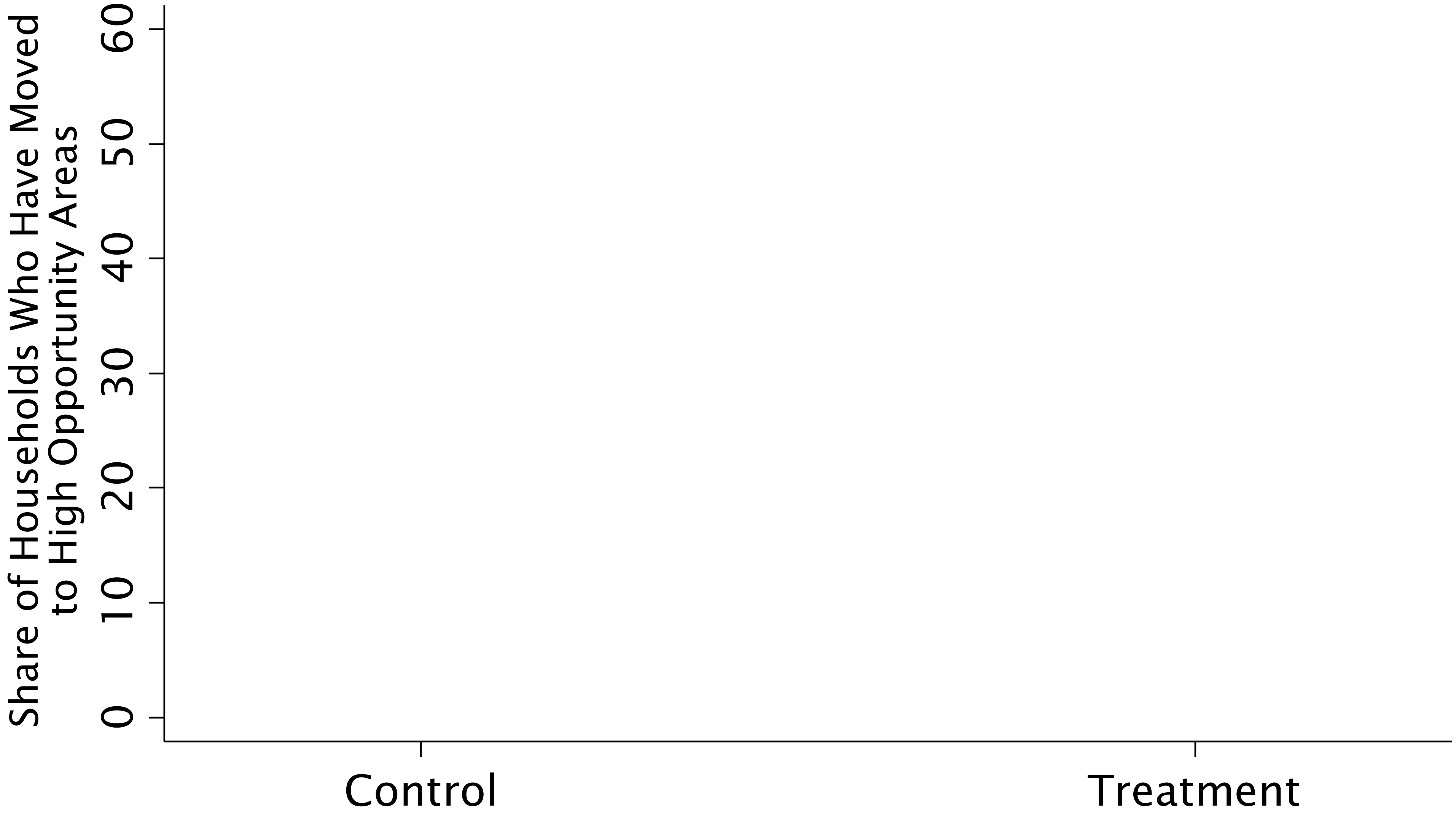
SHORT-TERM FINANCIAL ASSISTANCE

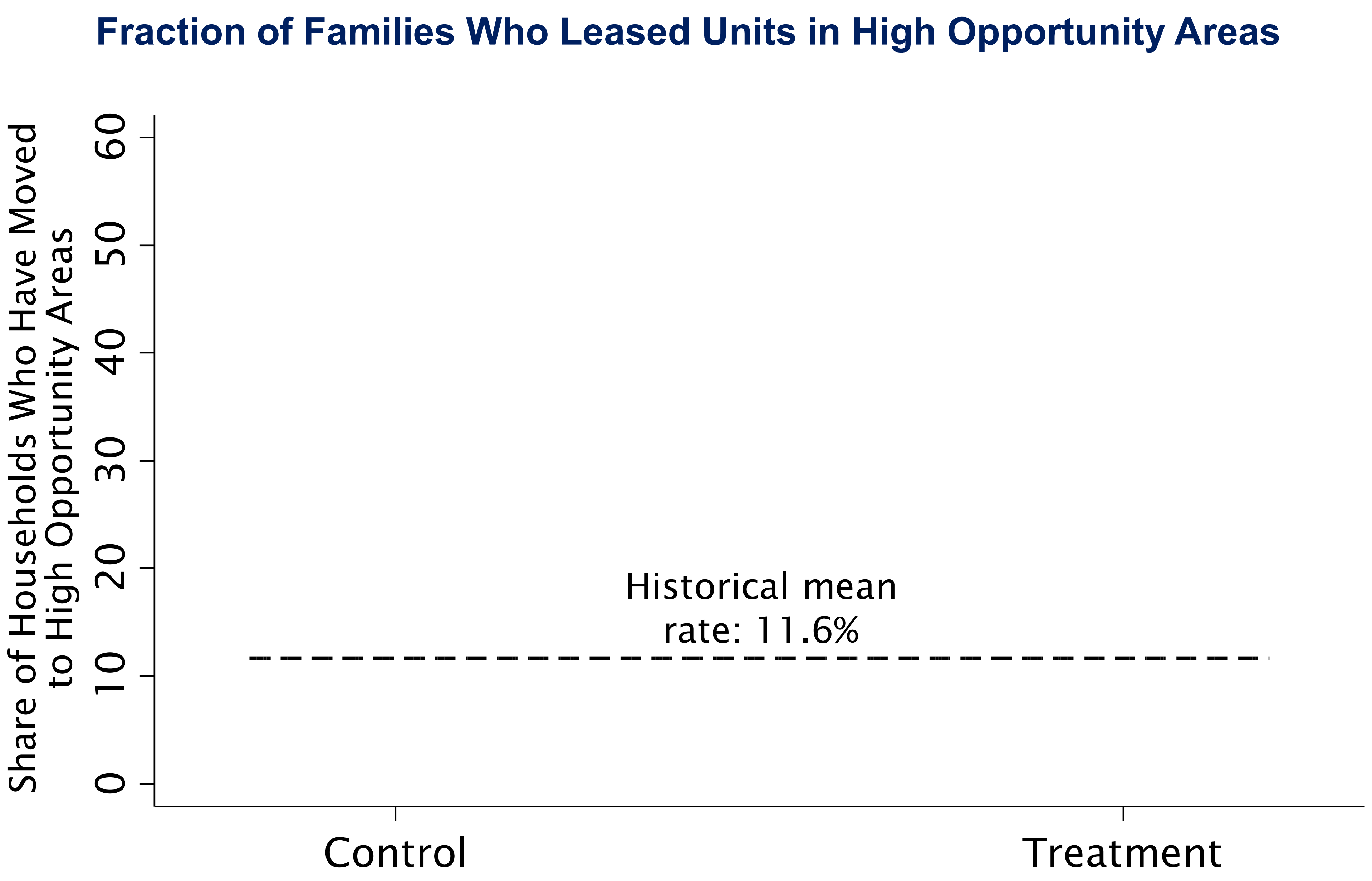
Average financial assistance of **$1,100** for security deposits, application fees, etc.

Program Cost: $2,600 per family issued a voucher
(2.2% of average voucher payments over 7 years)

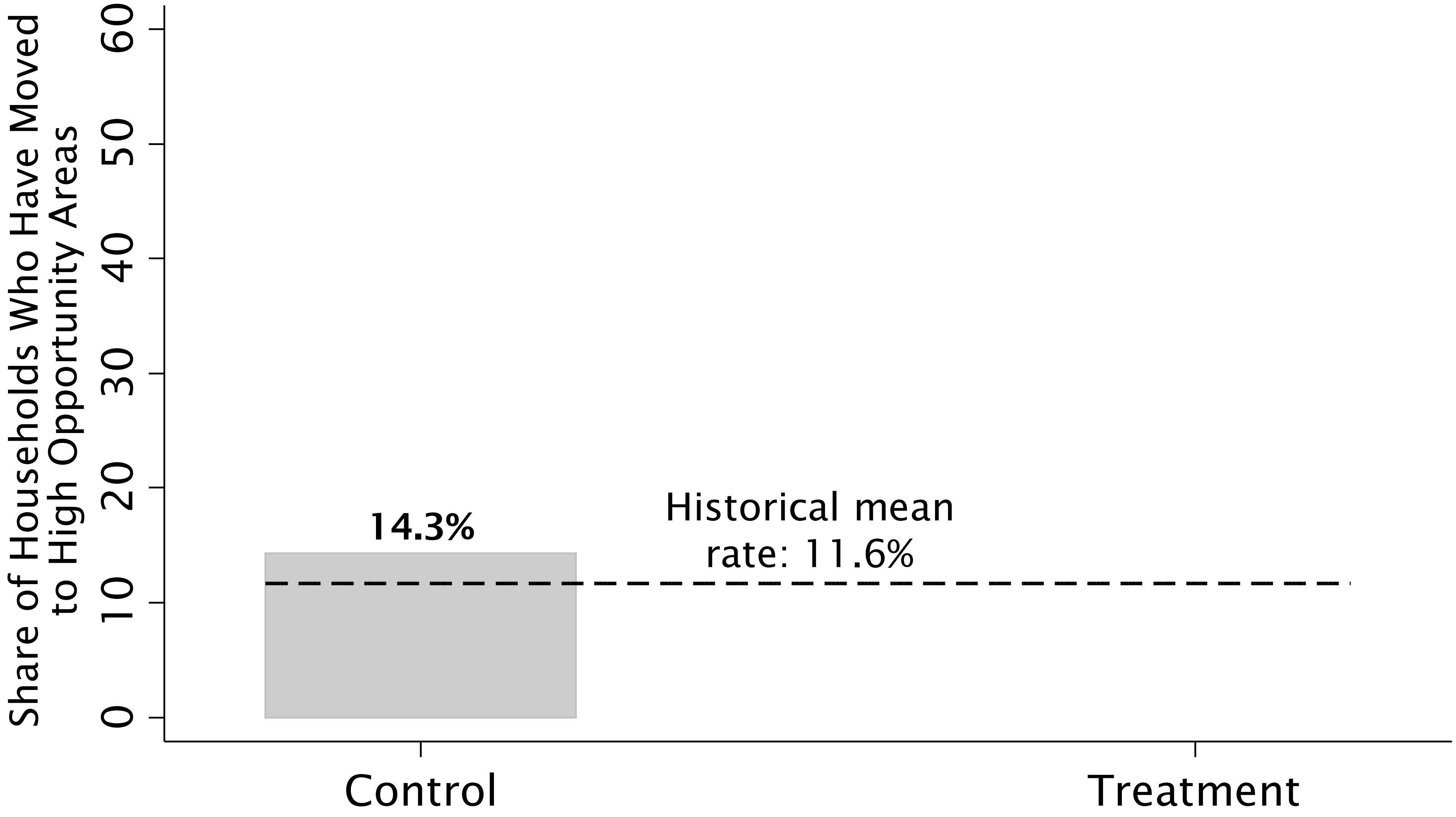
*Note: Families **not** required to move to high-opportunity areas*

Fraction of Families Who Leased Units in High Opportunity Areas

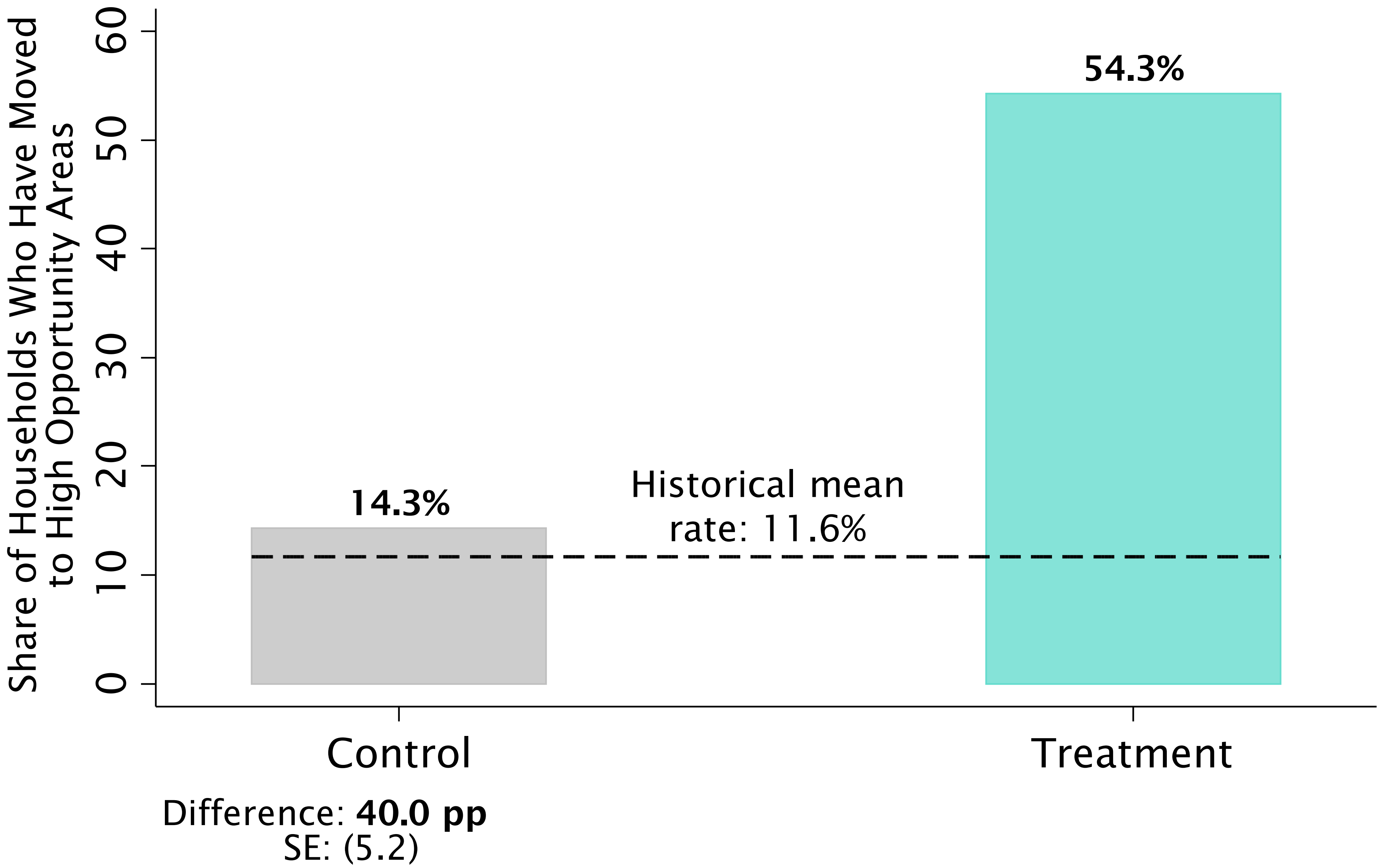



Fraction of Families Who Leased Units in High Opportunity Areas
Share of Households Who Have Moved to High Opportunity Areas
0
10
20
30
40
50
60
Historical mean rate: 11.6%
Control
Treatment

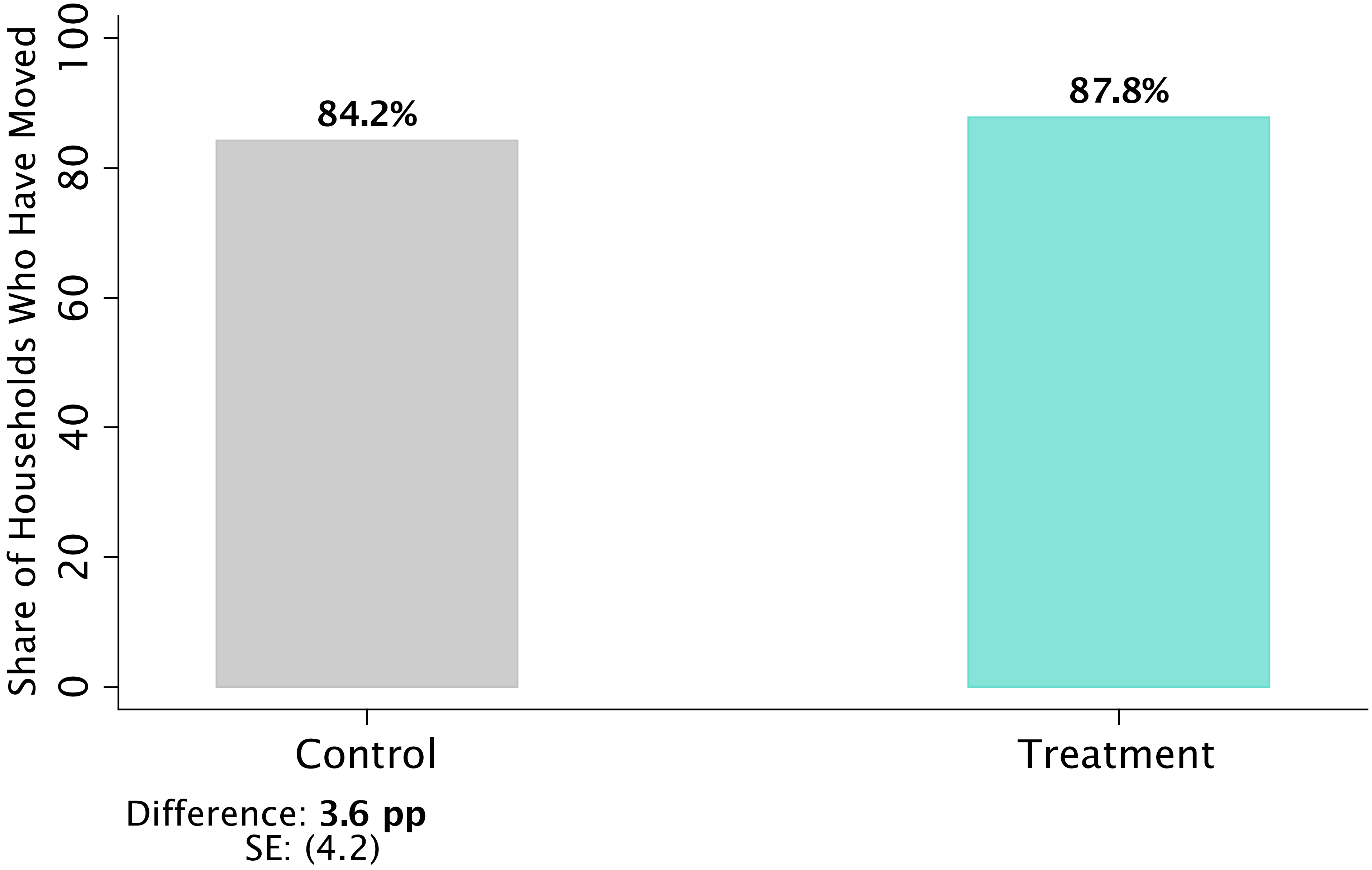
Fraction of Families Who Leased Units in High Opportunity Areas



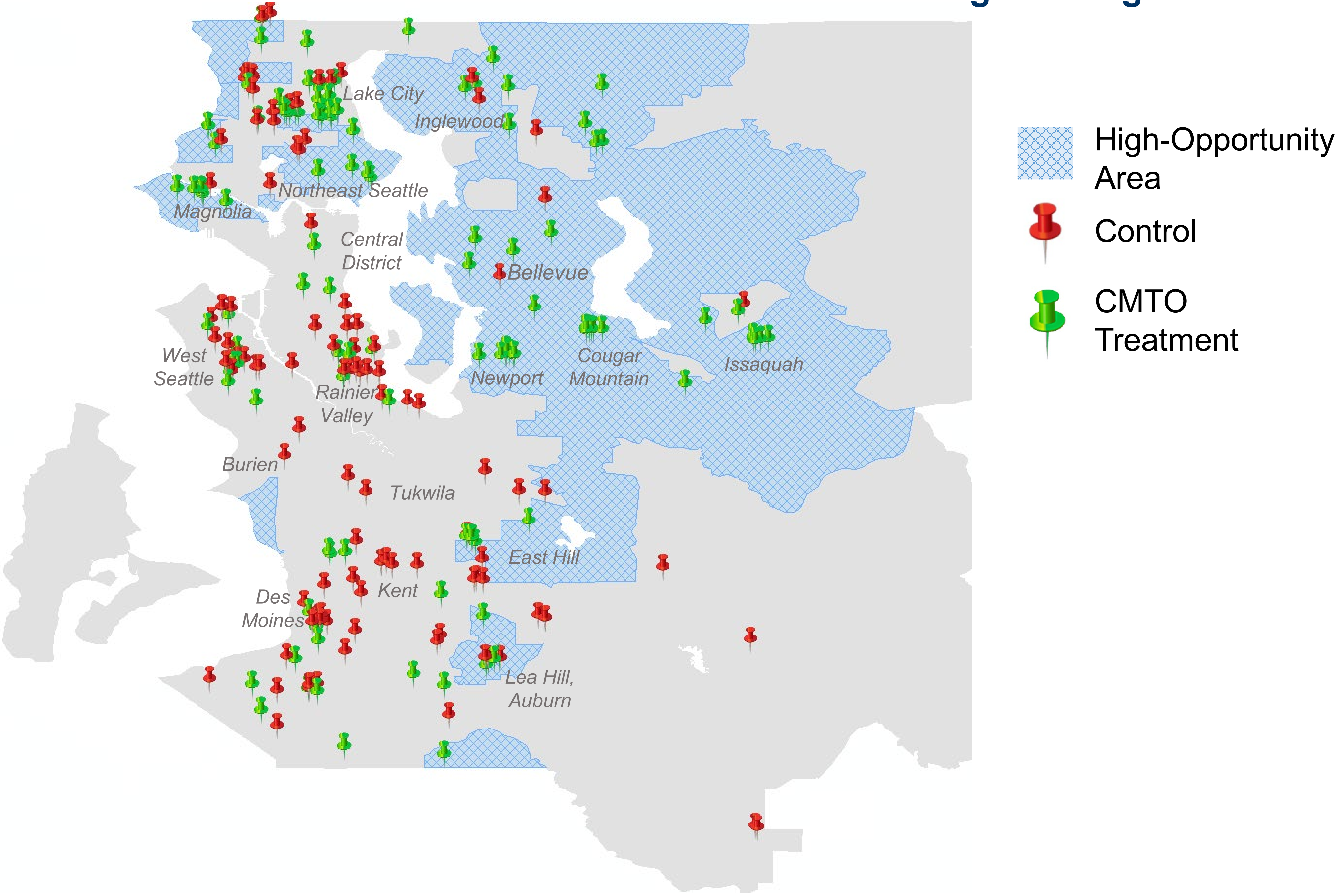
Fraction of Families Who Leased Units in High Opportunity Areas



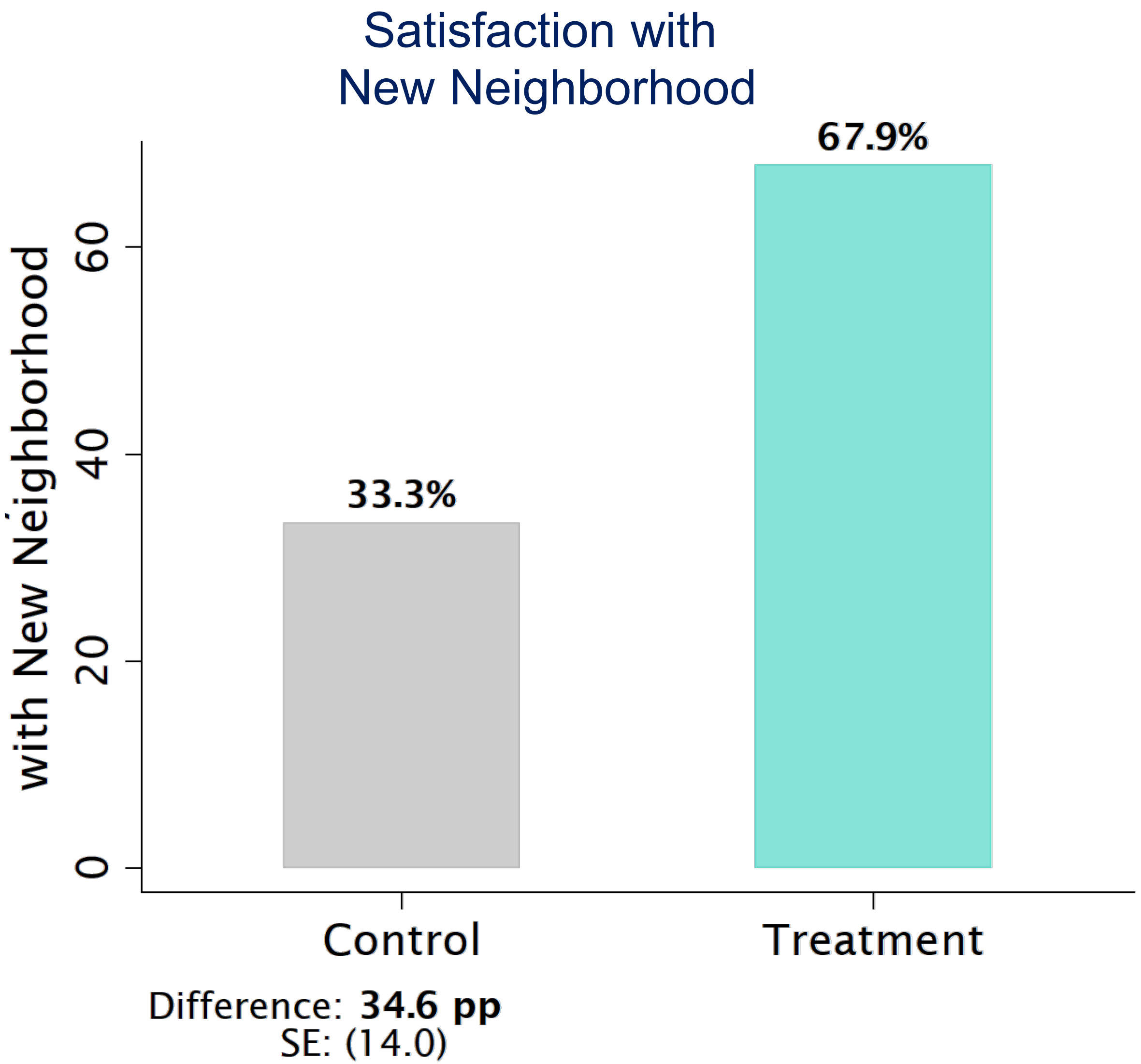
Fraction Who Has Leased Any Unit within Six Months of Voucher Issuance

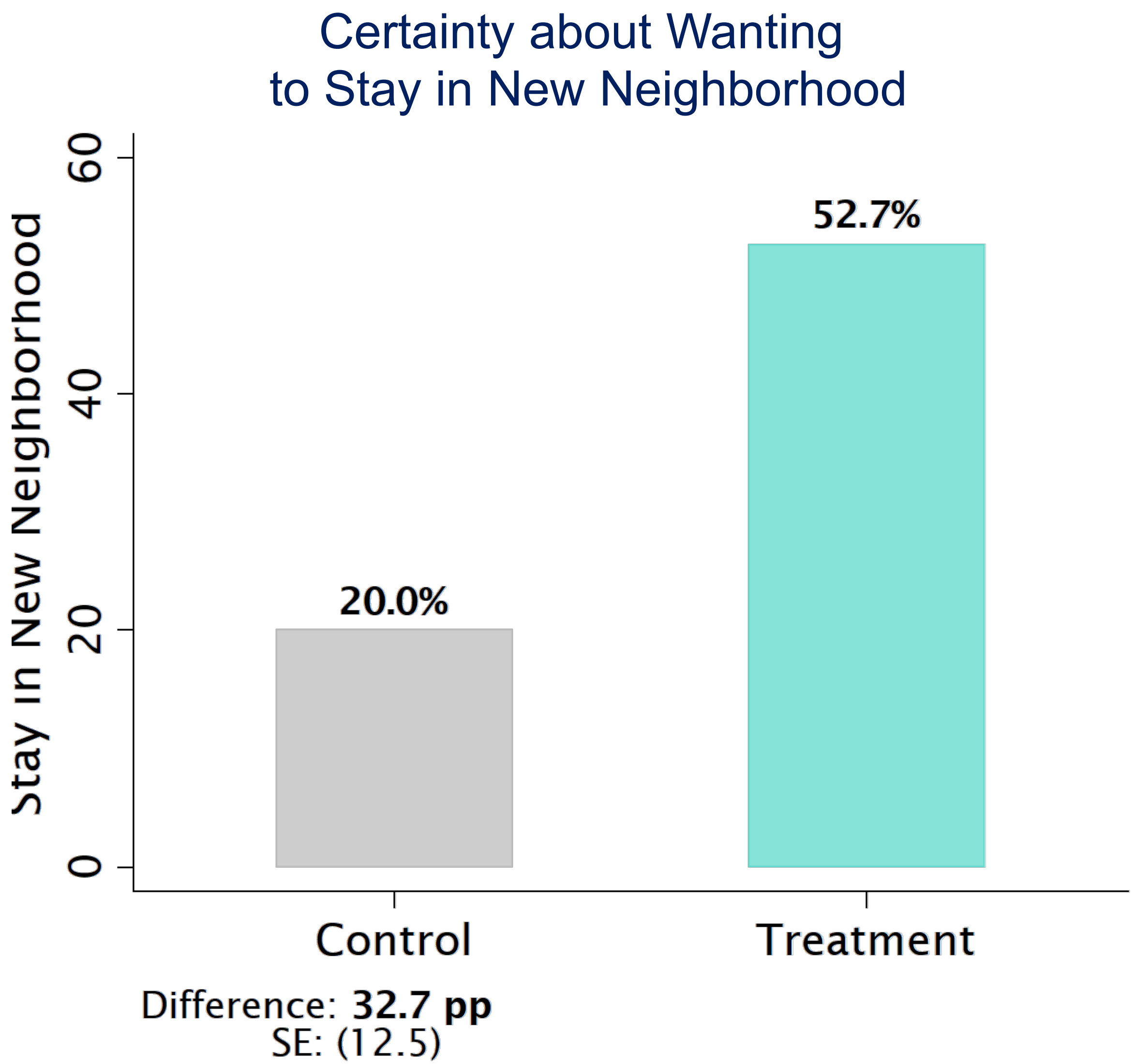


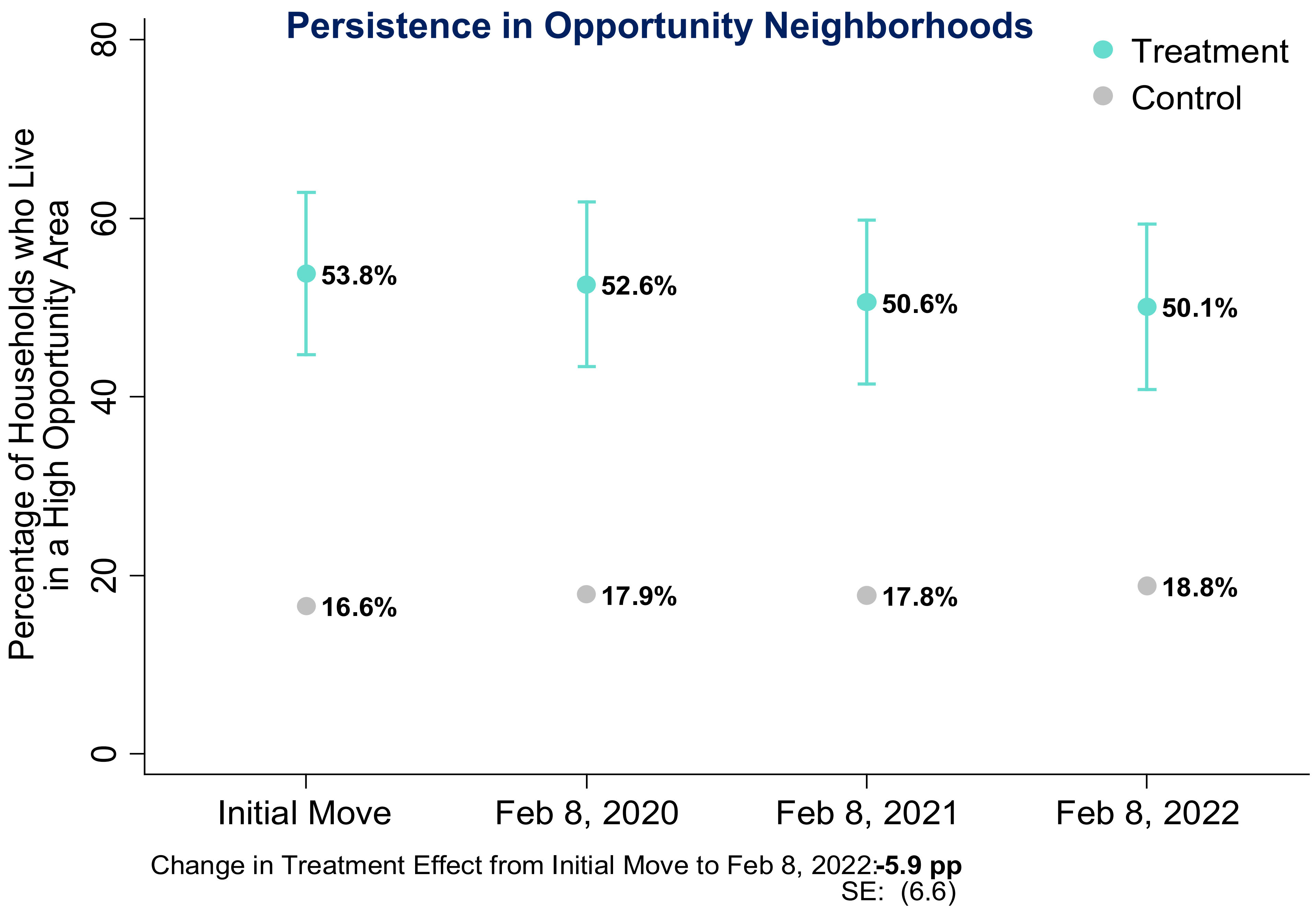
Destination Locations for Families that Leased Units Using Housing Vouchers



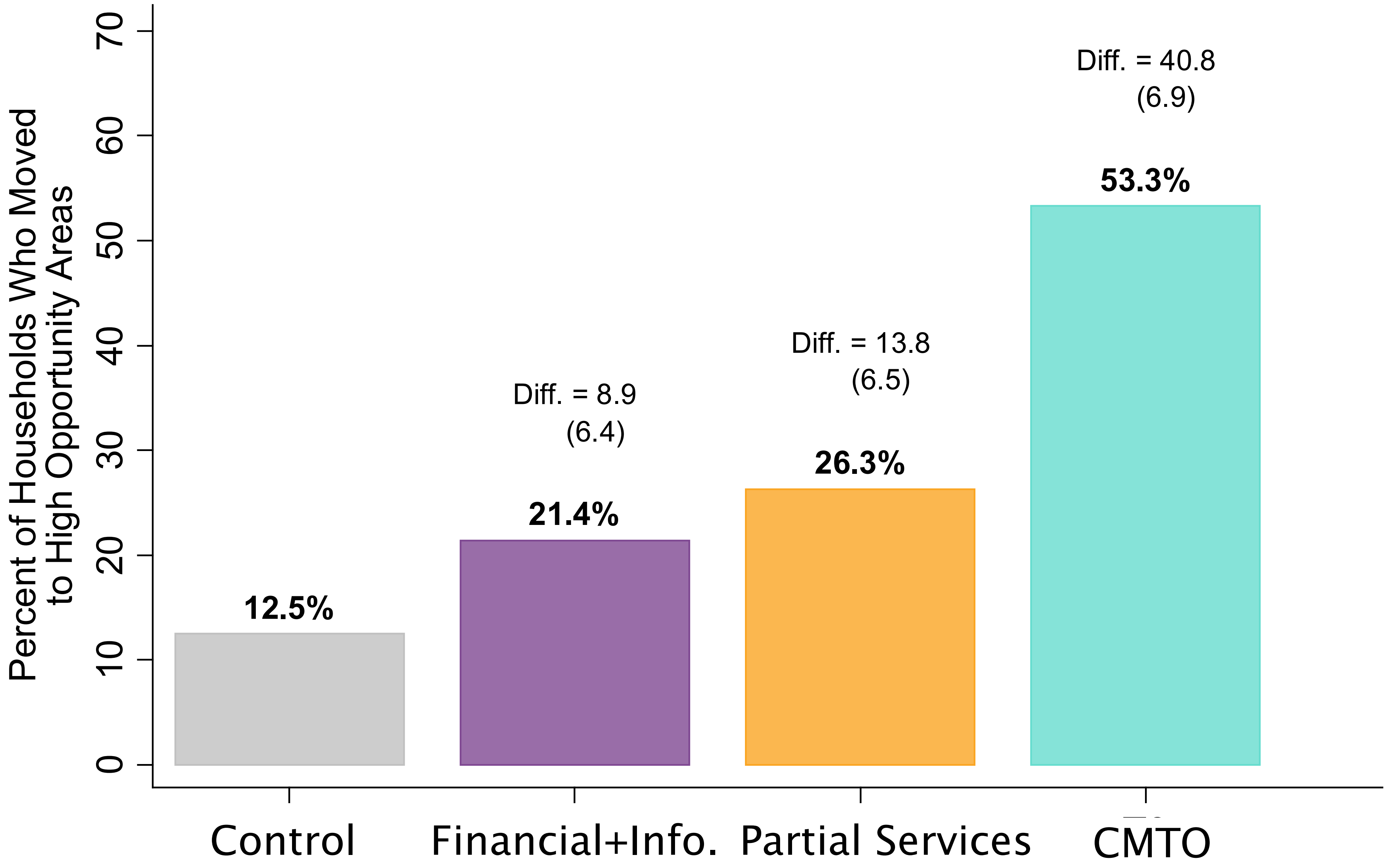
Satisfaction with New Neighborhoods
Based on Surveys Six Months Post-Move






Persistence in Opportunity Neighborhoods
Treatment
Control
Percentage of Households who Live in a High Opportunity Area
0
20
40
60
80
53.8%
52.6%
50.6%
50.1%
16.6%
17.9%
17.8%
18.8%
Initial Move
Feb 8, 2020
Feb 8, 2021
Feb 8, 2022
Change in Treatment Effect from Initial Move to Feb 8, 2022: -5.9 pp
SE: (6.6)

Phase 2 Treatment: Fraction who Move to Opportunity



Summary

- Dosage of navigator services affects moves to opportunity, not information and financial help
- Segregation Largely Driven by Barriers, not Preferences
  - Vouchers / income transfers do not lead to moves to opportunity
  - Argument for mobility services? How about place-based investments?
  - Similar frictions observed in other contexts such as health insurance, take up of govt benefits, etc?

Politics / Endogeneity of Policies / GE Effects

- Lastly, we’ve ignored the political history for where we got to today
- Some people don’t like low-income / minorities living nearby
- Are the “barriers” to moving to opportunity the result of an intentional historical policy response? What does this mean for future policy?

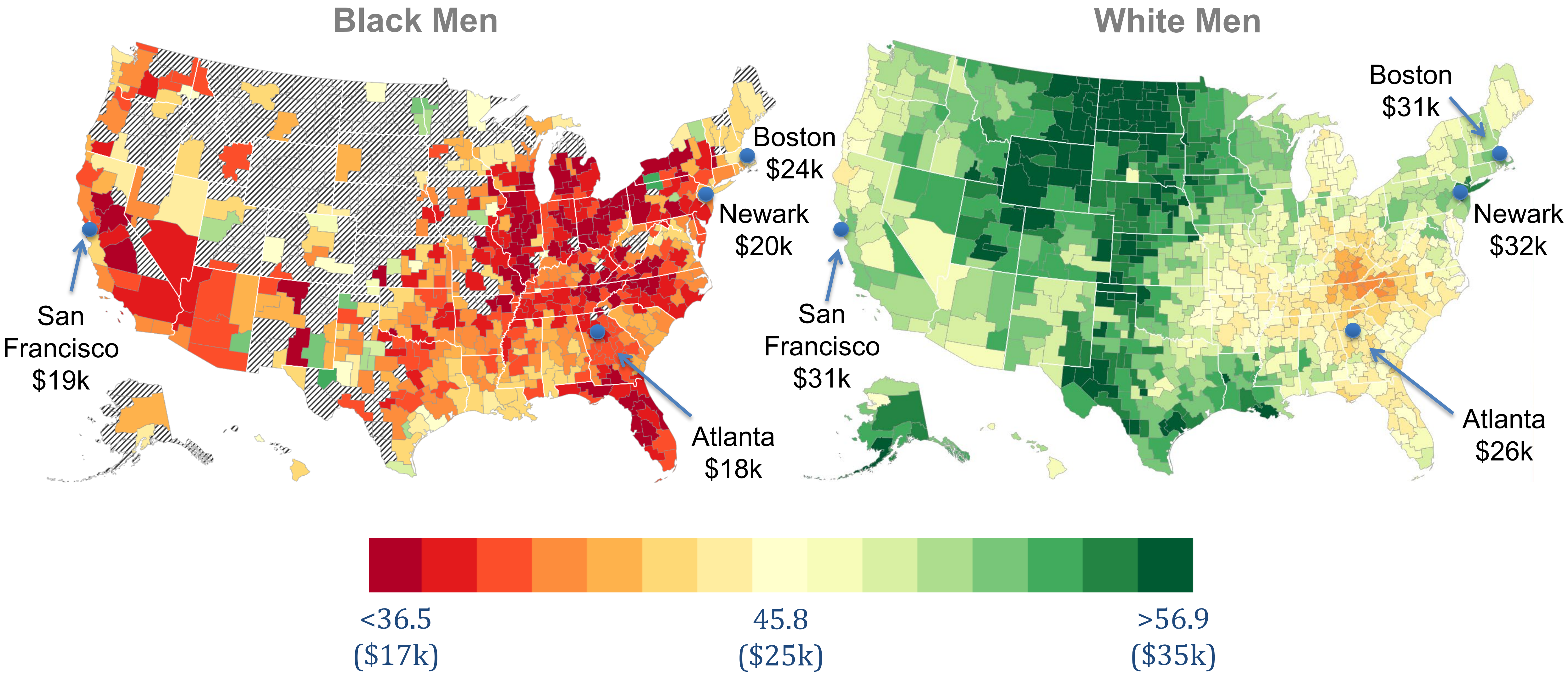
Derenoncourt (2021)

- Derenoncourt 2021 AER studies the causal effect of in-migration of black residents on the upward mobility of those destination locations

- Background: Large variation in upward mobility, but also large race gaps within every metro area in the US

Chetty Hendren Jones Porter 2020: The Geography of Upward Mobility by Race

Average Individual Income for Boys with Parents Earning $25,000 ($25^{th}$ percentile)



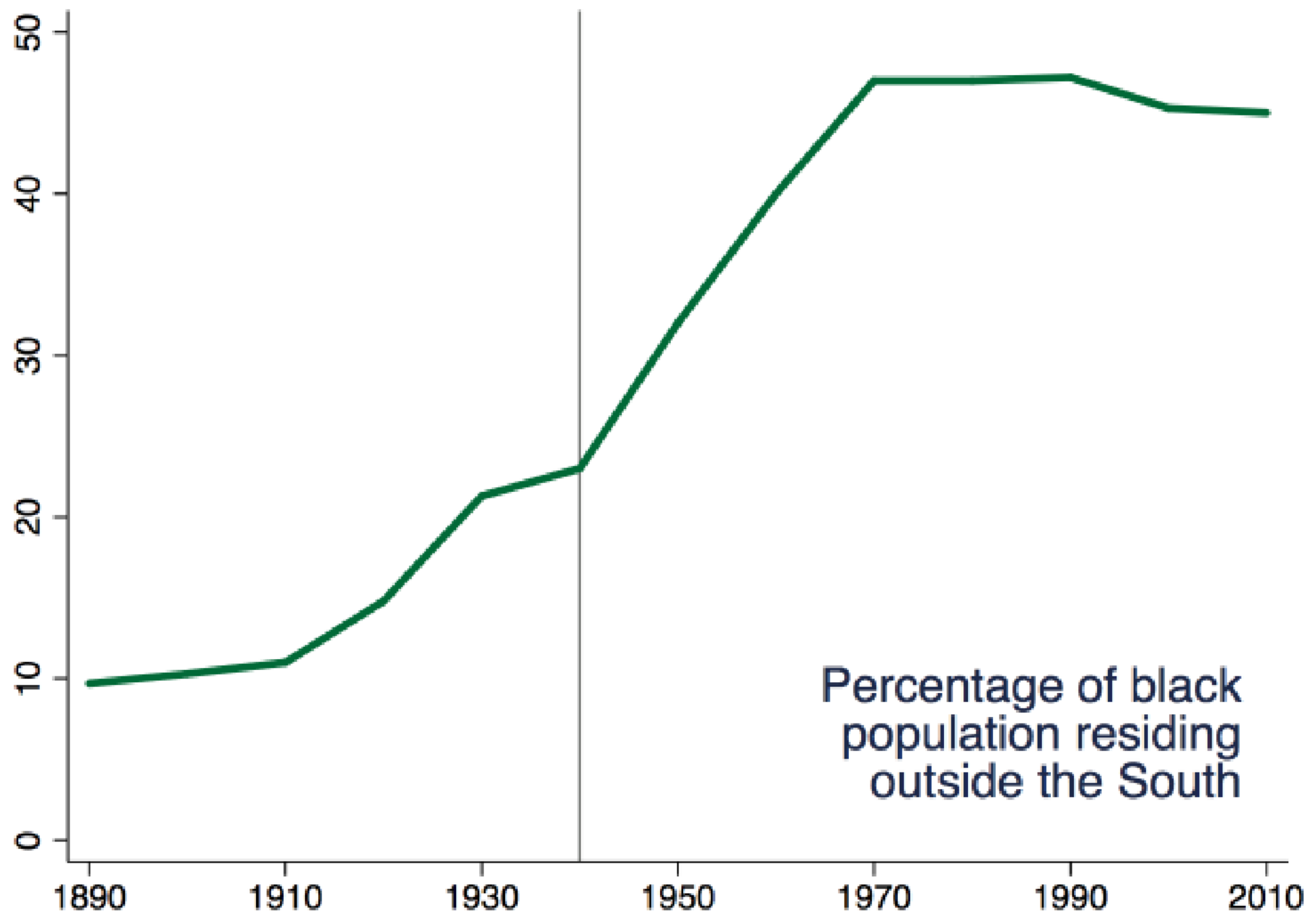
Note: Green = More Upward Mobility, Red = Less Upward Mobility; Grey = Insufficient Data

Endogenous Place Effects on the Race Gap

- Are these race gaps the result of policy responses within those places?
- If people move to a new place, is there an endogenous response in that destination that changes the upward mobility of the place?
- Derenoncourt (2021): Local policies and mobility outcomes are endogenous to historical shifts in racial composition generated through the Great Migration

Source: Derenoncourt (2021)

The Great Migration



Data from US Census.

Source: Derenoncourt (2021)

What Happened in the Destination Locations?

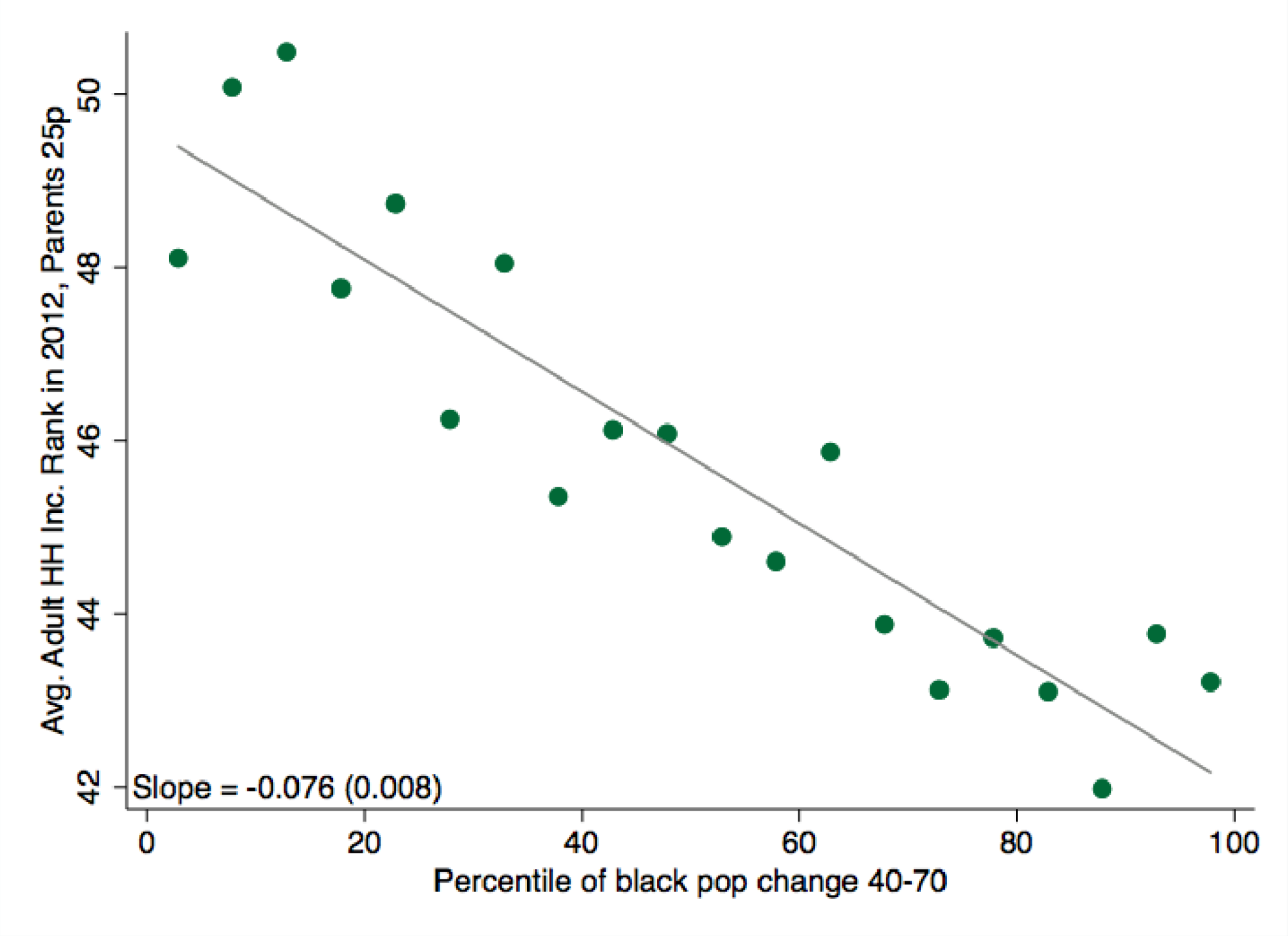
Reactions in the North

Riot against integrated federal housing project in Detroit, '42.

Source: LOC.

Source: Derenoncourt (2021)

Places with Greater Black Migration Have Lower Upward Mobility Today



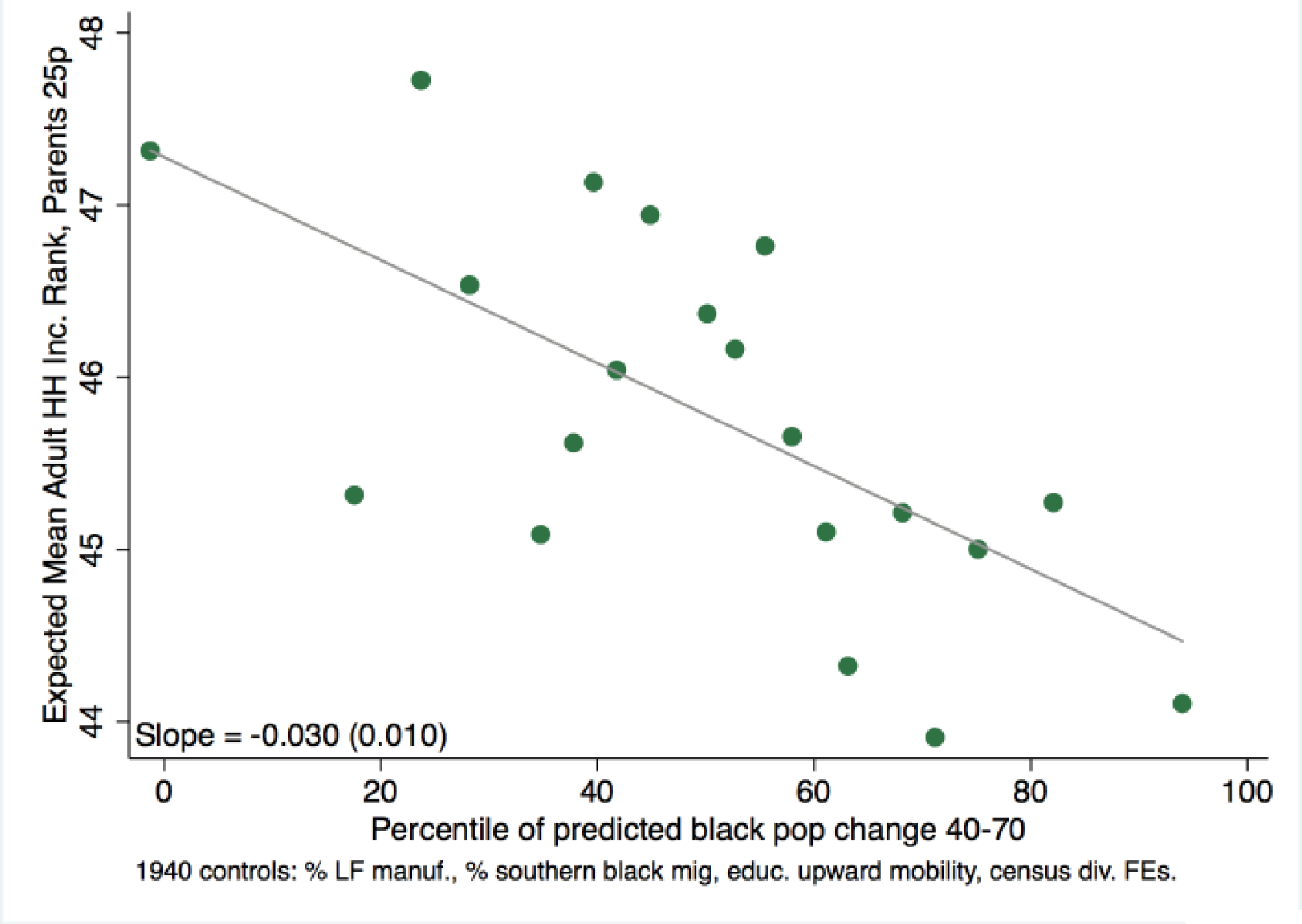
Source: Derenoncourt (2021)

Endogenous Place Effects on the Race Gap

- Need exogenous variation in inflow of black migrants
- Shift-share instrument:
  - Predict black population using interaction of migration shares from each origin to each destination multiplied by predicted migration from each origin

Source: Derenoncourt (2021)

Places with Higher Predicted In-Migration Have Lower Up. Mobility Today



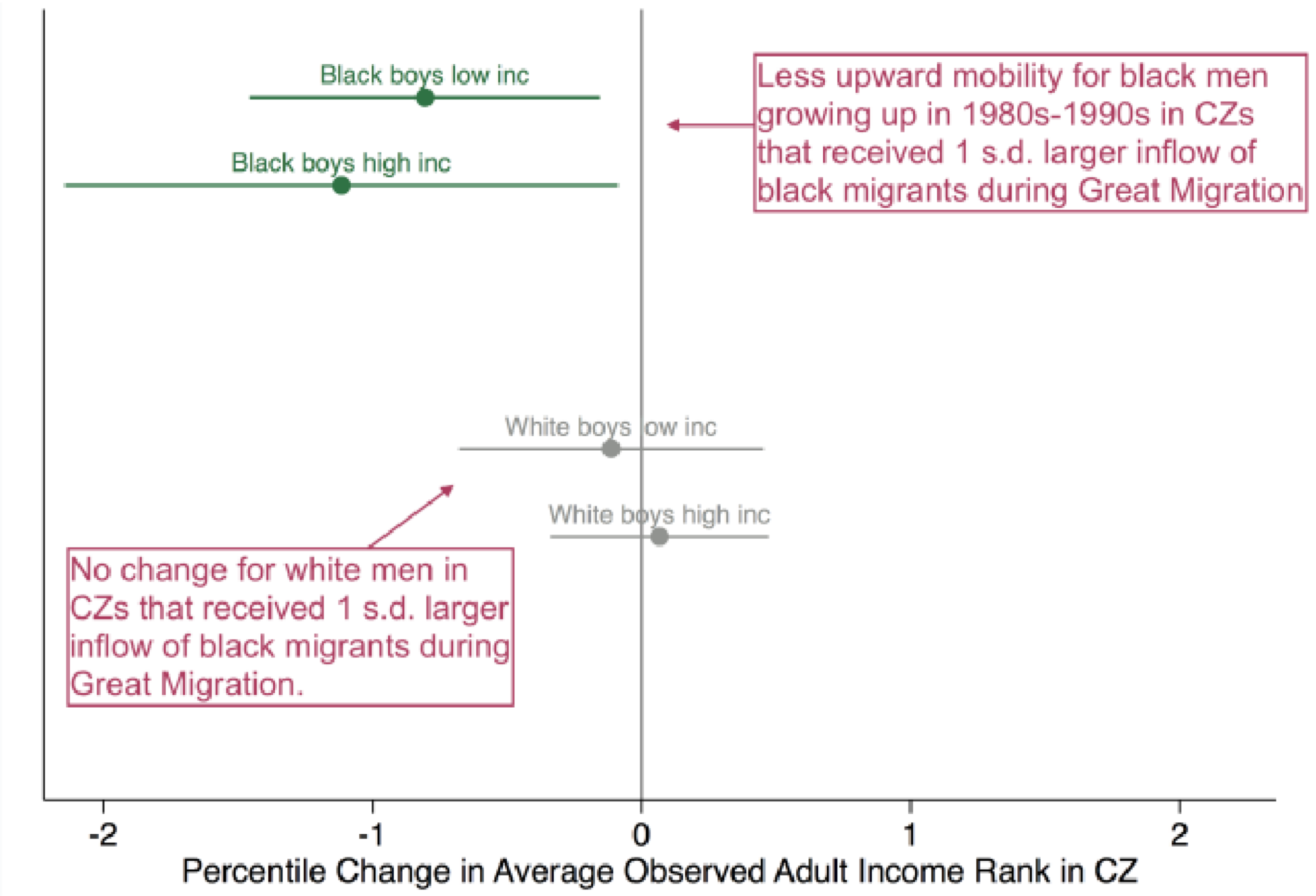
Source: Derenoncourt (2021)

Two Channels for Results

- Greater in-migration in the 1940-70s caused lower upward mobility today
- Broadly, there are two potential explanations:
  - **Causal effect on Selection:** In-migrants were persistently less upwardly mobile regardless of where they live
  - **Causal effect on the Causal Effect:** In-migration led to structural changes in the destination locations that caused the place to have lower mobility for everyone
- Two tests:
  - Race-specific effects
  - Effect on causal effect of place from Chetty and Hendren (2018B)

Source: Derenoncourt (2021)

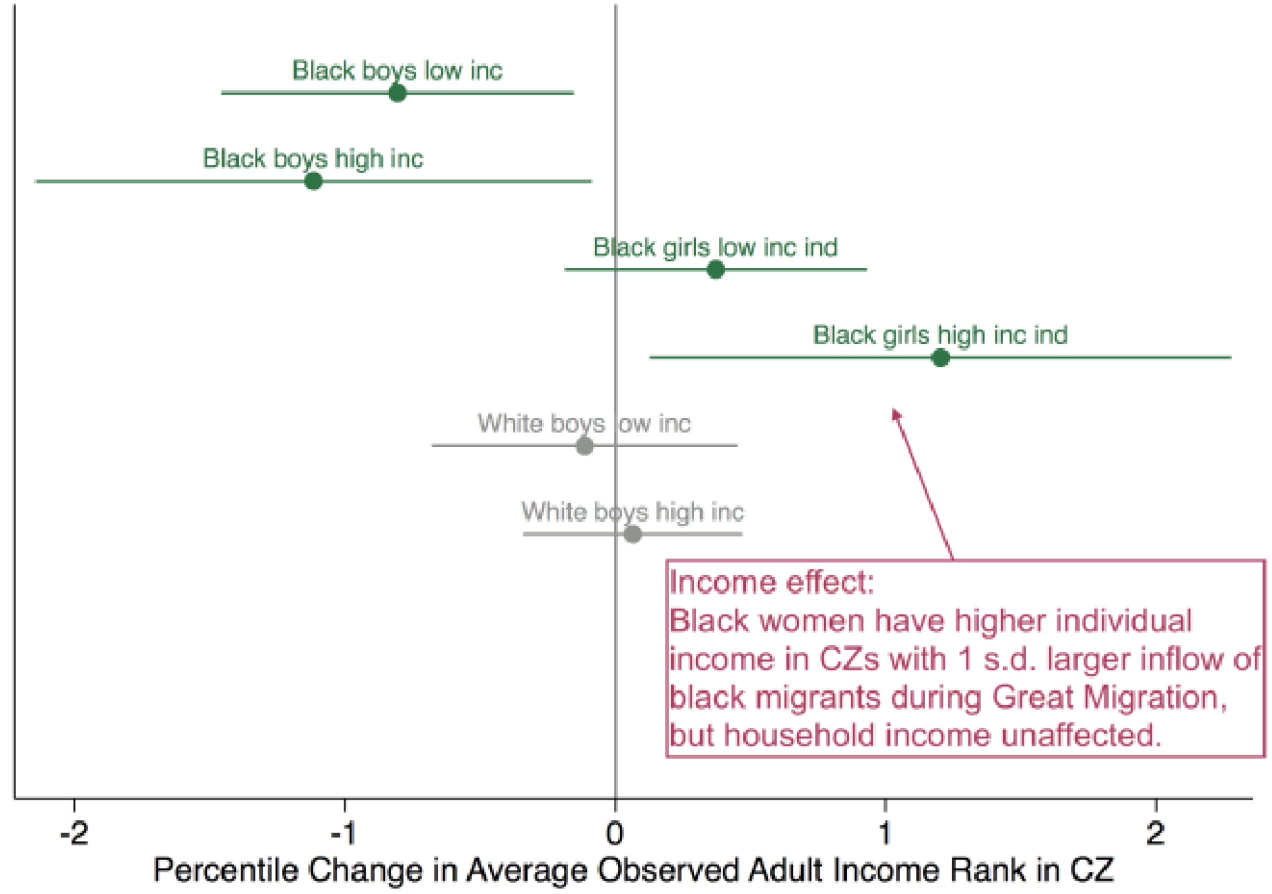
Inflow of Black Migration led to Lower Migration for Black Residents



Units of shock are 30 percentiles. Baseline controls included. Observations are northern commuting zones. *Data source*: Chetty-Hendren et al. (2018); IPUMS 1940 Census; City and County Data Books, 1944-1977; and Boustan (2016).

Source: Derenoncourt (2021)

Inflow of Black Migration led to Lower Migration for Black Residents

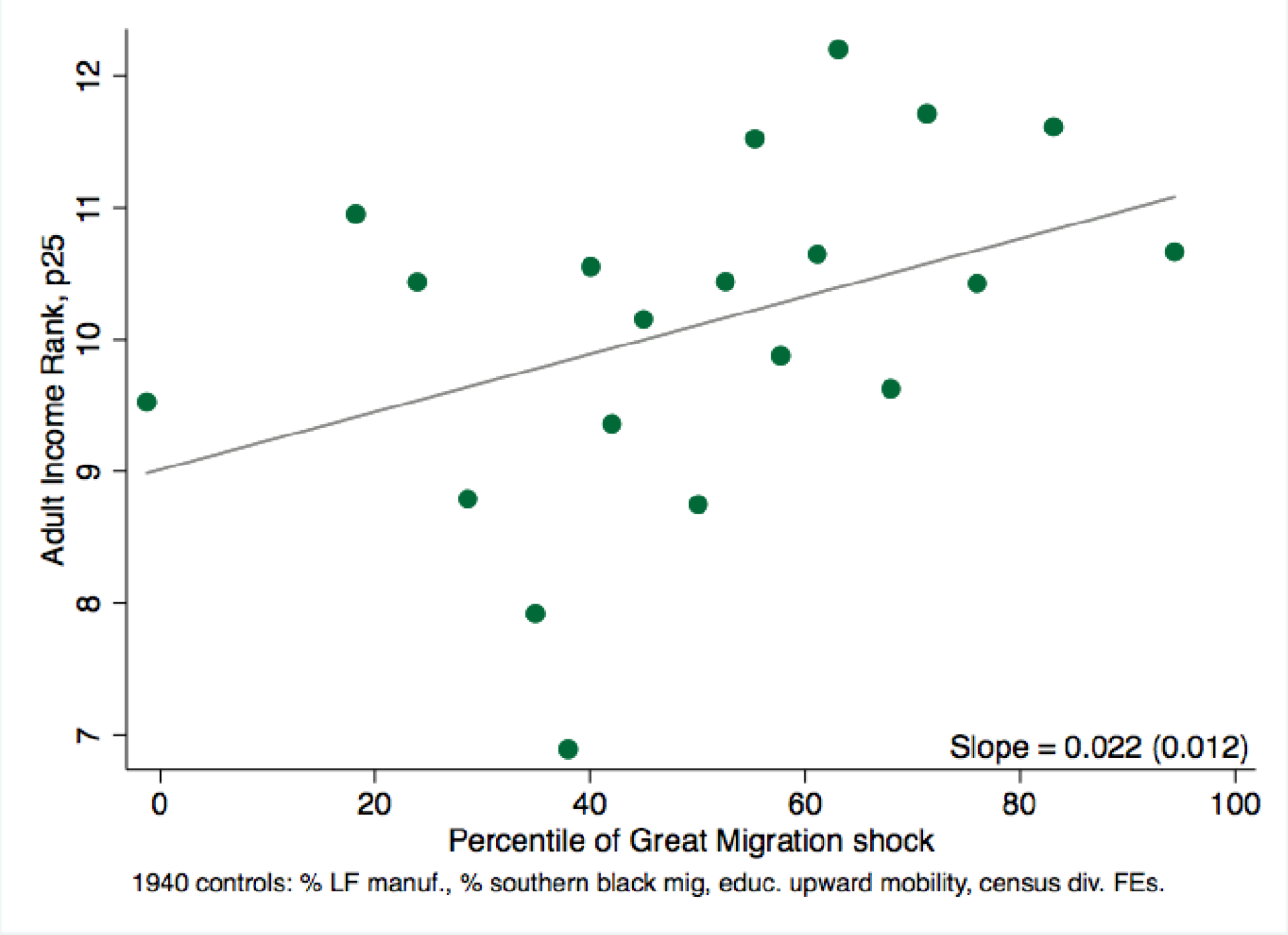


Units of shock are 30 percentiles. Baseline controls included. Observations are northern commuting zones. *Data source*: Chetty-Hendren et al. (2018); IPUMS 1940 Census; City and County Data Books, 1944-1977; and Boustan (2016).

Household income | Proxied HH income, by race

Source: Derenoncourt (2021)

Inflow of Black Migration Expanded Black-White Race Gap in Up. Mobility

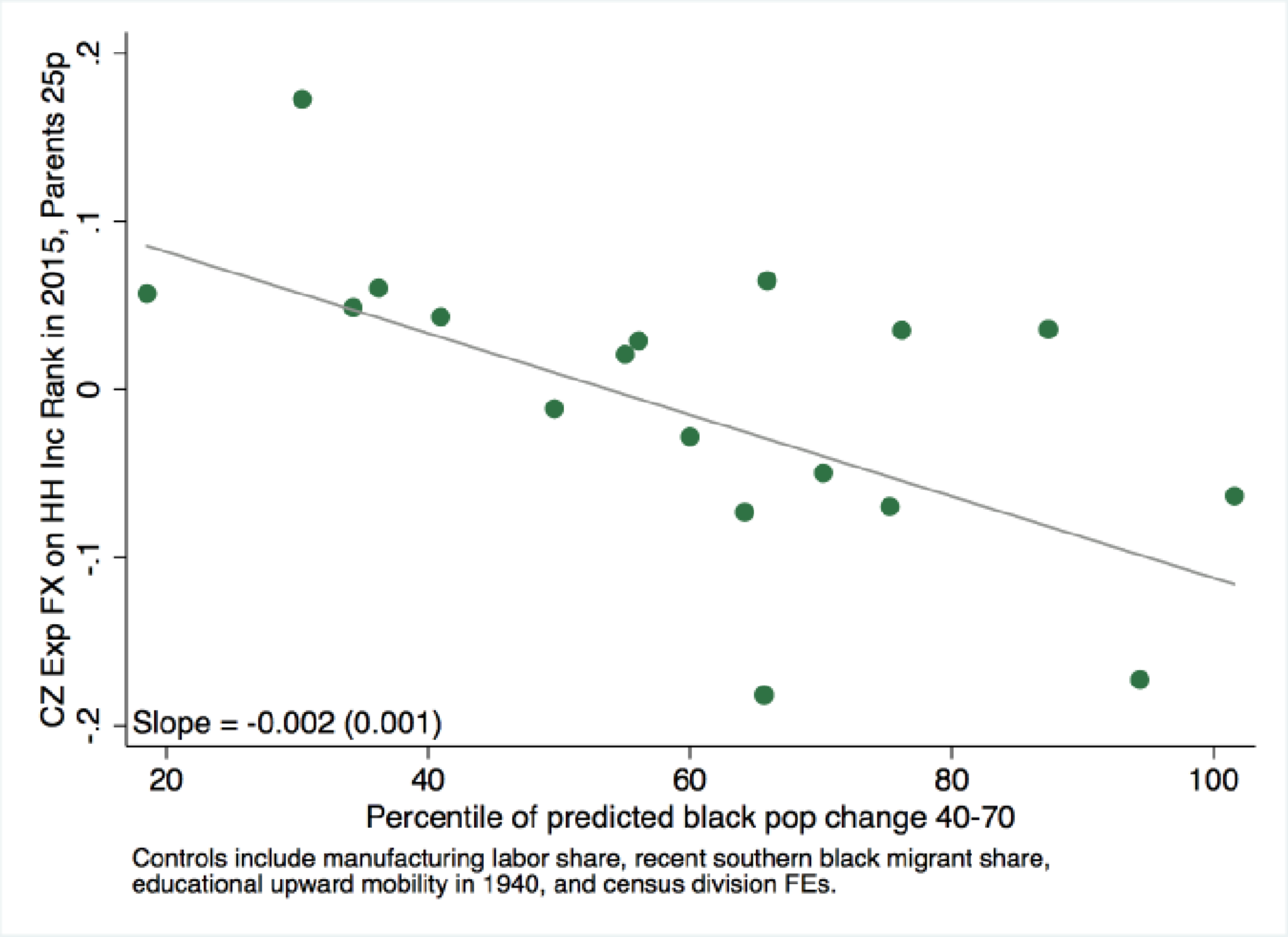


Observations are northern commuting zones. Data: Chetty, Hendren, Jones, and Porter (2018); IPUMS 1940 Census; CCDB; and Boustan (2016).

Back

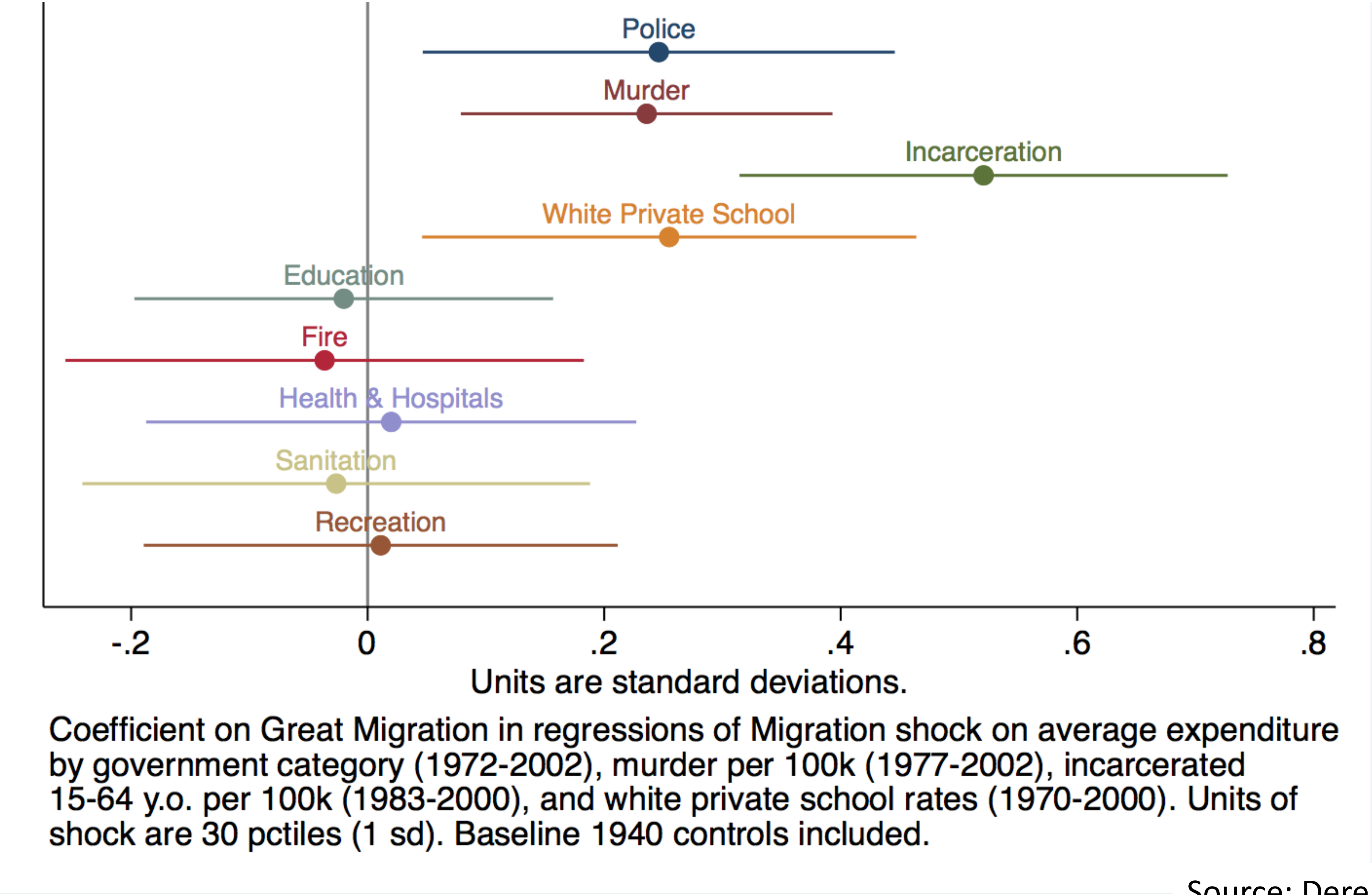
Source: Derenoncourt (2021)

Inflow of Black Migration led to Lower Causal Exposure Effects from Chetty and Hendren (2018)



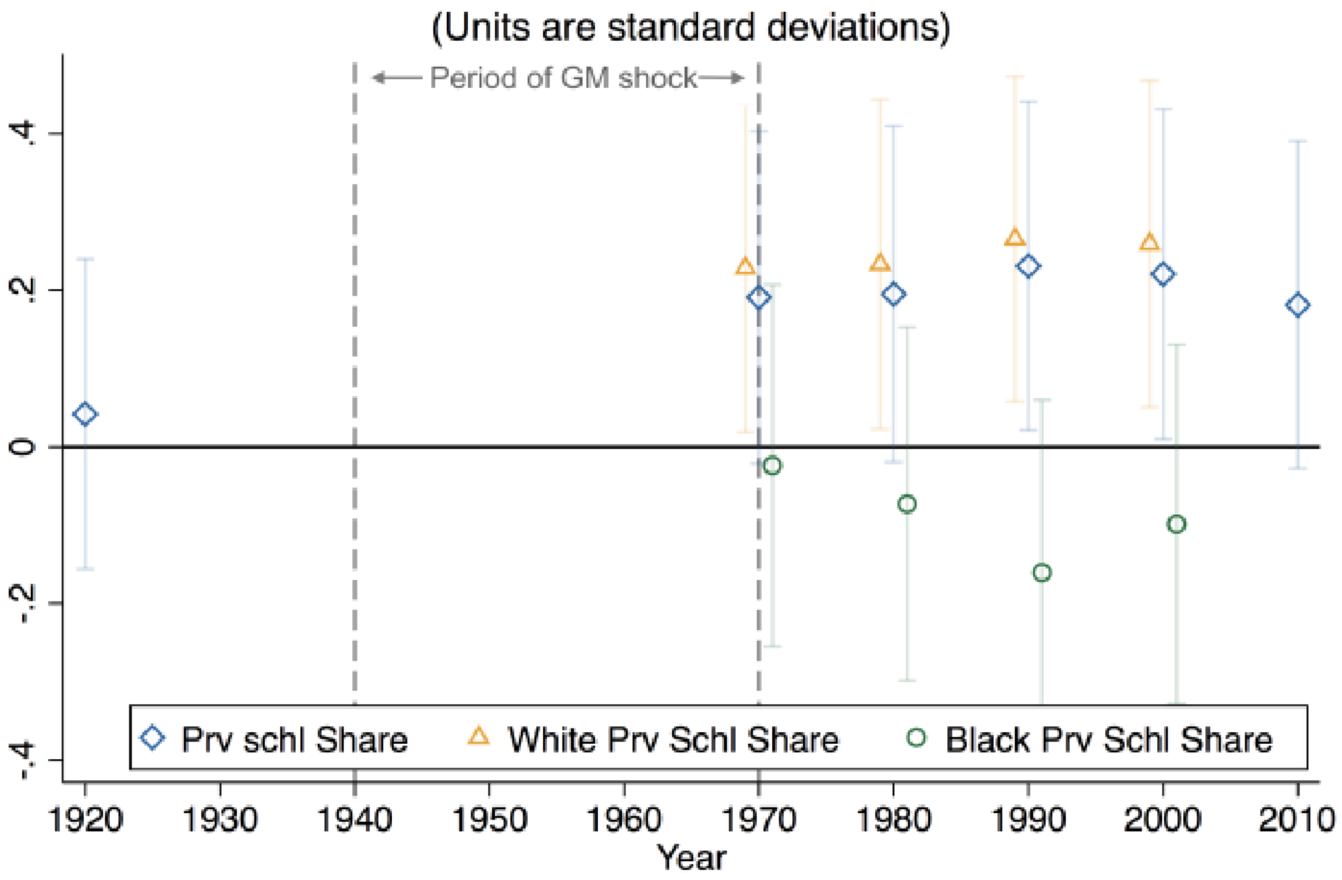
Source: Derenoncourt (2021)

Impact on Local Government Spending



Source: Derenoncourt (2021)

Impact on Private School Enrollment

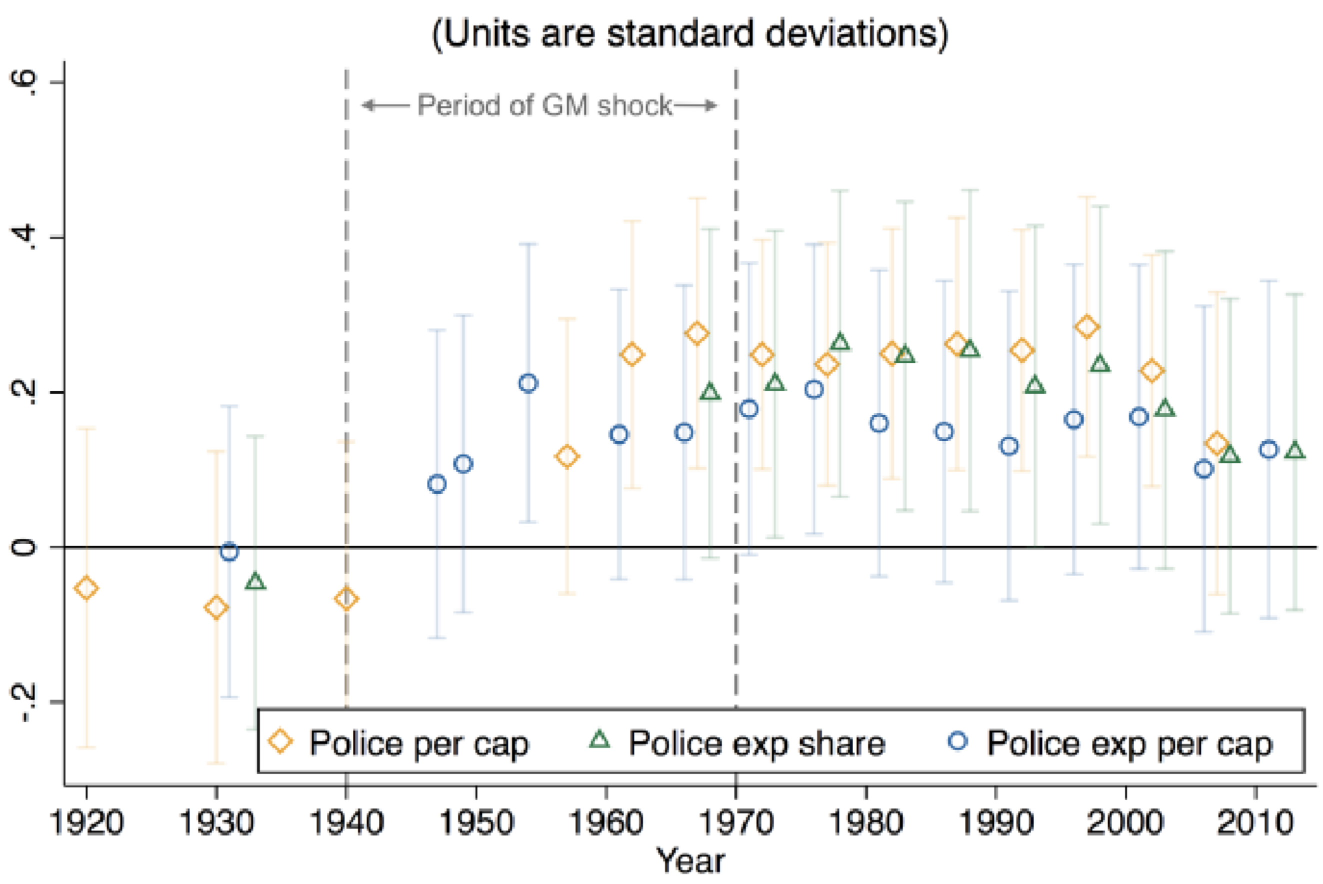


Reduced form coefficients of mechanism on Great Migration shock, estimated separately each year.

Units of shock are 30 percentiles. *Data Source*: PF-NBHDS database for CZs, 1920-2015.

Source: Derenoncourt (2021)

Impact on Police Expenditure

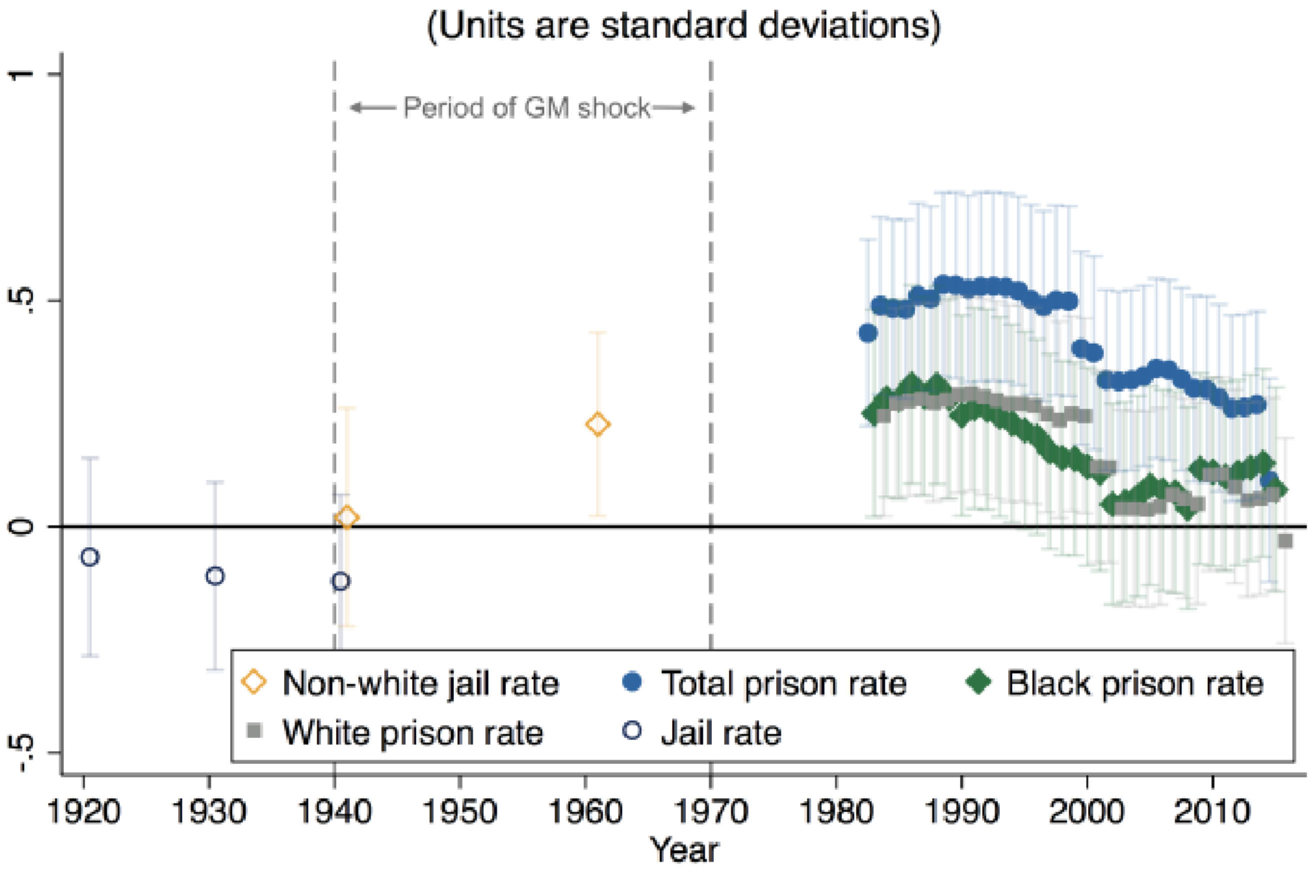


Reduced form coefficients of mechanism on Great Migration shock, estimated separately each year.

Units of shock are 30 percentiles. *Data Source*: PF-NBHDS, 1920-2015. ▸ Fire

Source: Derenoncourt (2021)

Impact on Incarceration Rates



Reduced form coefficients of mechanism on Great Migration shock, estimated separately each year.

Units of shock are 30 percentiles. *Data Source*: PF-NBHDS, 1920-2015.

Source: Derenoncourt (2021)

Conclusion

- Places have causal effects on children's long-term outcomes
  - Also evidence place has causal effects on health outcomes

- Rationale for policy intervention rests on place being different from other consumption goods
  - Evidence of significant barriers in choosing where to live
  - And endogenous policy responses in destination locations

- Areas for future work:
  - Welfare impacts of place-based investments (as opposed to choice-based policies)
  - Relative welfare impact of place-based vs. person-based policies
  - Endogenous policy responses / political economy of place and location choices
  - Implications for federal vs. local policymaking / fiscal federalism

Appendix: Causal Fixed Effects and Optimal Shrinkage

- What neighborhoods have the highest causal effect on children's outcomes?
- Note the observed variation across places contains both sorting and causal components
  - 2/3 may be causal, but 1/3 is still sorting

Objectives:

- Can we construct unbiased estimates of the true causal effect?
- Can we construct optimal forecasts of the place with the highest causal effect?
- Key question: Why are these objectives different?

Causal Effects of Each County

- Chetty and Hendren (2018b) 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

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

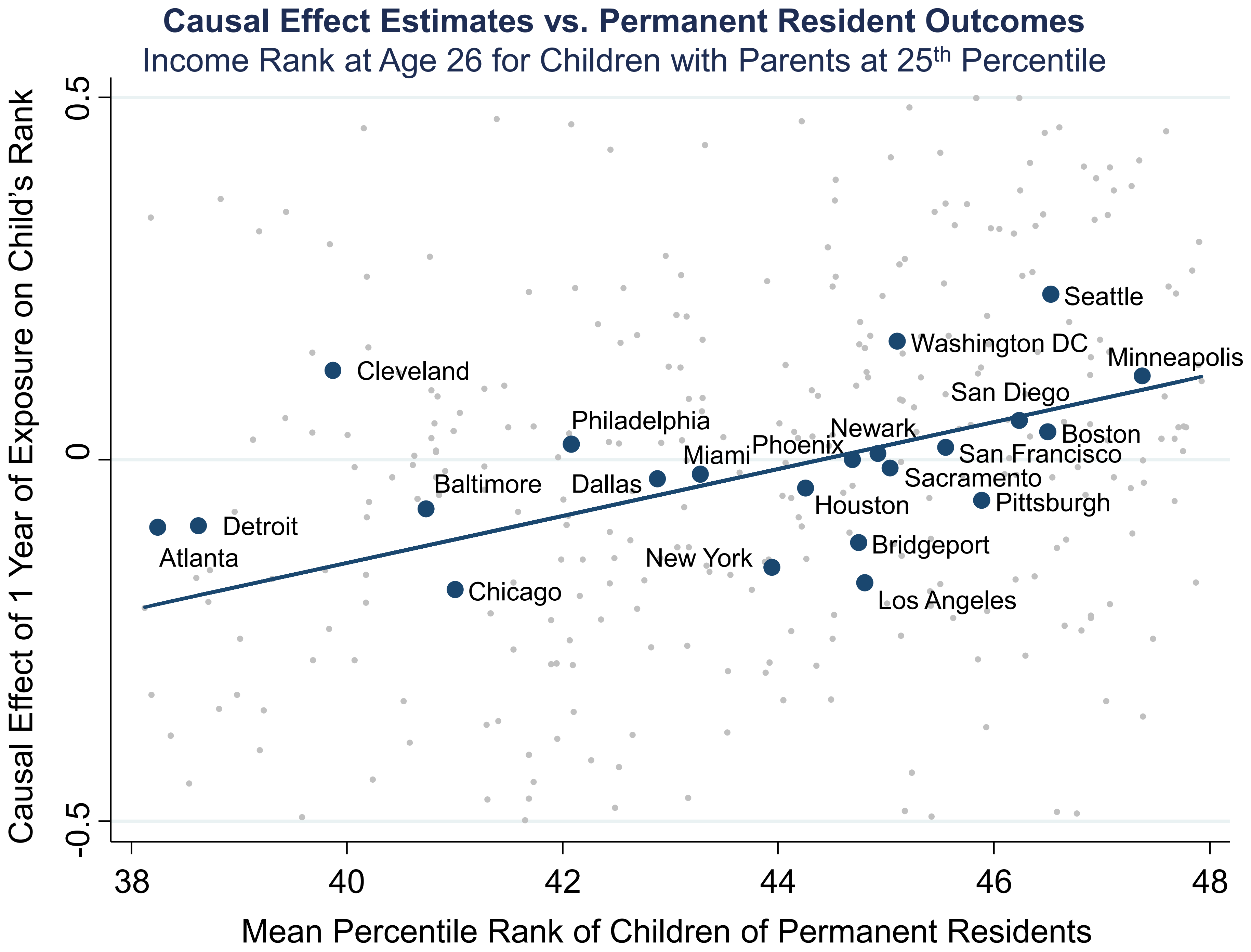
$$y_i = \underbrace{(T_c - m)}_{\text{Exposure}} \left[\underbrace{\mu_d 1\left\{d\left(i\right) = d\right\}}_{\text{Dest. FE}} - \underbrace{\mu_o 1\left\{o\left(i\right) = o\right\}}_{\text{Orig. FE.}} \right] + \underbrace{\alpha_{odps}}_{\text{orig x Dest FE}} + \eta_i$$

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

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

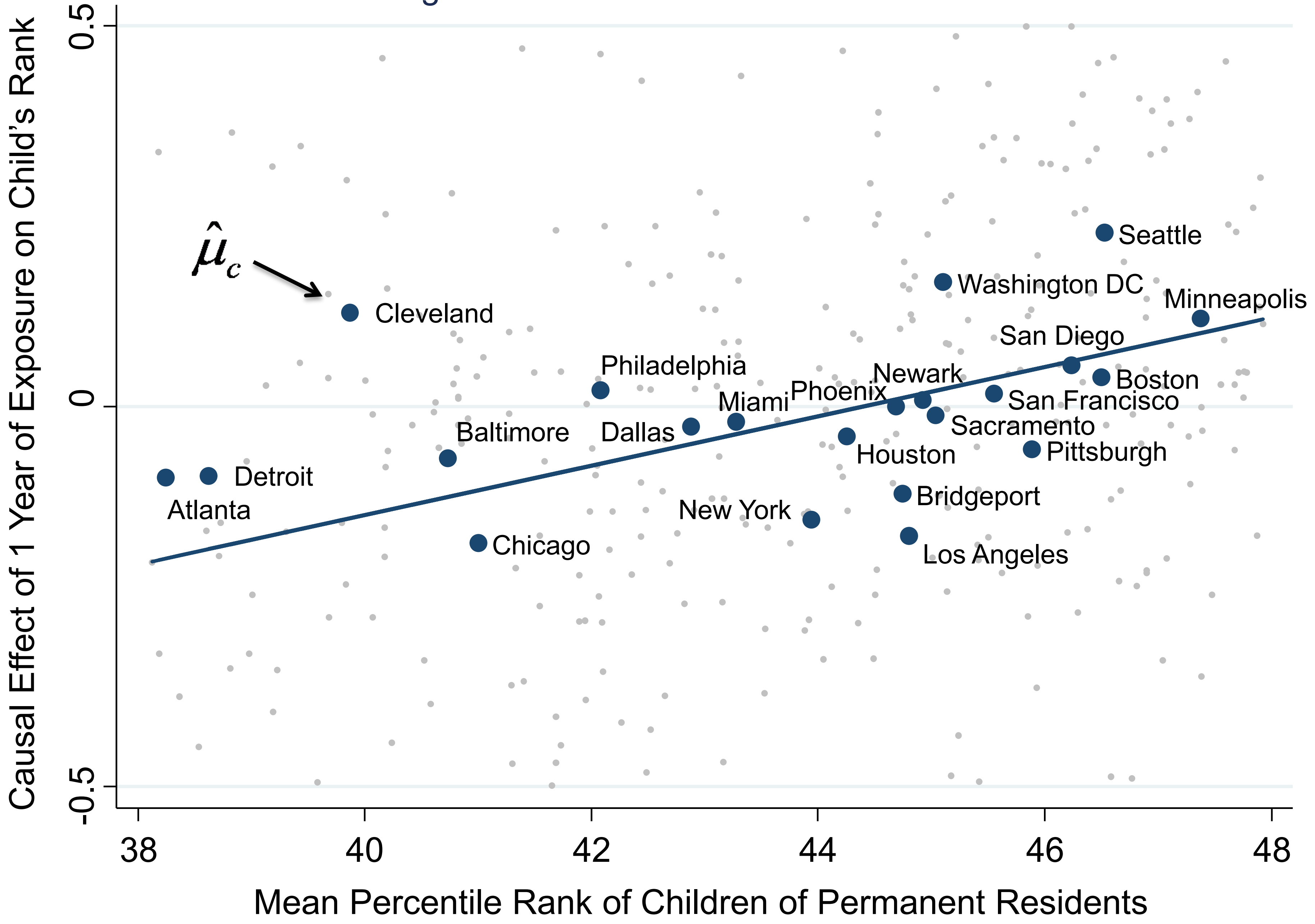
- Include origin-by-destination fixed effects to isolate variation in exposure

- 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
Phoenix
Boston
Miami
San Francisco
Baltimore
Dallas
Sacramento
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles

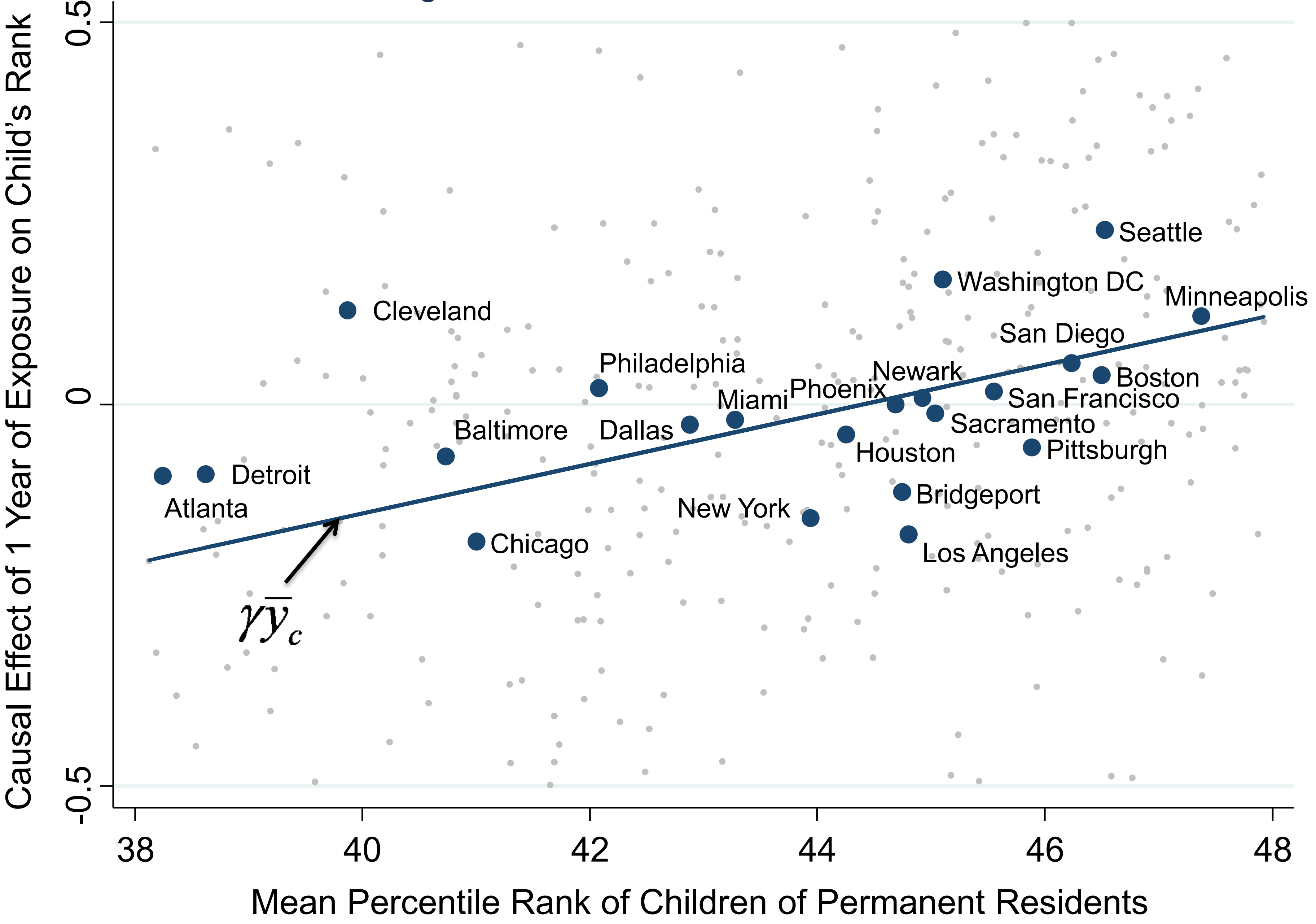
Causal Effect Estimates vs. Permanent Resident Outcomes

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



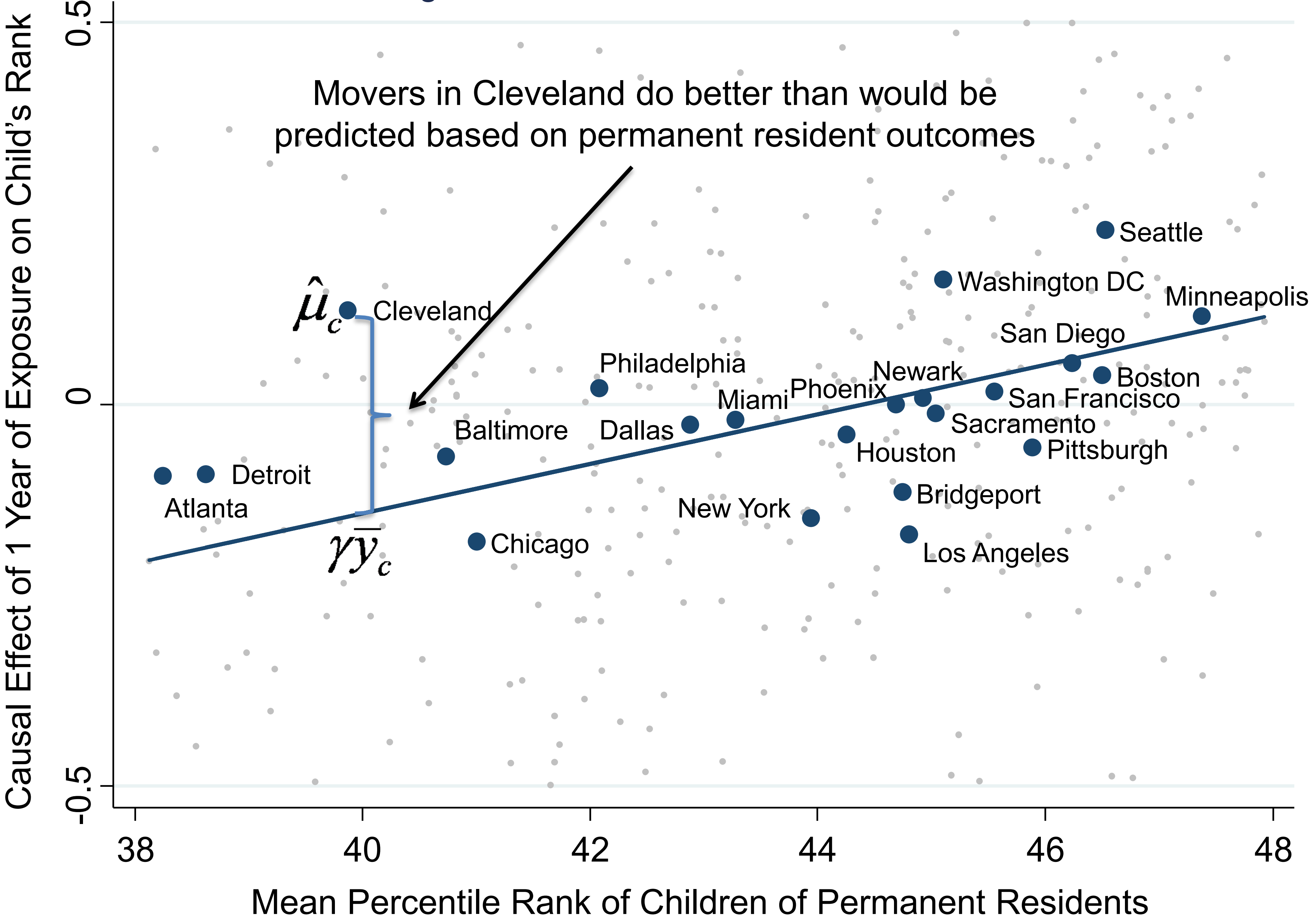
Causal Effect Estimates vs. Permanent Resident Outcomes

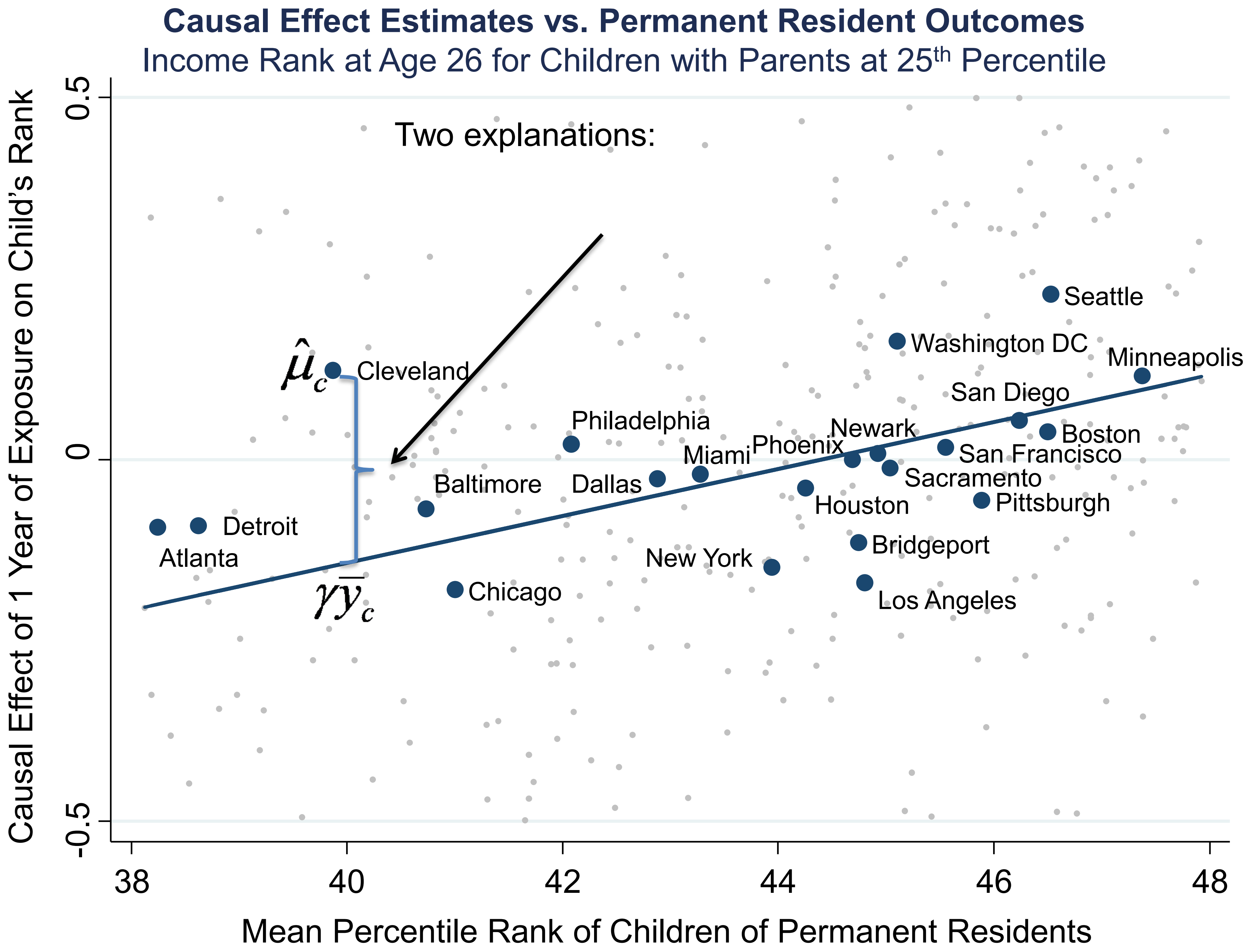
Income Rank at Age 26 for Children with Parents at 25th Percentile



Causal Effect Estimates vs. Permanent Resident Outcomes

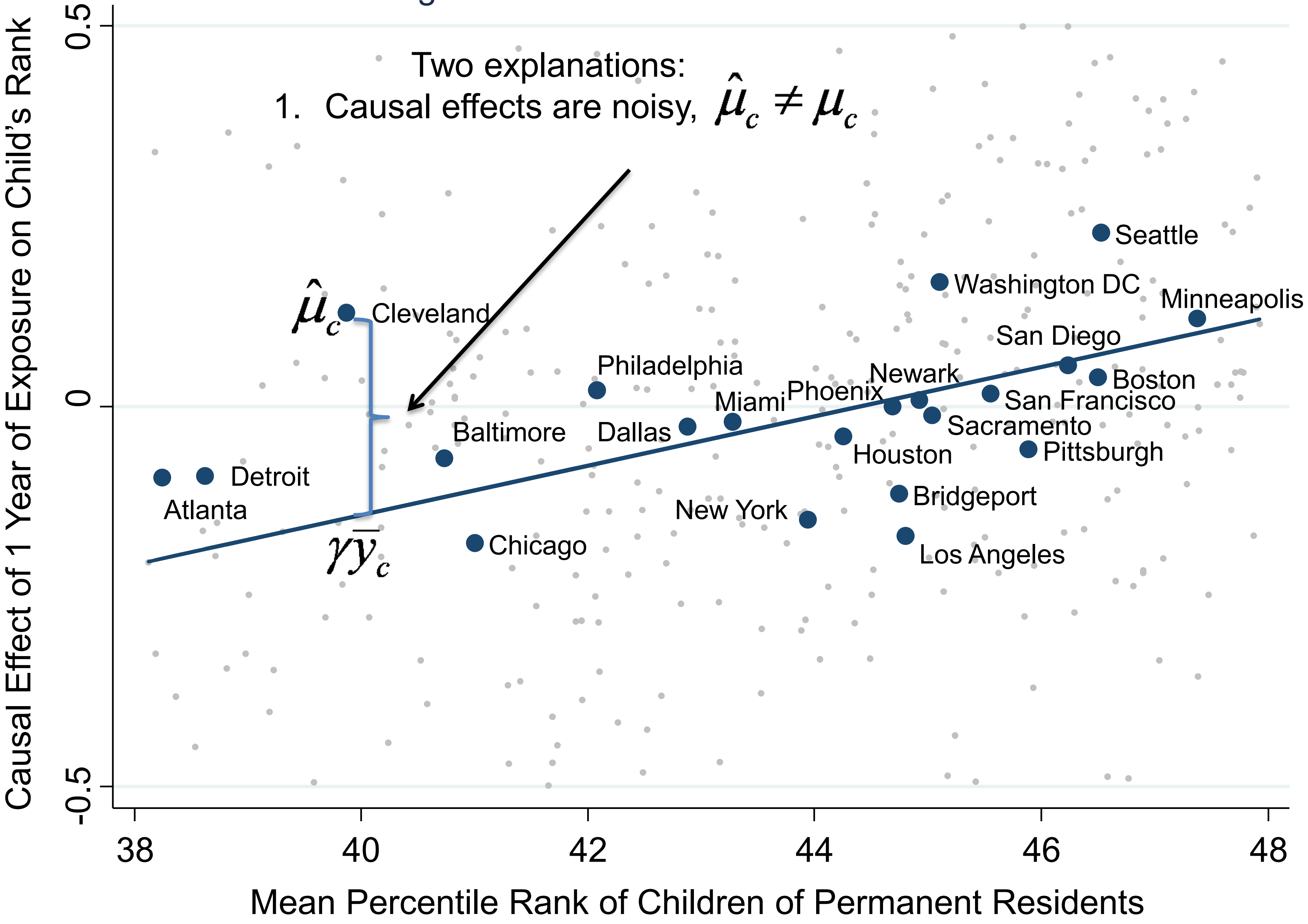
Income Rank at Age 26 for Children with Parents at 25th Percentile




Causal Effect 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
San Diego
Cleveland
Philadelphia
Newark
Boston
Phoenix
Miami
San Francisco
Sacramento
Baltimore
Dallas
Houston
Pittsburgh
Detroit
Atlanta
Bridgeport
New York
Chicago
Los Angeles
0.5
0
-0.5
38
40
42
44
46
48
Causal Effect of 1 Year of Exposure on Child's Rank
Mean Percentile Rank of Children of Permanent Residents

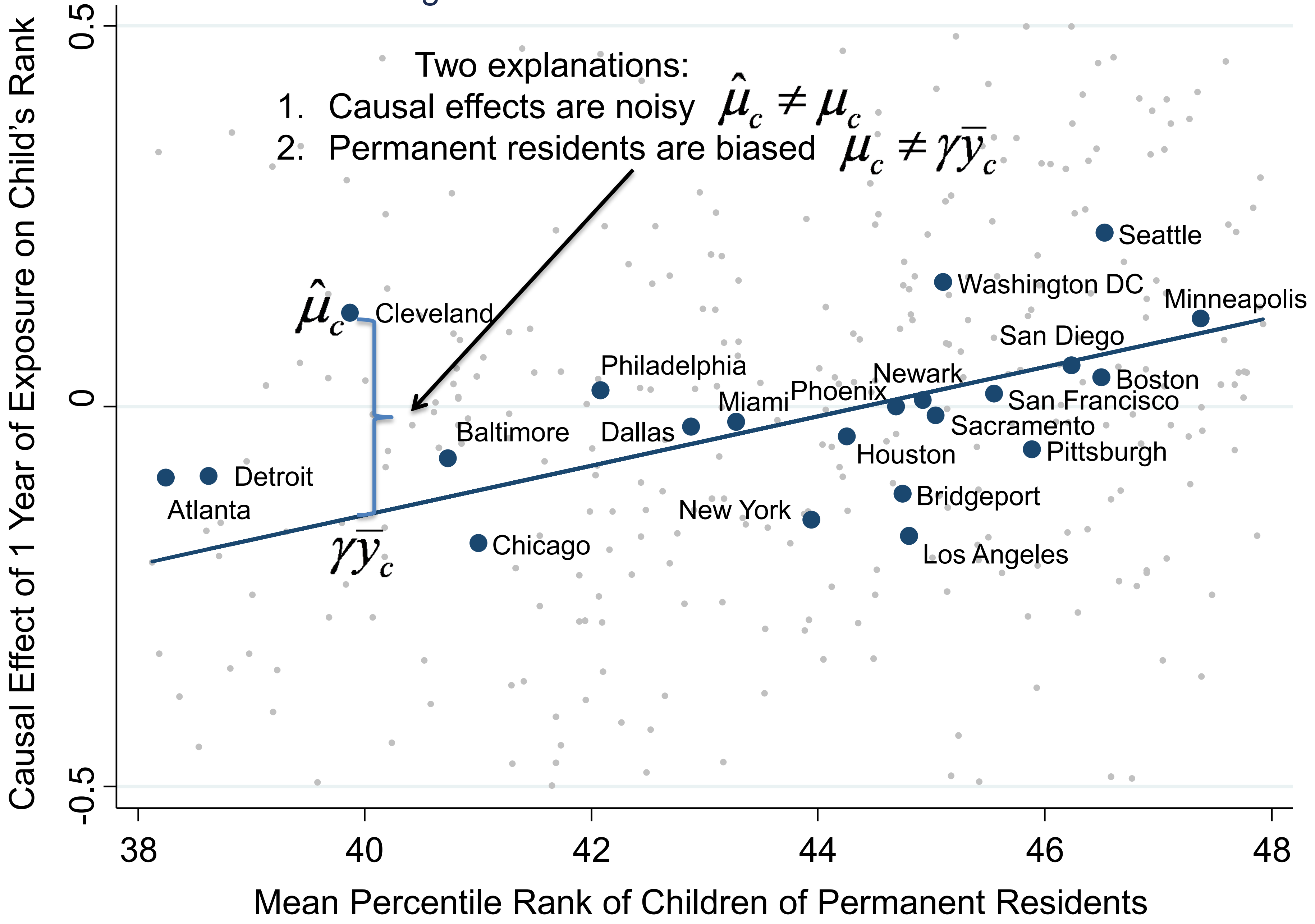
Causal Effect Estimates vs. Permanent Resident Outcomes

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



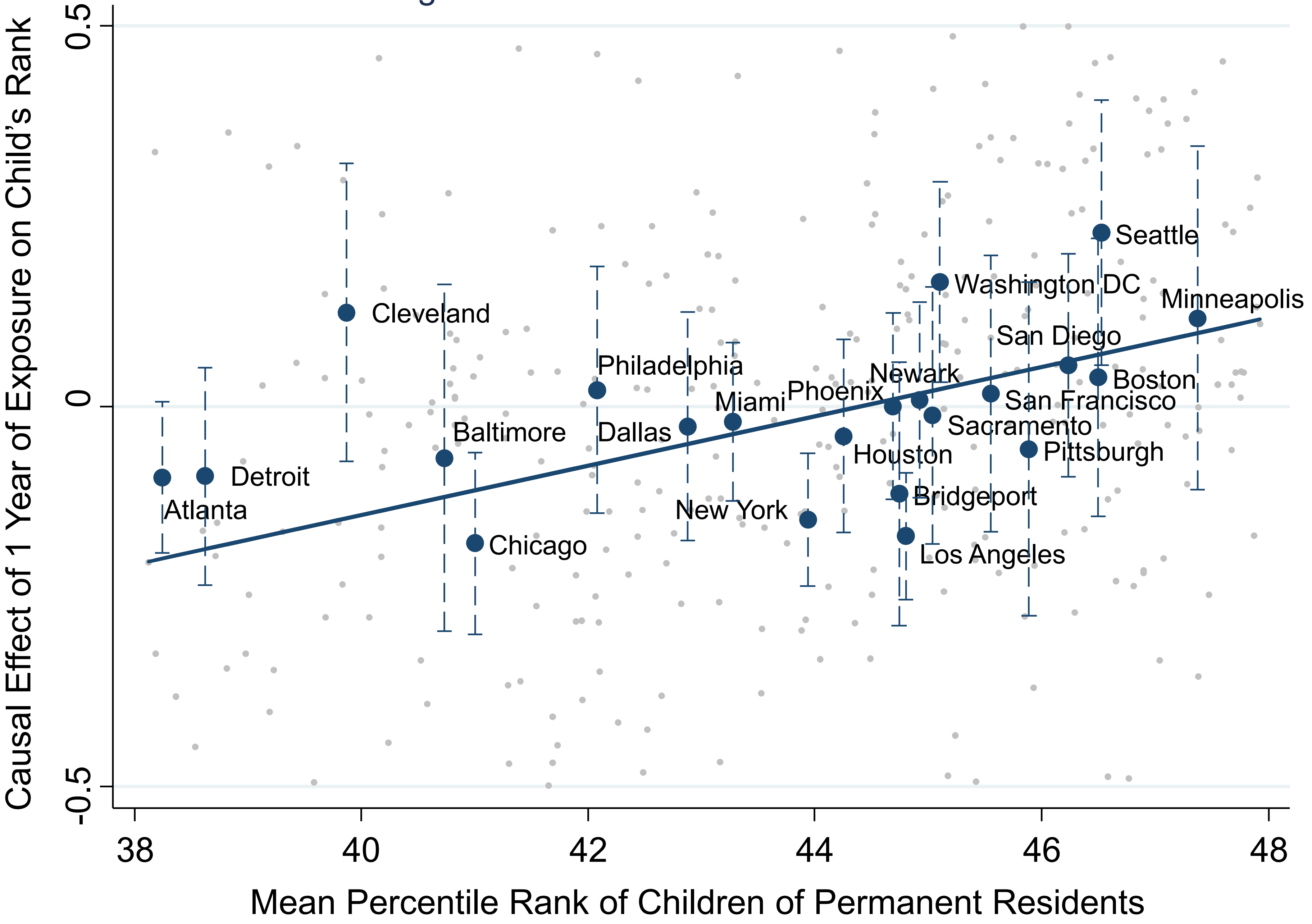
Causal Effect Estimates vs. Permanent Resident Outcomes

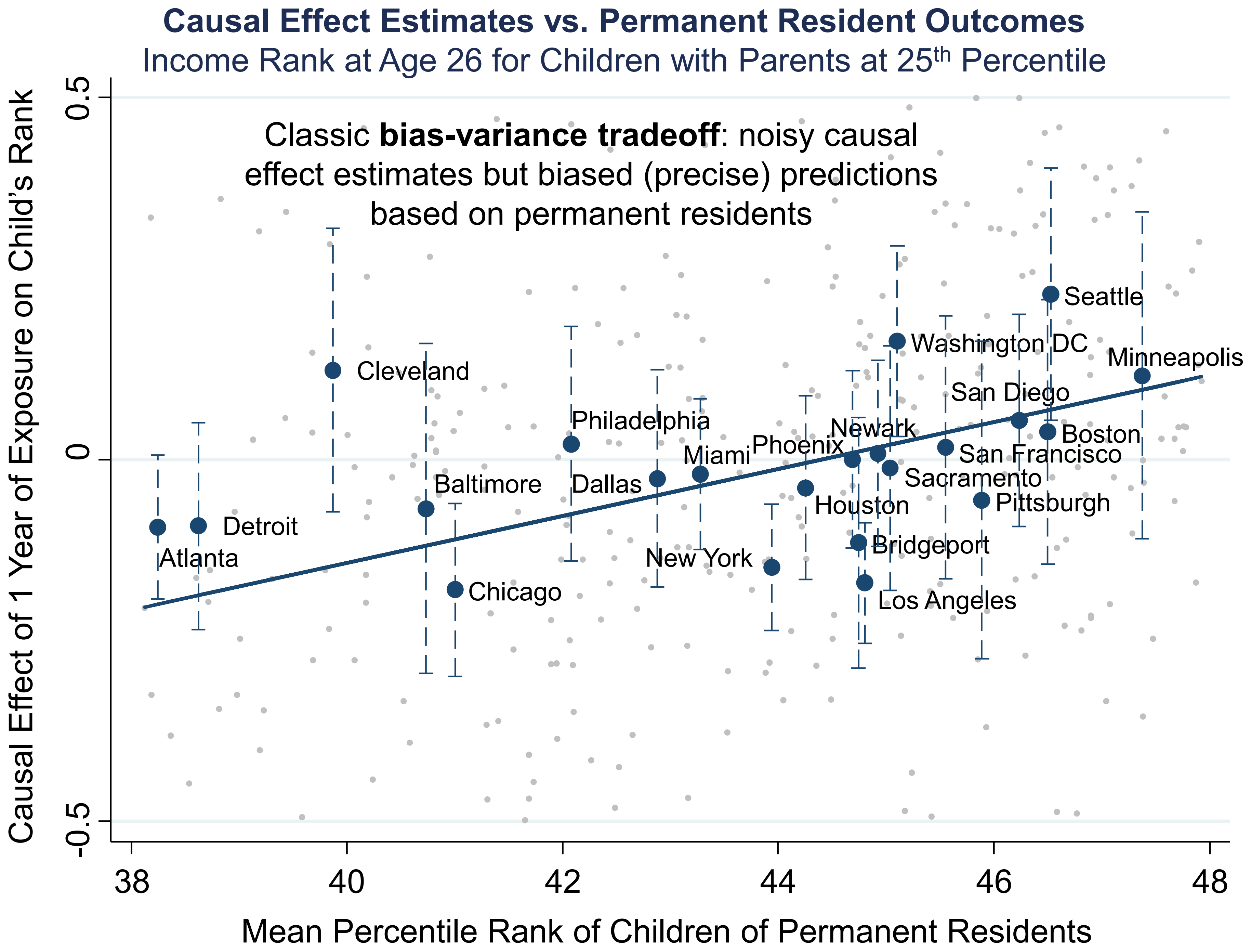
Income Rank at Age 26 for Children with Parents at 25th Percentile



Causal Effect 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
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
San Diego
Boston
San Francisco
Newark
Sacramento
Pittsburgh
Phoenix
Houston
Bridgeport
Los Angeles
New York
Miami
Dallas
Philadelphia
Cleveland
Baltimore
Chicago
Detroit
Atlanta

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 ε_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:

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

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

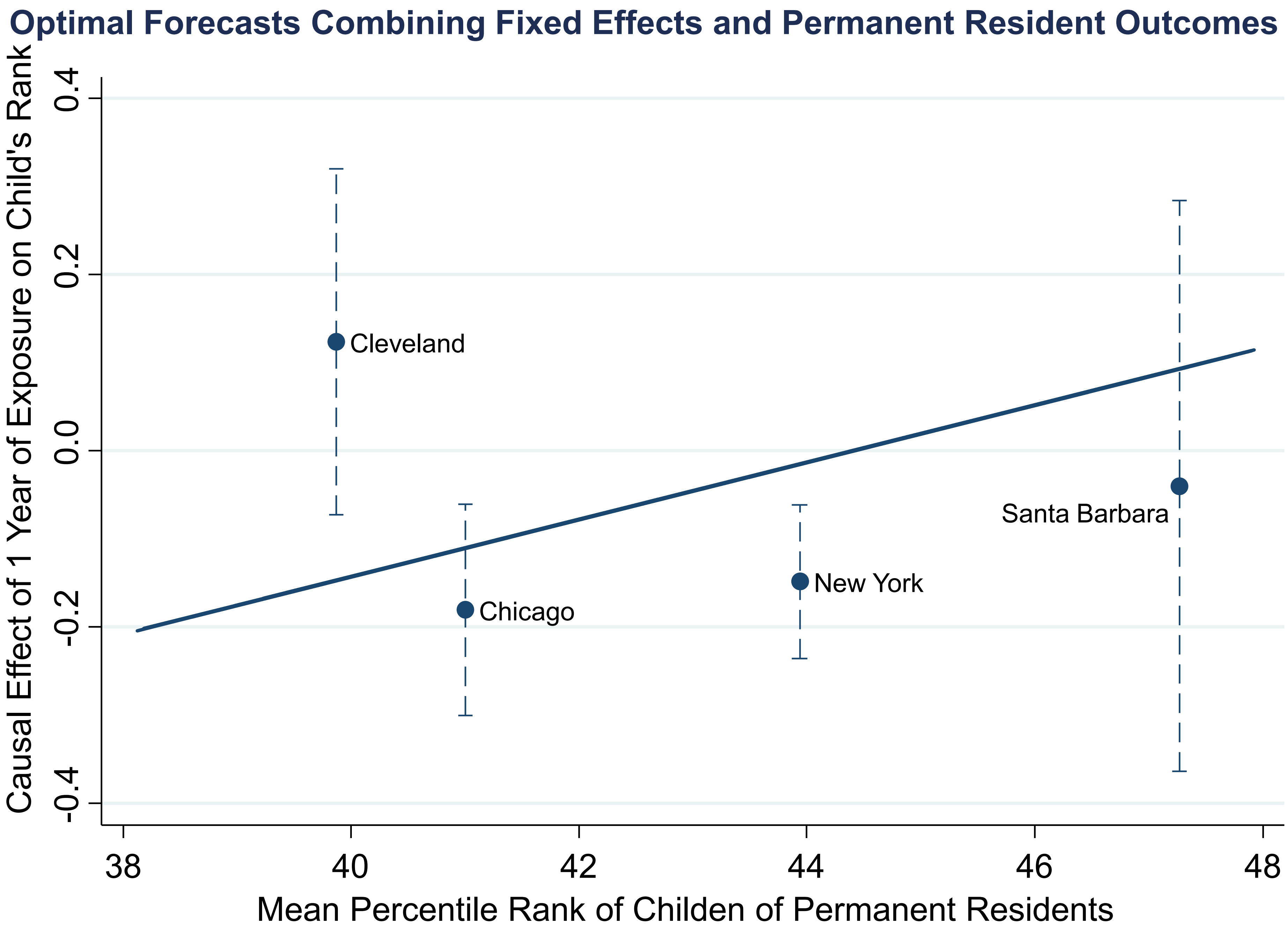
- 1 year of exposure to a 1SD better place increases earnings by 0.18 percentiles

  - 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

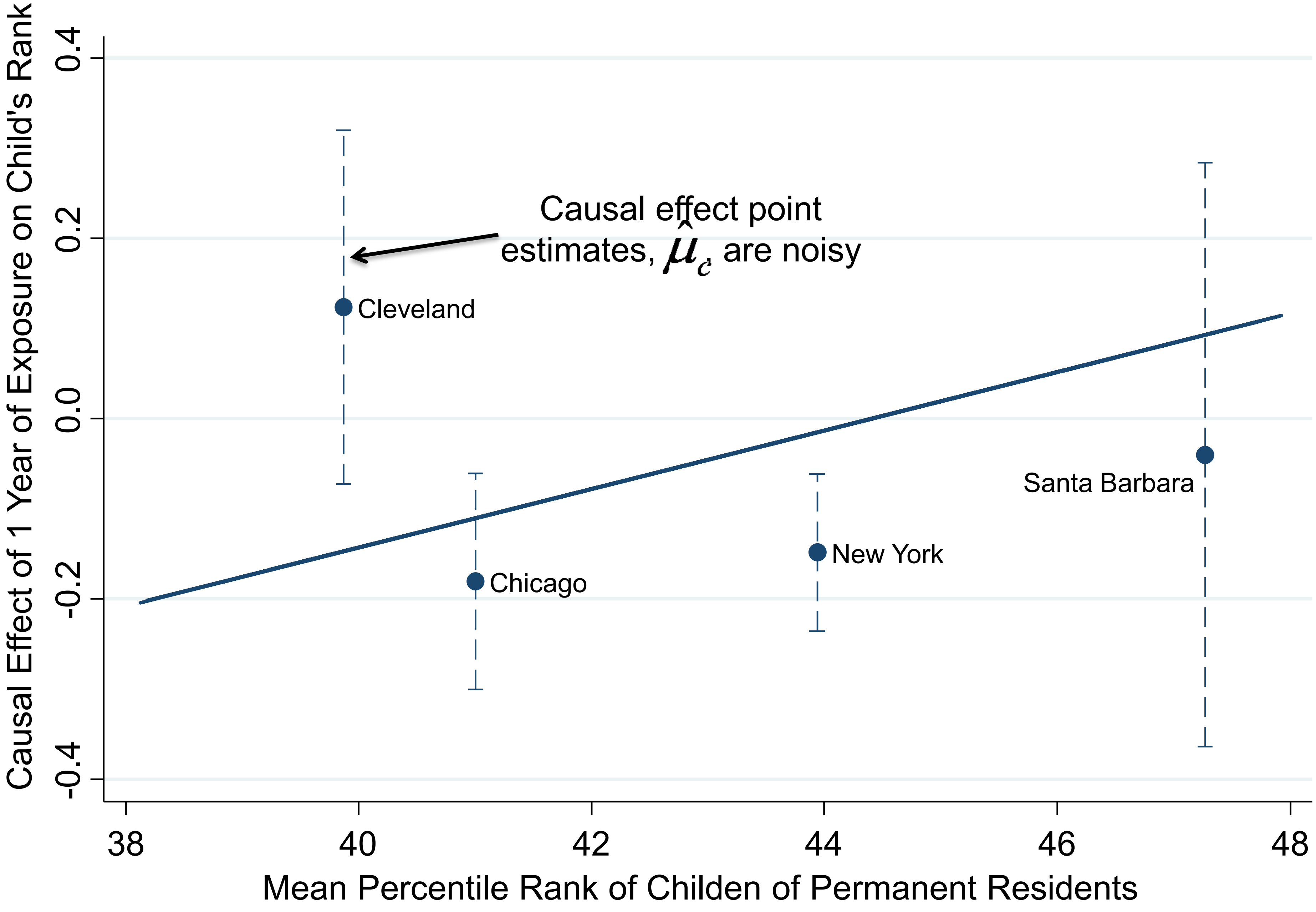
Objective 2: Forecasts of Best and Worst Areas

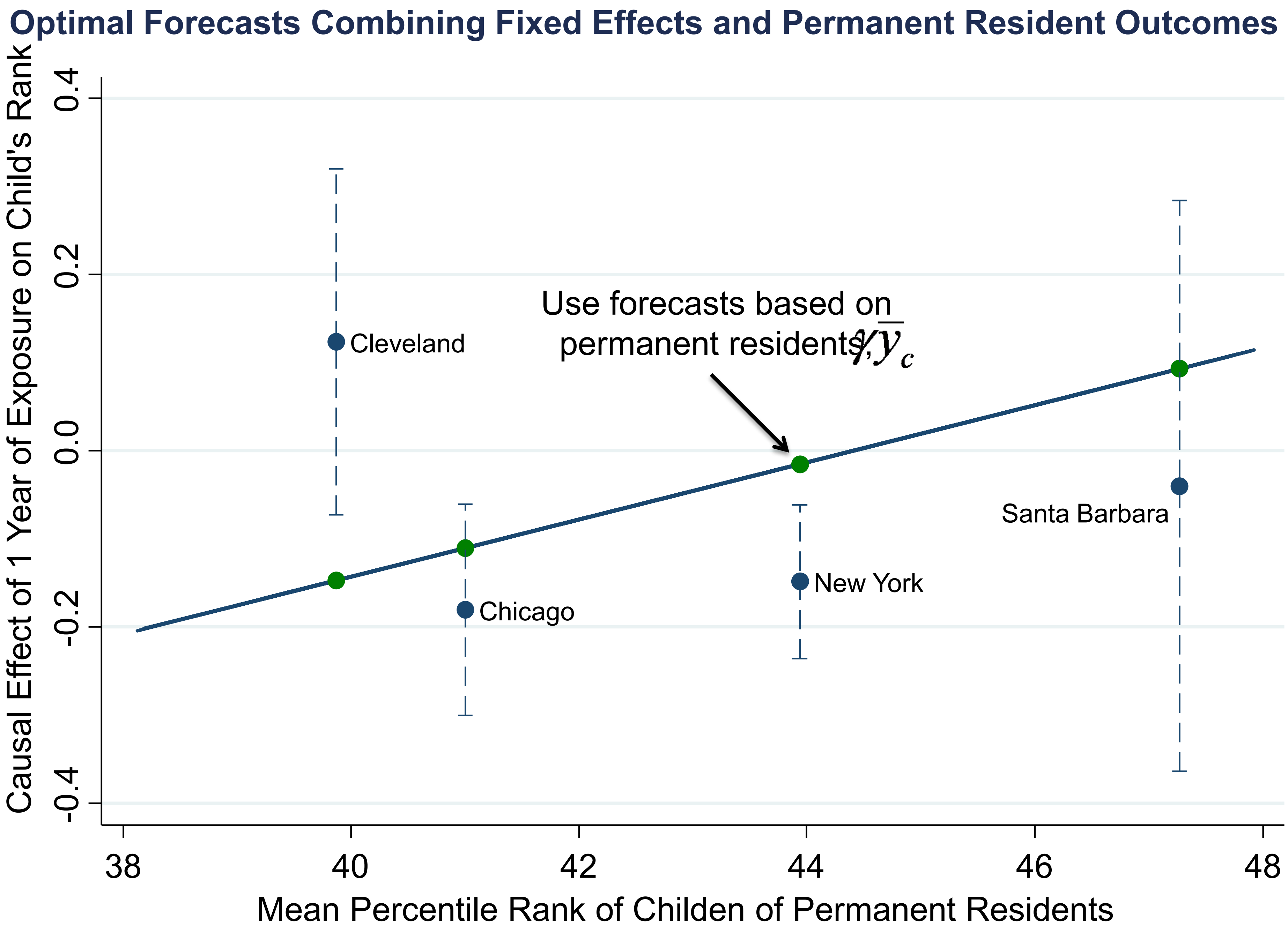
- What are the best and worst places to grow up?
- Construct forecasts that minimize mean-squared-error of predicted impact for a family moving to a new area
- Raw fixed effect estimates have high MSE because of sampling error
- Reduce MSE by combining fixed effects (unbiased, but imprecise) with permanent 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
Causal Effect of 1 Year of Exposure on Child's Rank
0.4
0.2
0.0
-0.2
-0.4
Cleveland
Chicago
New York
Santa Barbara
38
40
42
44
46
48
Mean Percentile Rank of Childen of Permanent Residents

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
0.4
0.2
0.0
-0.2
-0.4
38
40
42
44
46
48
Mean Percentile Rank of Childen of Permanent Residents
Use forecasts based on
permanent residents, $\bar{y}_c$
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

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

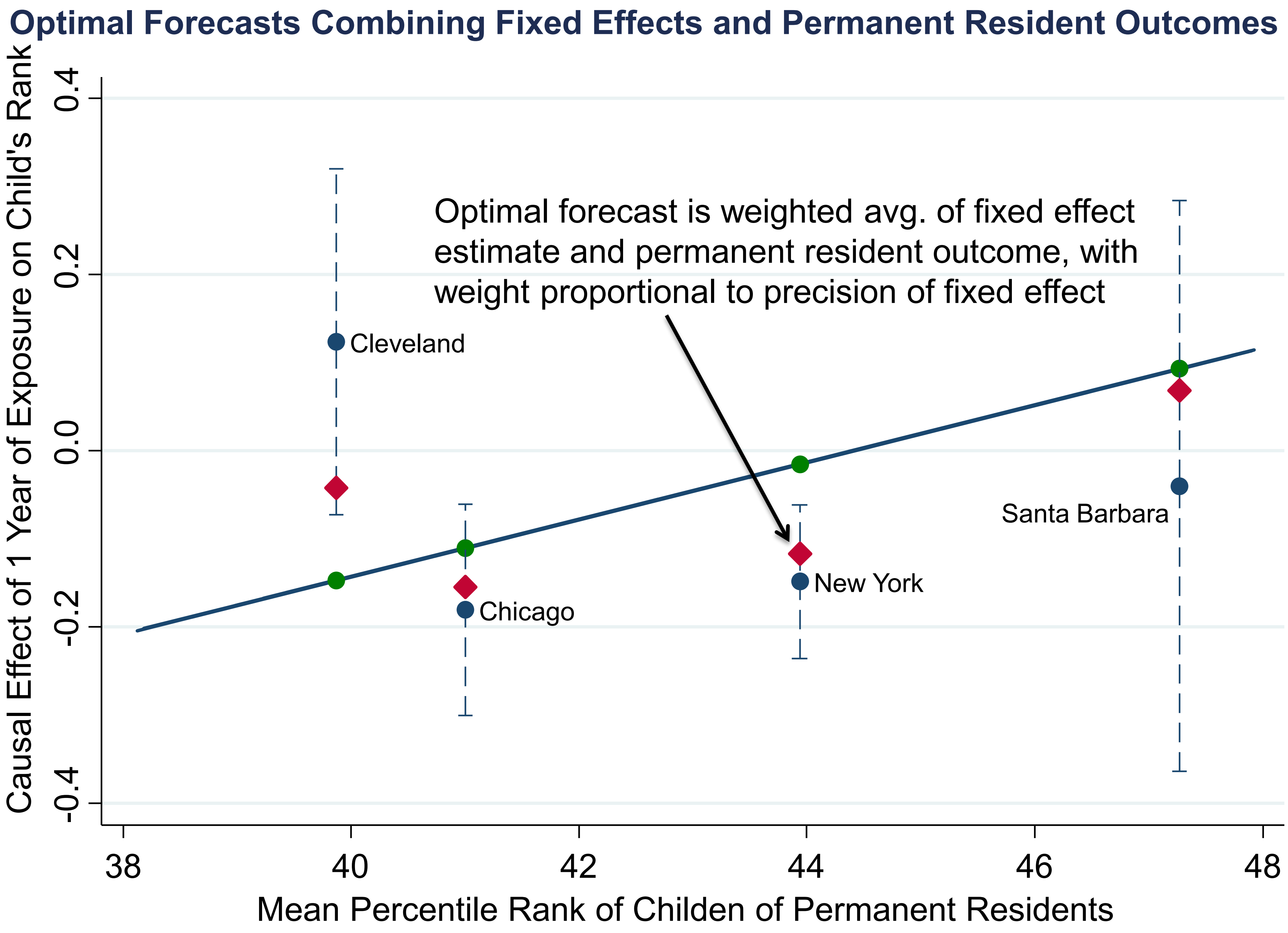
- Part 1 shows that $E\left[y_i \mid \bar{y}_c\right] = \gamma\bar{y}_c$, so that the regression coeffs are:

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

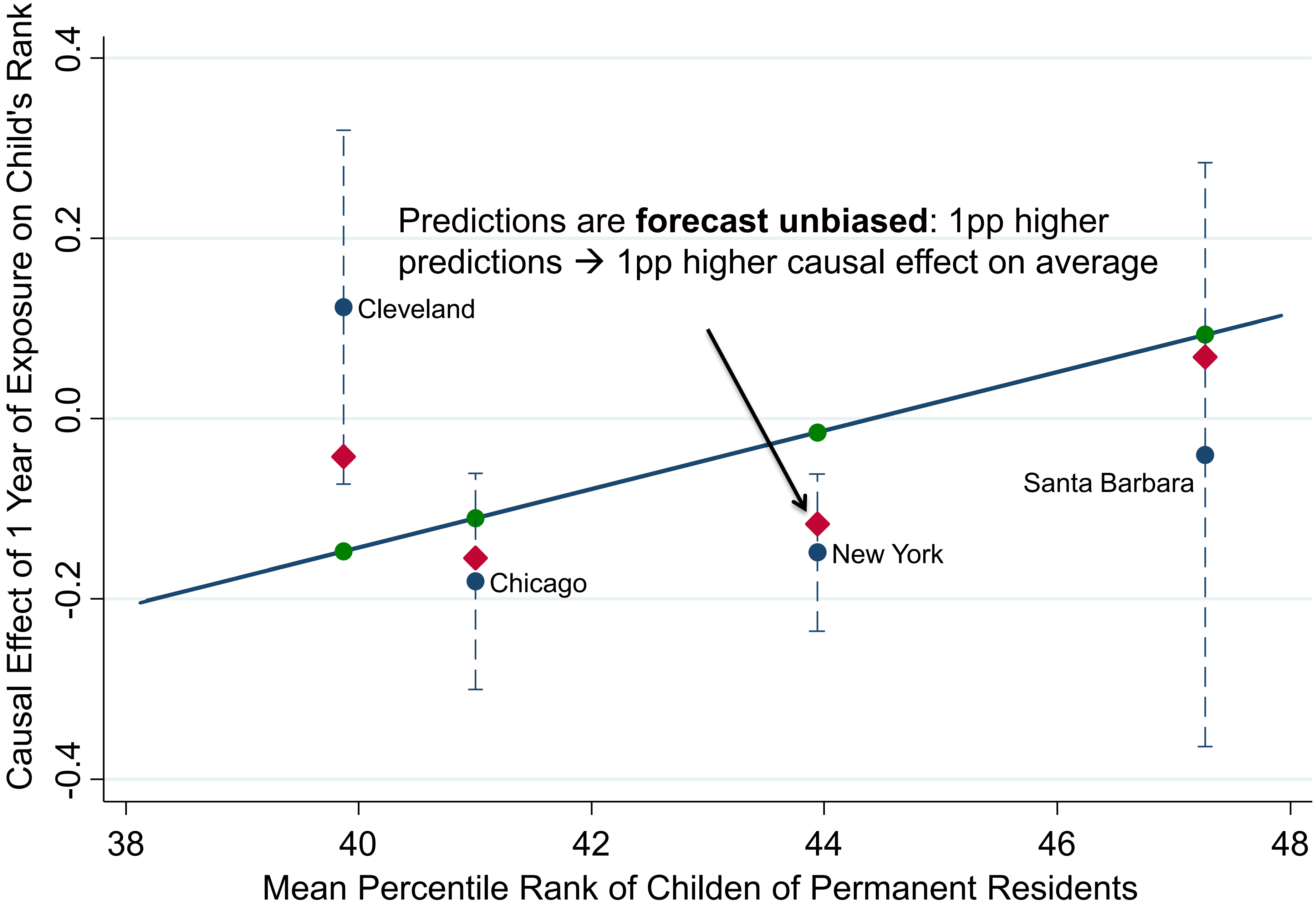
where:

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

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


Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Causal Effect of 1 Year of Exposure on Child's Rank
0.4
0.2
0.0
-0.2
-0.4
Optimal forecast is weighted avg. of fixed effect estimate and permanent resident outcome, with weight proportional to precision of fixed effect
Cleveland
Chicago
New York
Santa Barbara
38
40
42
44
46
48
Mean Percentile Rank of Childen of Permanent Residents

Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes



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:

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

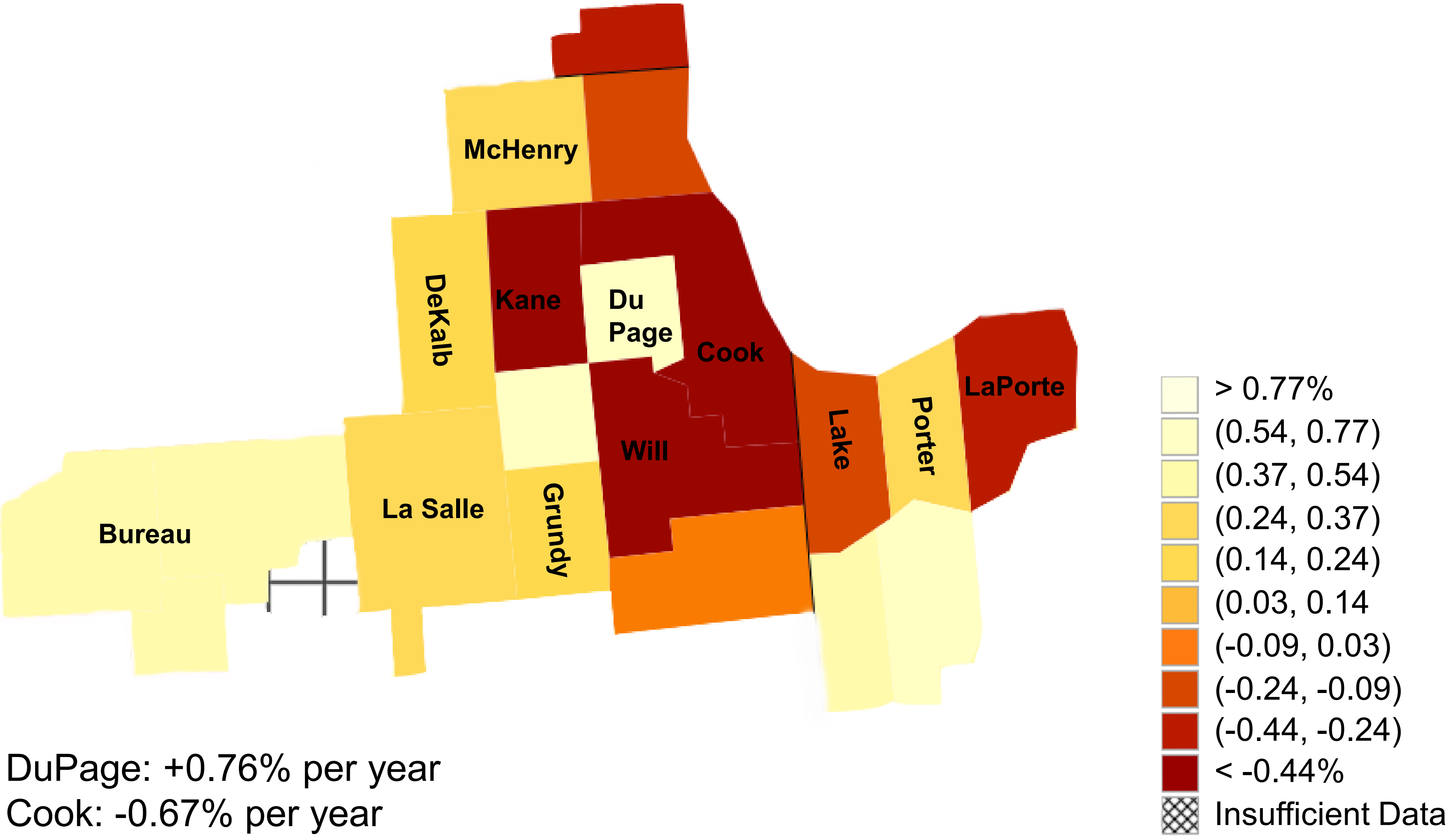
where:

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

- $\sigma^2_{noise,c} = s_c^2$ 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

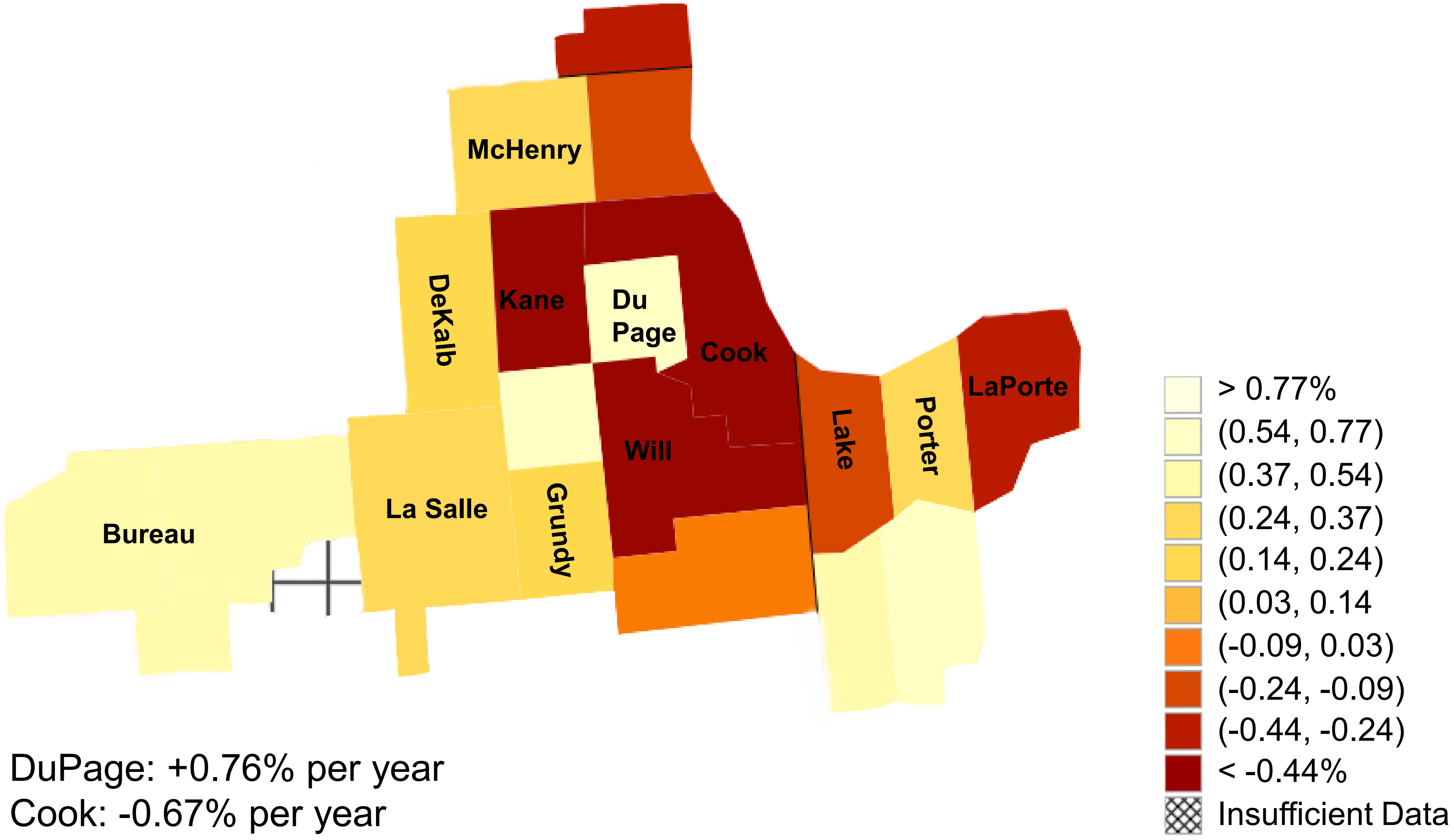


DuPage: +0.76% per year

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



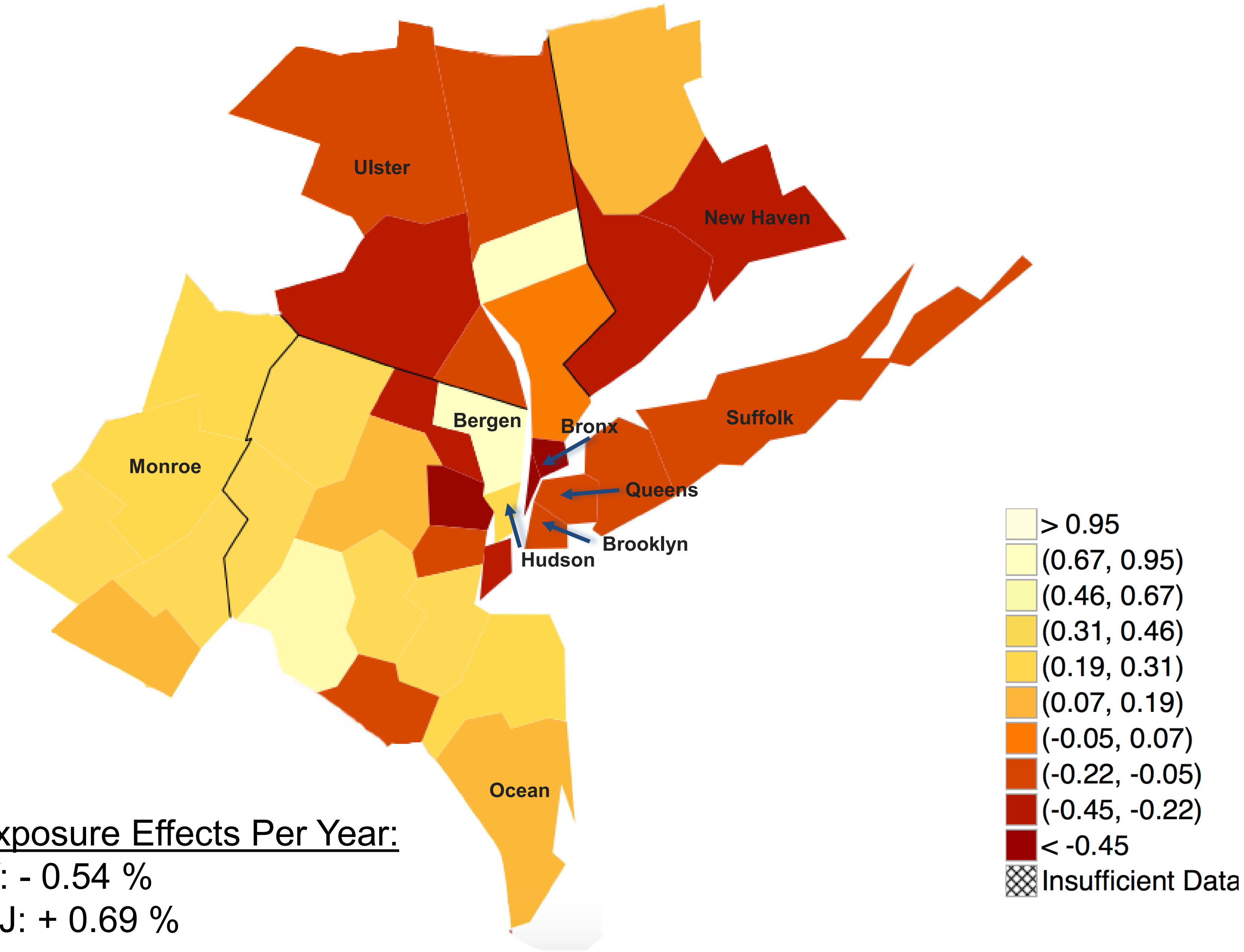
DuPage: +0.76% per year

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



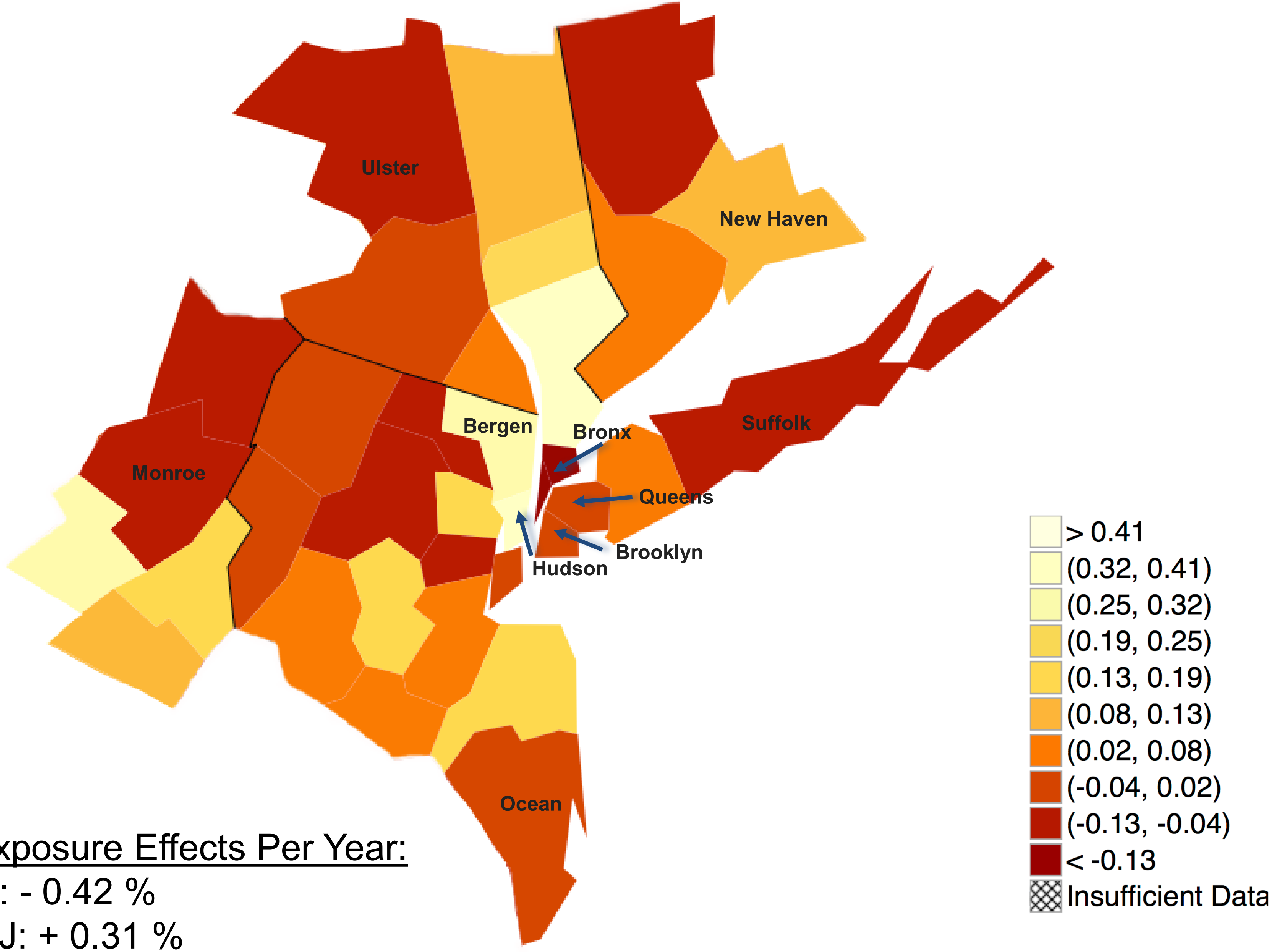
<u>Causal Exposure Effects Per Year:</u>

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



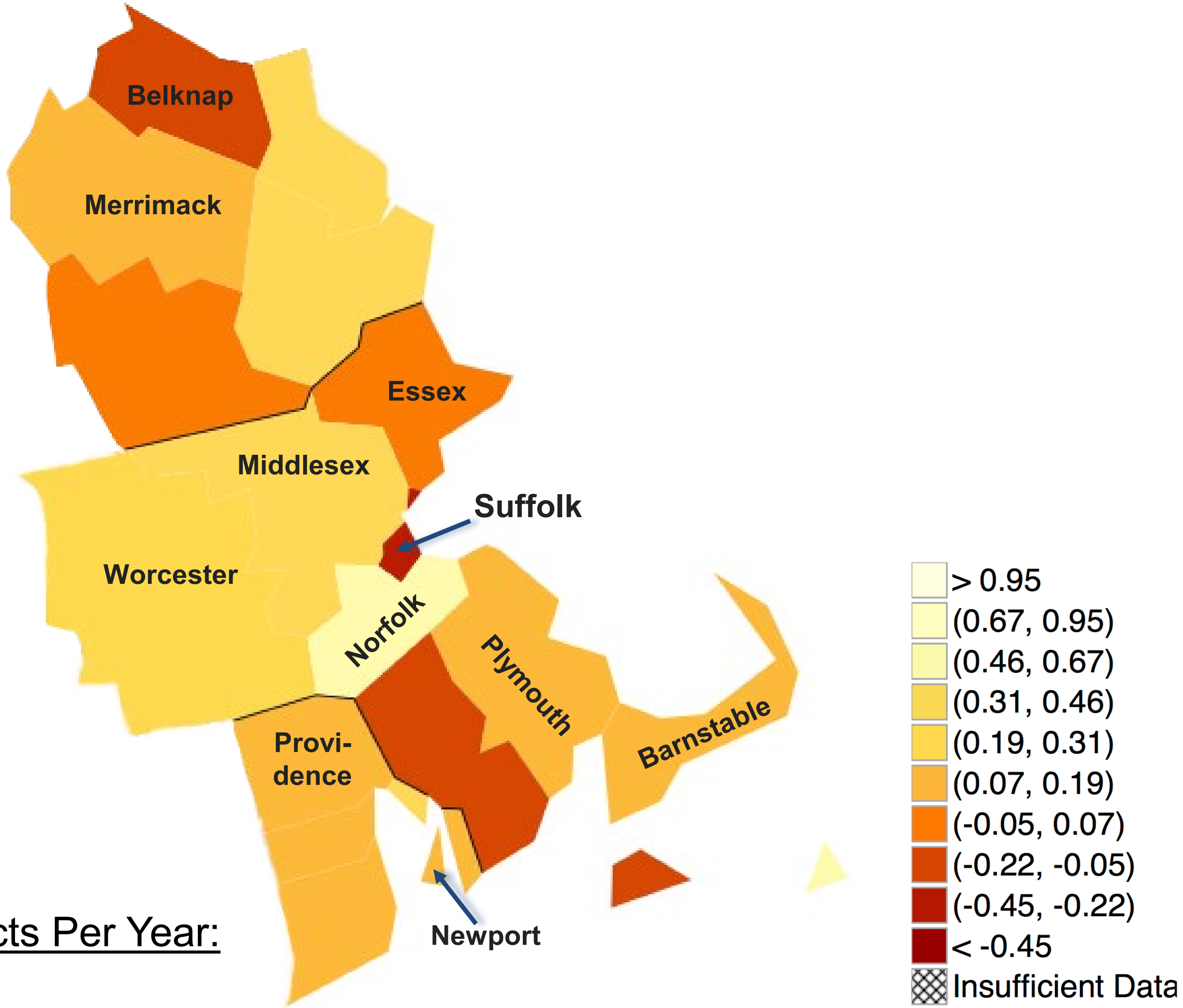
<u>Causal Exposure Effects Per Year:</u>

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



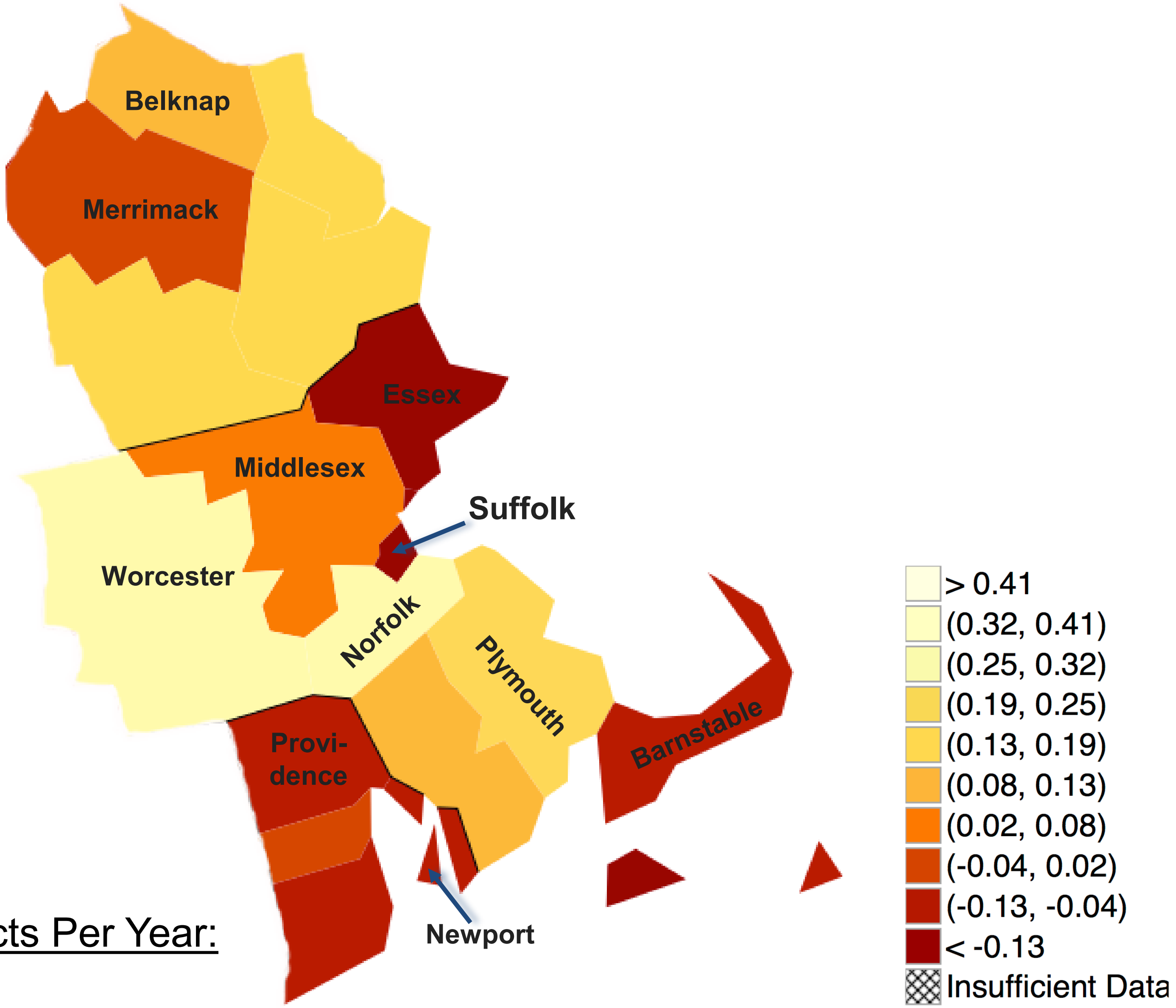
<u>Causal Exposure Effects Per Year:</u>

Suffolk MA: - 0.31 %

Middlesex MA: + 0.39 %

Exposure Effects on Income in the Boston CSA

For Children with Parents at 75th Percentile of Income Distribution



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

Suffolk MA: - 0.18 %

Middlesex MA: + 0.03 %

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

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

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

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

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

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

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

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

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

Male Children

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

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

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

Female Children

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

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