The Opportunity Atlas
Mapping the Childhood Roots of Social Mobility

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Neighborhood Effects and Children's Outcomes

- Growing body of evidence shows that where children grow up has substantial causal effects on their prospects for upward income mobility.

  [Chetty, Hendren, Katz 2016; Chetty and Hendren 2018a; Chyn 2018; Deutscher 2018; Laliberté 2018 building on Wilson 1987, Case and Katz 1991, Massey & Denton 1993, Cutler & Glaeser 1997, Sampson et al. 2002]

- Natural question: which neighborhoods offer the best opportunities for children?
  - Previous work either focuses on a small set of neighborhoods (e.g., Moving to Opportunity experiment) or broad geographies.

This Paper: An Opportunity Atlas

- We construct publicly available estimates of children's earnings in adulthood (and other long-term outcomes) by Census tract and subgroup, for the entire U.S.
  - Granular definition of neighborhoods: 70,000 Census tracts; 4,250 people per tract.
- Key difference from prior work on geographic variation: identify roots of outcomes such as poverty and incarceration by tracing them back to where children **grew up**.
  - Large literature on place-based policies and local labor markets has documented importance of place for production. [e.g., Moretti 2011, Glaeser 2011, Moretti 2012, Kline & Moretti 2014]
  - Here we focus on the role of place in the development of human capital and show that patterns differ in important ways.

1. Data
2. Methods to Construct Tract-Level Estimates
3. Observational Variation and Targeting
4. Causal Effects and Neighborhood Choice

1. **Data**
2. Methods to Construct Tract-Level Estimates
3. Observational Variation and Targeting
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Data Sources and Sample Definitions

- Data sources: Census data (2000, 2010, ACS) covering U.S. population linked to federal income tax returns from 1989-2015.

- Link children to parents based on dependent claiming on tax returns.

- Target sample: Children in 1978-83 birth cohorts who were born in the U.S. or are authorized immigrants who came to the U.S. in childhood.

- Analysis sample: 20.5 million children, 96% coverage rate of target sample.

Variable Definitions

- Parents' pre-tax household incomes: mean Adjusted Gross Income from 1994-2000, assigning non-filers zeros.

- Children's pre-tax incomes measured in 2014-15 (ages 31-37).

  – Non-filers assigned incomes based on W-2's (available since 2005).

- To mitigate lifecycle bias, focus on percentile ranks: rank children relative to others in their birth cohort and parents relative to other parents.

- Also examine other outcomes: marriage, teenage birth, incarceration, …

1 Data

2 Methods to Construct Tract-Level Estimates

3 Observational Variation and Targeting

4 Causal Effects and Neighborhood Choice

Empirical Objectives

- Goal: estimate children's expected outcomes given their parent's income percentile *p*, race *r*, and gender *g*, conditional on growing up from birth in tract *c*:

$$\bar{y}_{cprg} = E[yi|c(i) = c, p(i) = p, r(i) = r, g(i) = g]$$

- Focus on tracts where kids *grow up* given evidence that childhood location is what matters for outcomes in adulthood. [Chetty, Hendren, Katz 2016; Chetty and Hendren 2018a]

- Two challenges:

  1. Not enough data to estimate $\bar{y}_{cprg}$ non-parametrically in every cell.
  2. Relatively few kids stay in a single tract for their entire childhood.

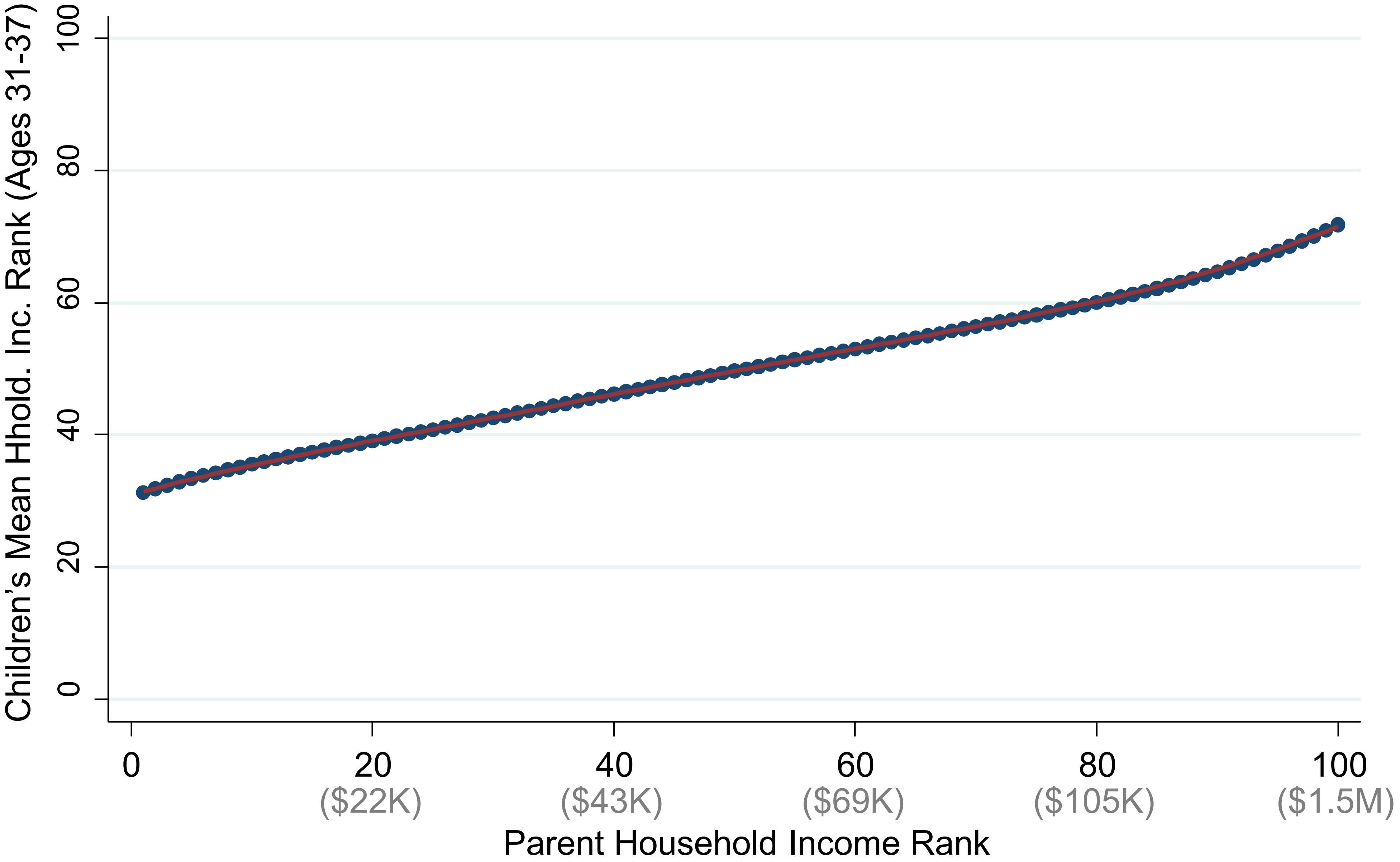
Estimating Mean Outcomes by Tract

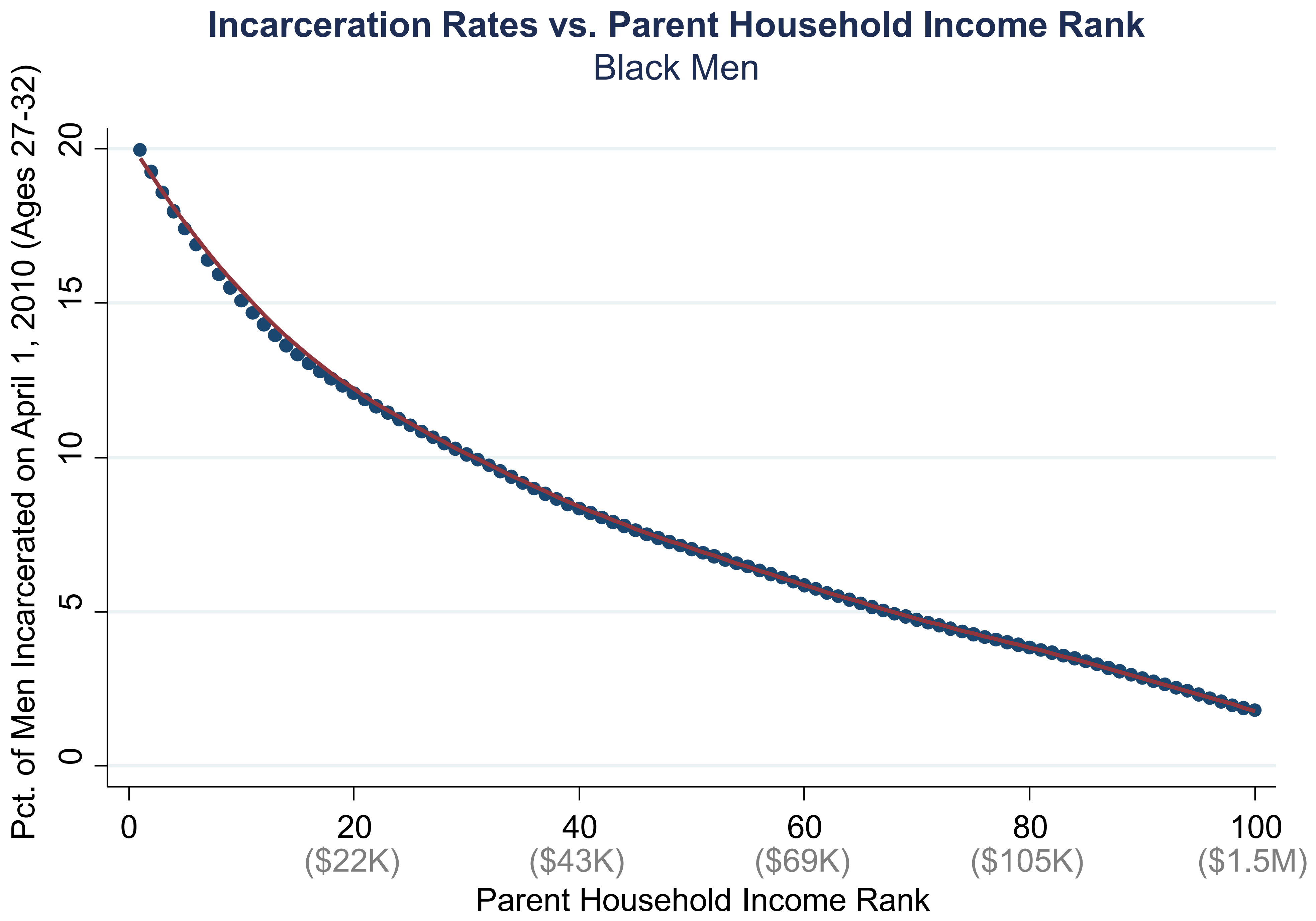
- In each tract *c*, for each race *r* and gender *g*, regress children's outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \varepsilon_{icprg}$$

- Function f_{rg} estimated non-parametrically in national data, by race and gender.

Mean Child Household Income Rank vs. Parent Household Income Rank





Incarceration Rates vs. Parent Household Income Rank
Black Men
Pct. of Men Incarcerated on April 1, 2010 (Ages 27-32)
0
5
10
15
20
0
20
($22K)
40
($43K)
60
($69K)
80
($105K)
100
($1.5M)
Parent Household Income Rank

Estimating Mean Outcomes by Tract

- In each tract *c*, for each race *r* and gender *g*, regress children's outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \varepsilon_{icprg}$$

- Function f_{rg} estimated non-parametrically in national data, by race and gender.

  – Key assumption: shape of conditional expectation of outcome given parental income at national level is preserved in each tract, up to an affine transformation.

  – We validate this assumption by testing effects of including higher-order terms and using non-parametric estimates at broader geographies.

Estimating Mean Outcomes by Tract

- In each tract *c*, for each race *r* and gender *g*, regress children's outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \varepsilon_{icprg}$$

- Function f_{rg} estimated non-parametrically in national data, by race and gender.

- Finally, account for the fact that many children move across tracts in childhood.
  - Weight children in each tract-level regression by fraction of childhood (up to age 23) spent in that tract.

Estimating Mean Outcomes by Tract

- Focus on predicted values at selected parental income percentiles, especially p=25 (low income).
  - Extrapolate to all percentiles even in areas with predominantly low- or high-income populations.
  - Mask cells with fewer than 20 children in the relevant subgroup.
  - To limit disclosure risk, add noise to tract-level estimates; SD of noise added is typically an order of magnitude smaller than standard error.
- Translate mean rank outcomes to dollar values based on income distribution of children in their mid-30s (in 2015) for ease of interpretation.

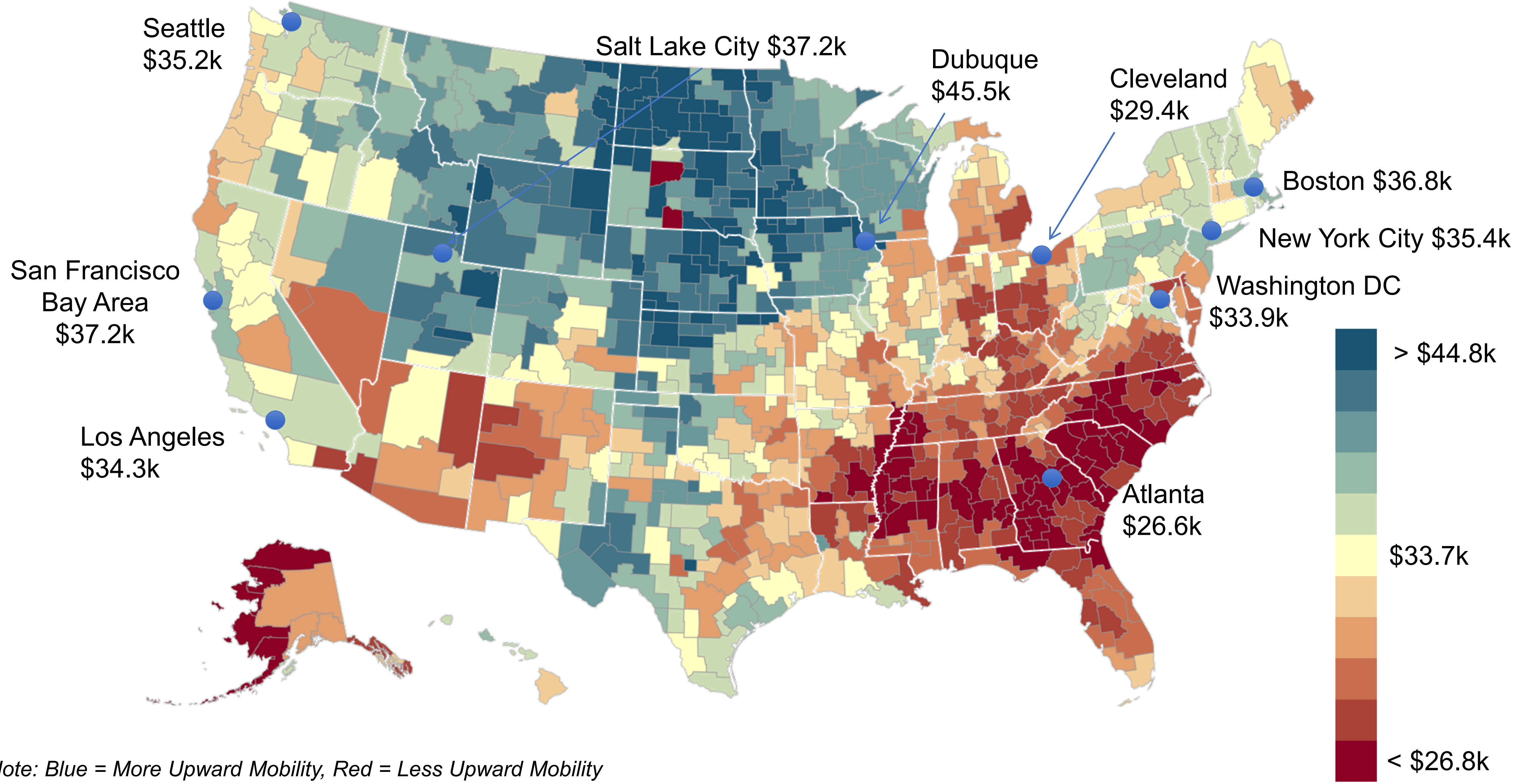
1. Data
2. Methods to Construct Tract-Level Estimates
3. **Observational Variation and Targeting**
4. Causal Effects and Neighborhood Choice

Observational Variation and Targeting

- Many policies target areas based on characteristics such as the poverty rate.
  - E.g. tax policies (Empowerment zones, Opportunity zones) and local services (Head Start, mentoring programs).
- For such "tagging" applications, observed outcomes are of direct interest in standard optimal tax models. [Akerlof 1978, Nichols and Zeckhauser 1982]
  - Isolating causal effects of neighborhoods not necessarily relevant.
- Motivated by these applications, begin with a descriptive characterization of how children's outcomes vary across tracts.

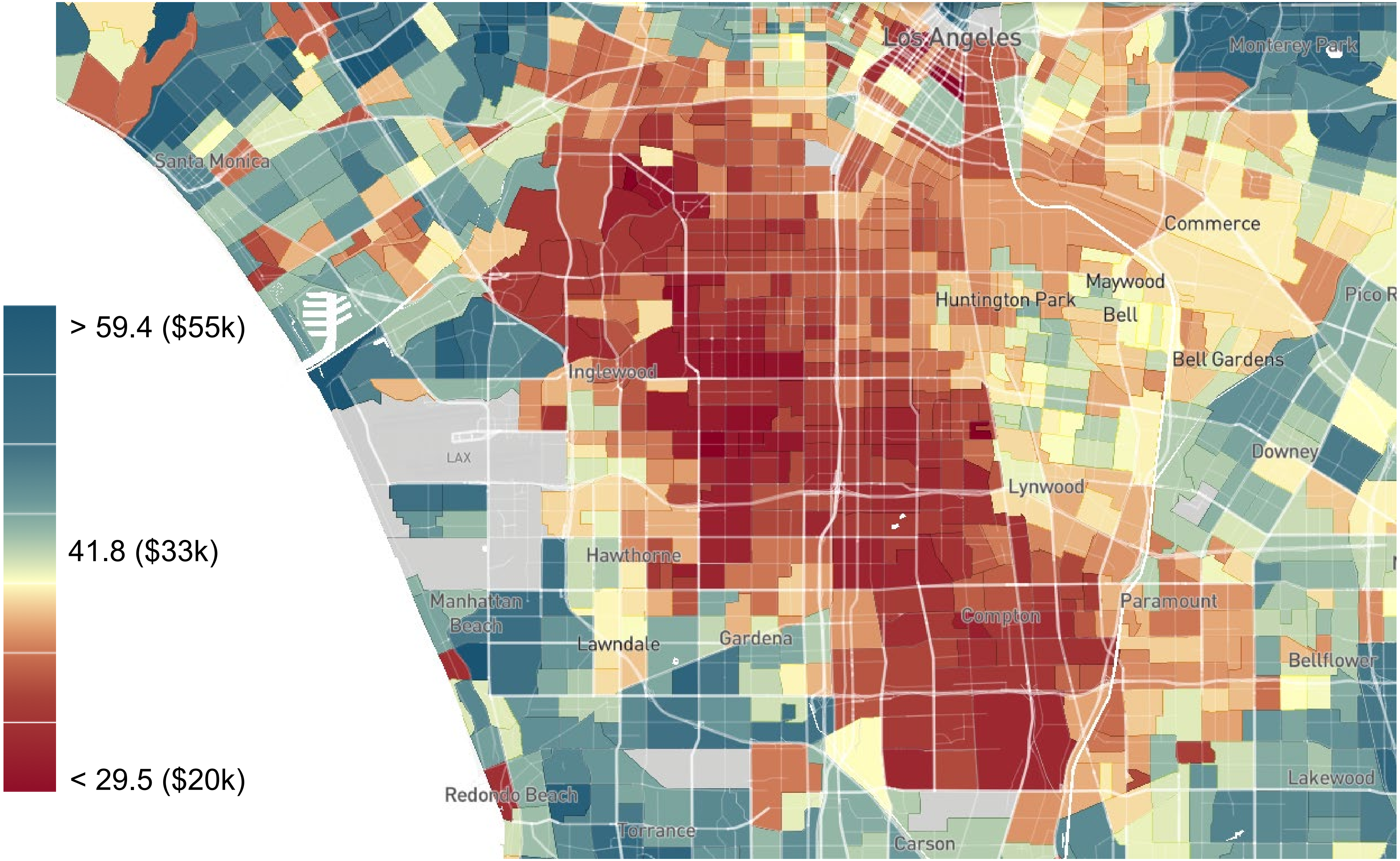
The Geography of Upward Mobility in the United States

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

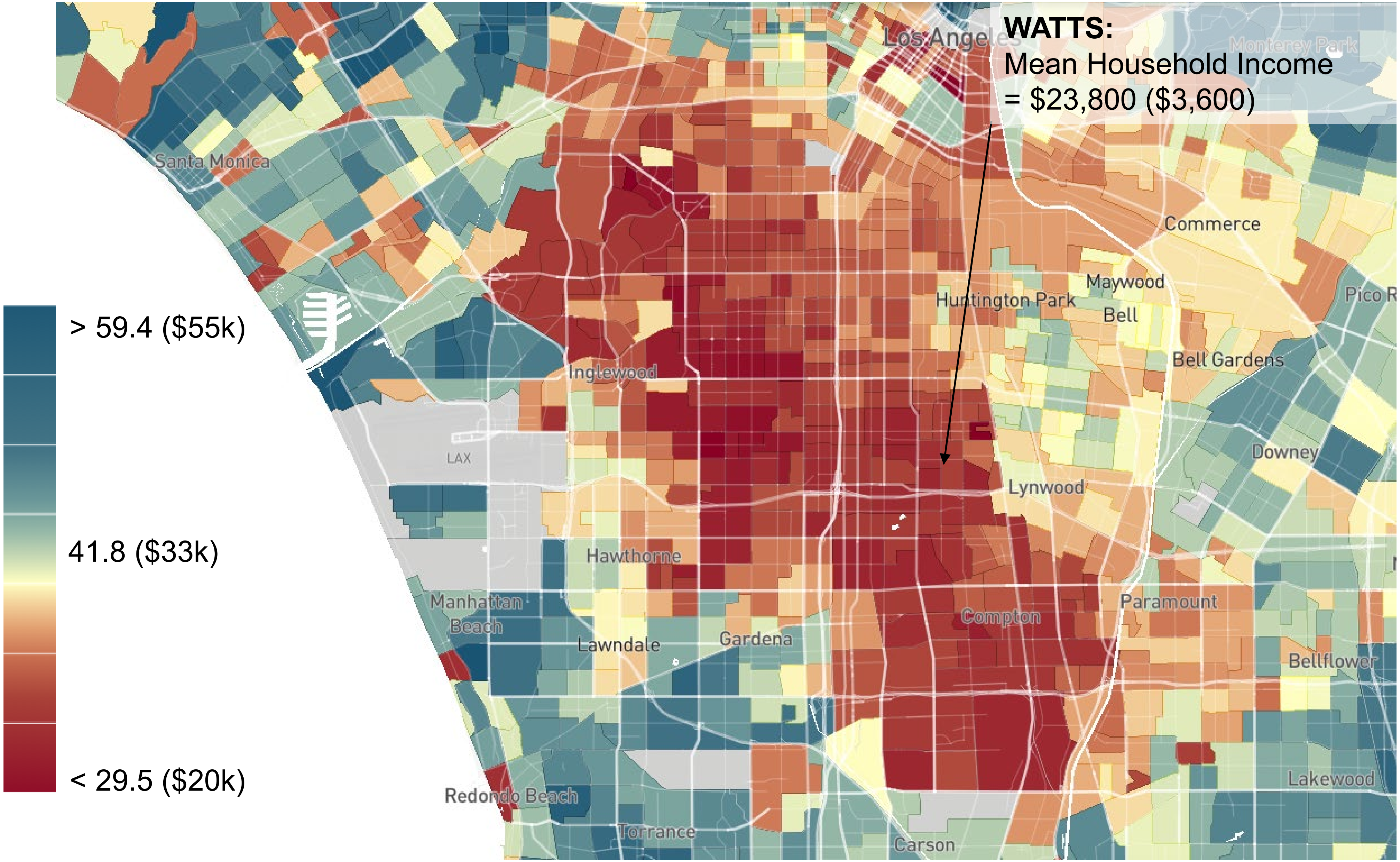


Note: Blue = More Upward Mobility, Red = Less Upward Mobility

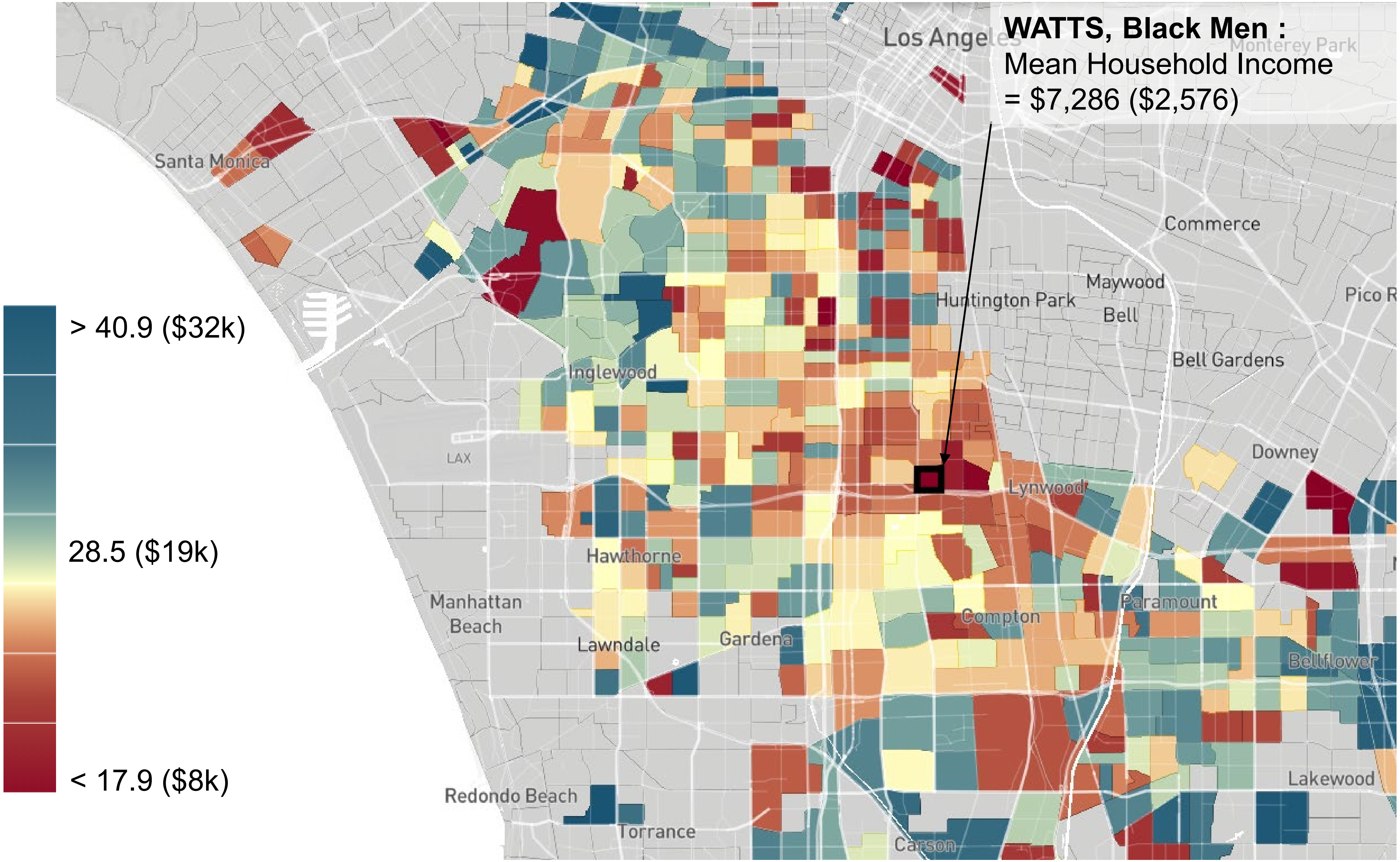
Mean Household Income for Children in Los Angeles with Parents Earning $27,000 (25th percentile)



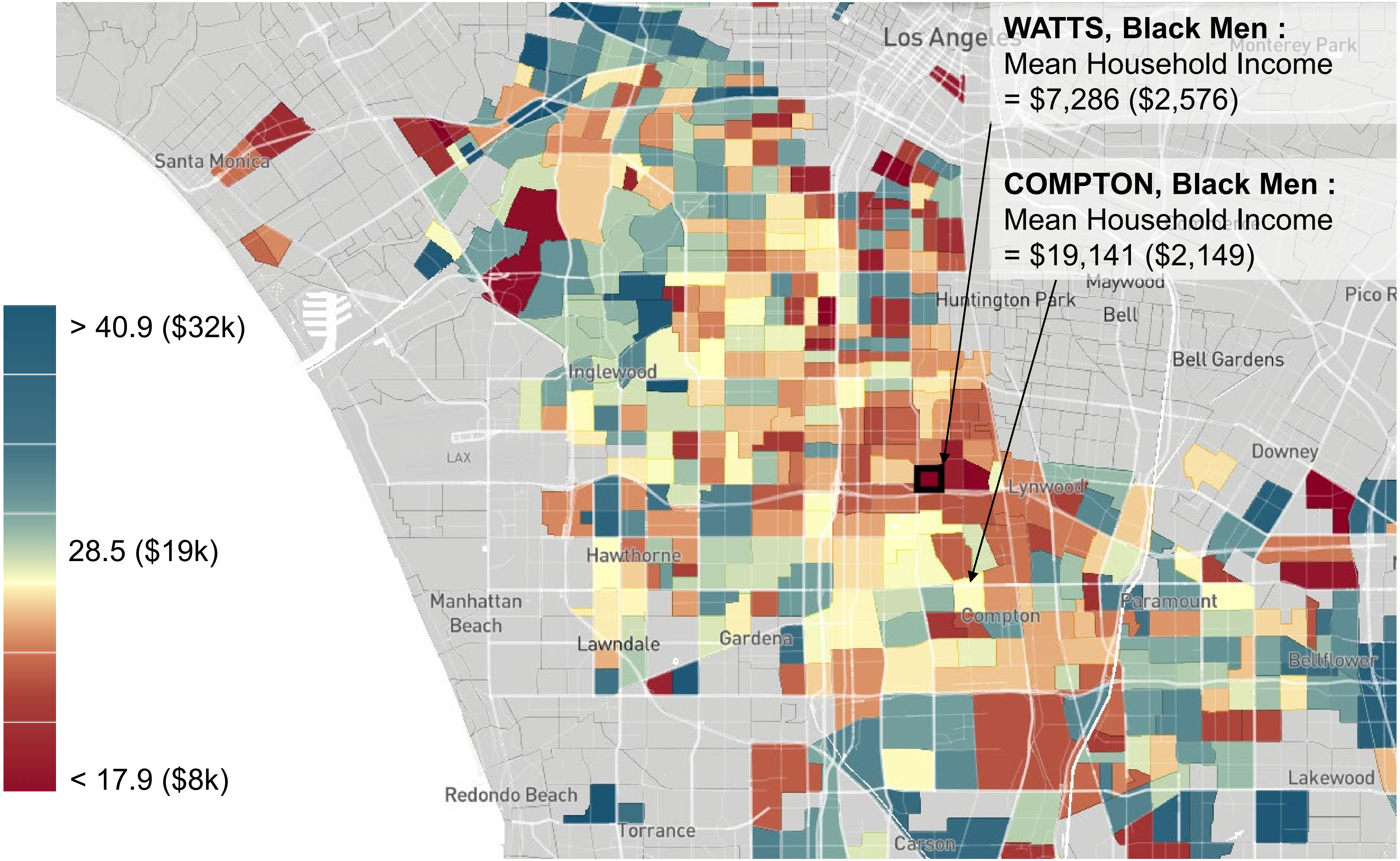
Mean Household Income for Children in Los Angeles with Parents Earning $27,000 (25th percentile)



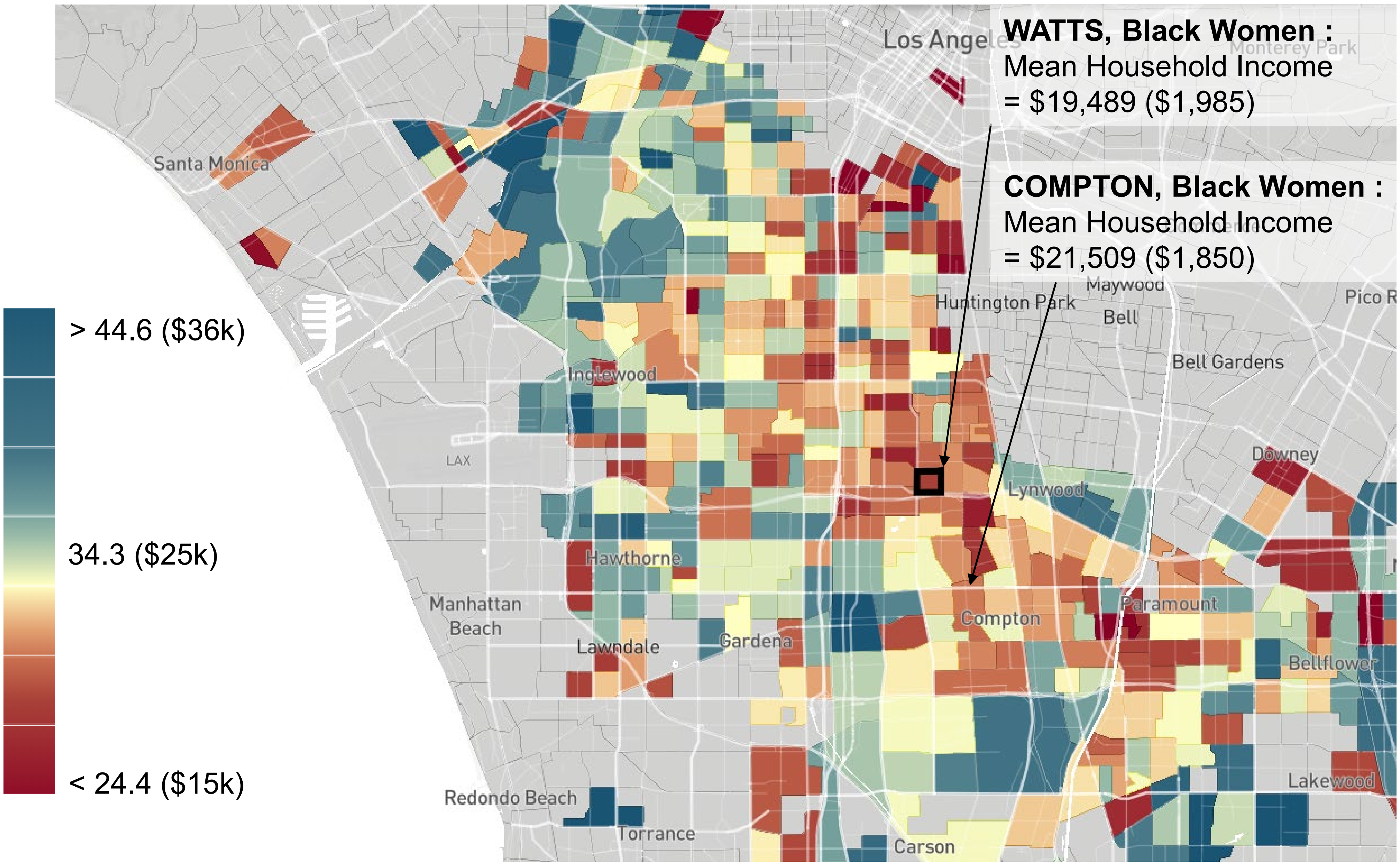
Mean Household Income for Black Men in Los Angeles with Parents Earning $27,000 (25th percentile)



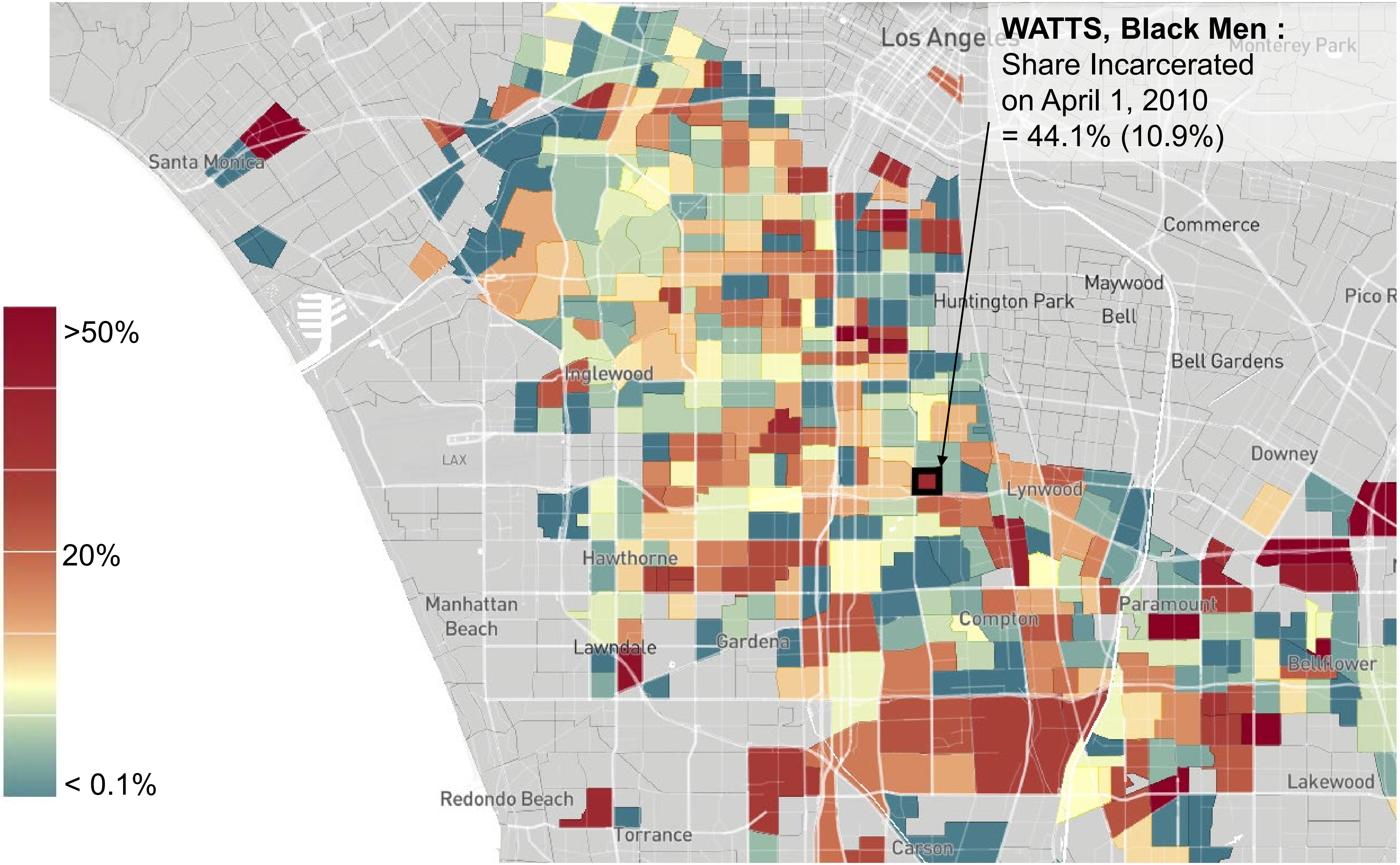
Mean Household Income for Black Men in Los Angeles with Parents Earning $27,000 (25th percentile)



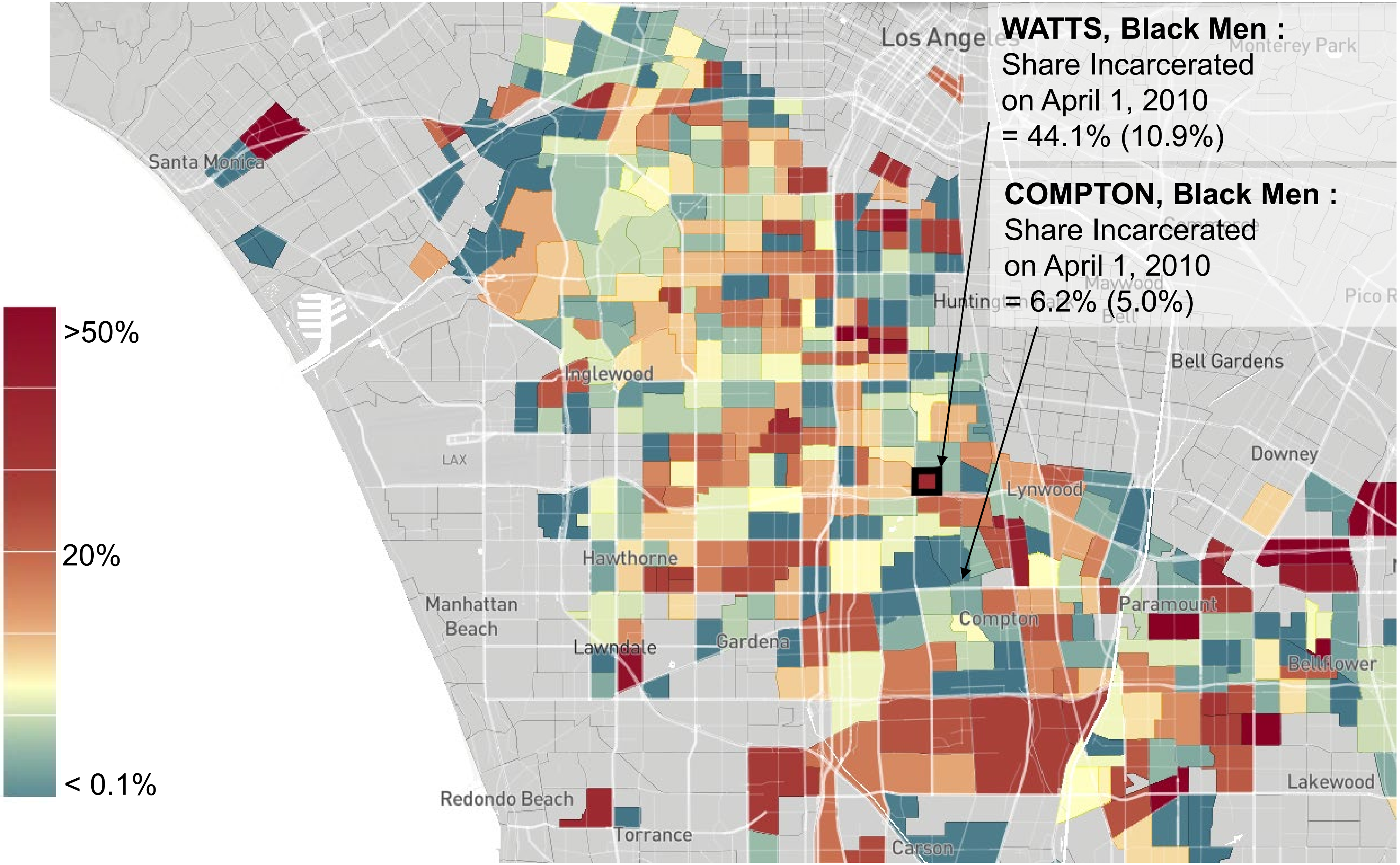
Mean Household Income for Black Women in Los Angeles with Parents Earning $27,000 (25th percentile)



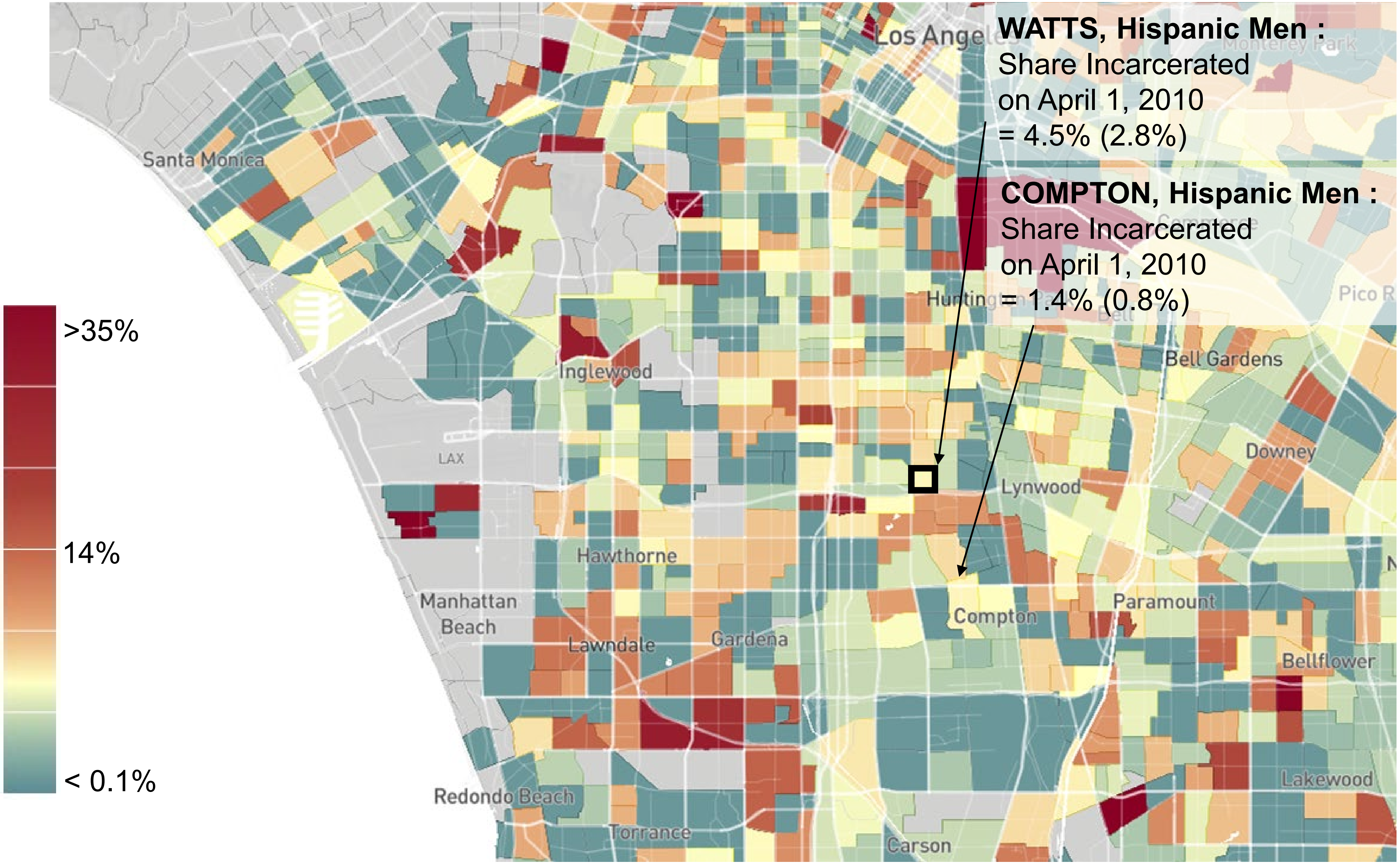
Incarceration Rates for Black Men in Los Angeles with Parents Earning < $2,200 (1st percentile)



Incarceration Rates for Black Men in Los Angeles with Parents Earning < $2,200 (1st percentile)



Incarceration Rates for Hispanic Men in Los Angeles with Parents Earning < $2,200 (1st percentile)

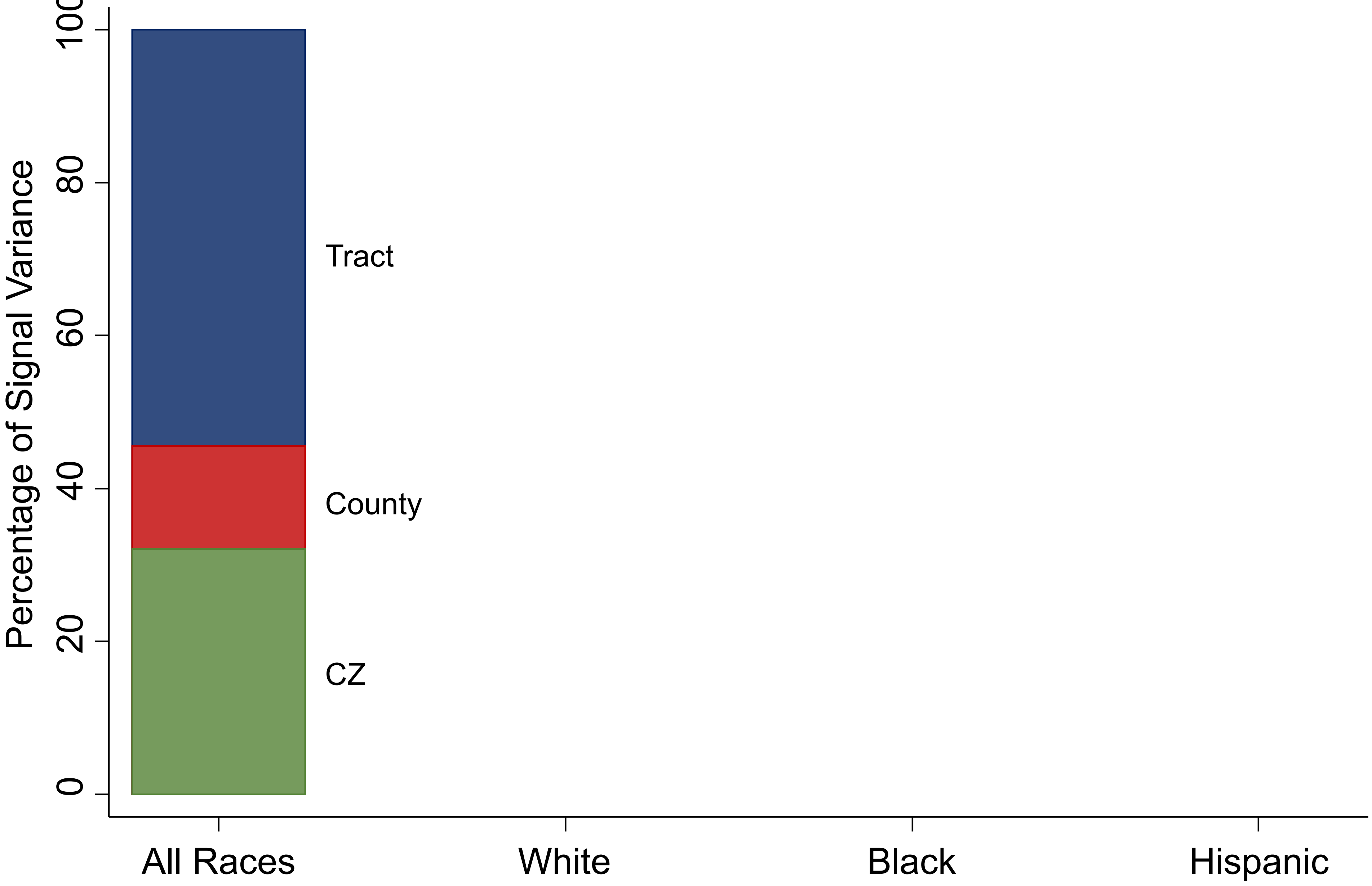


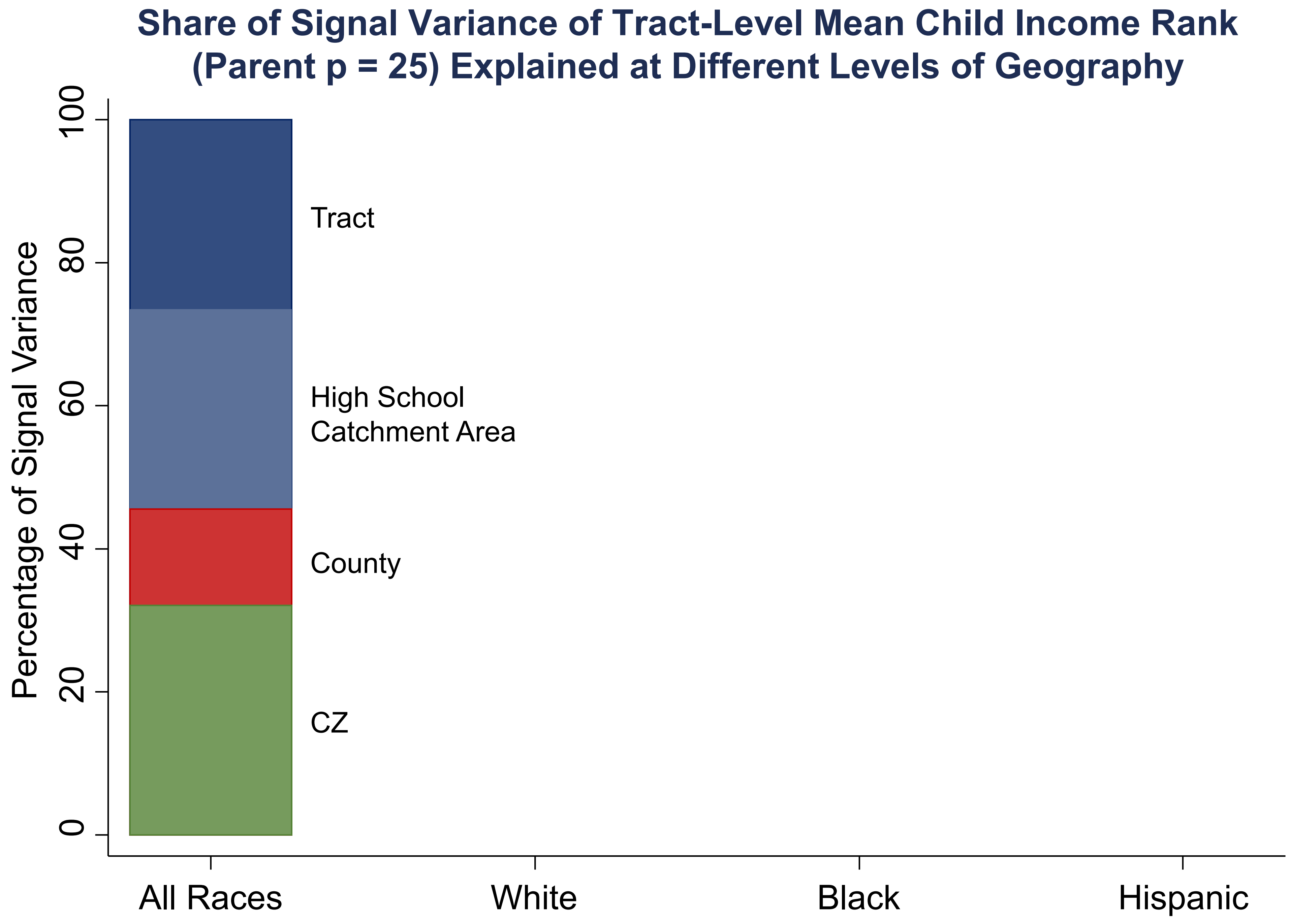
Targeting Place-Based Policies

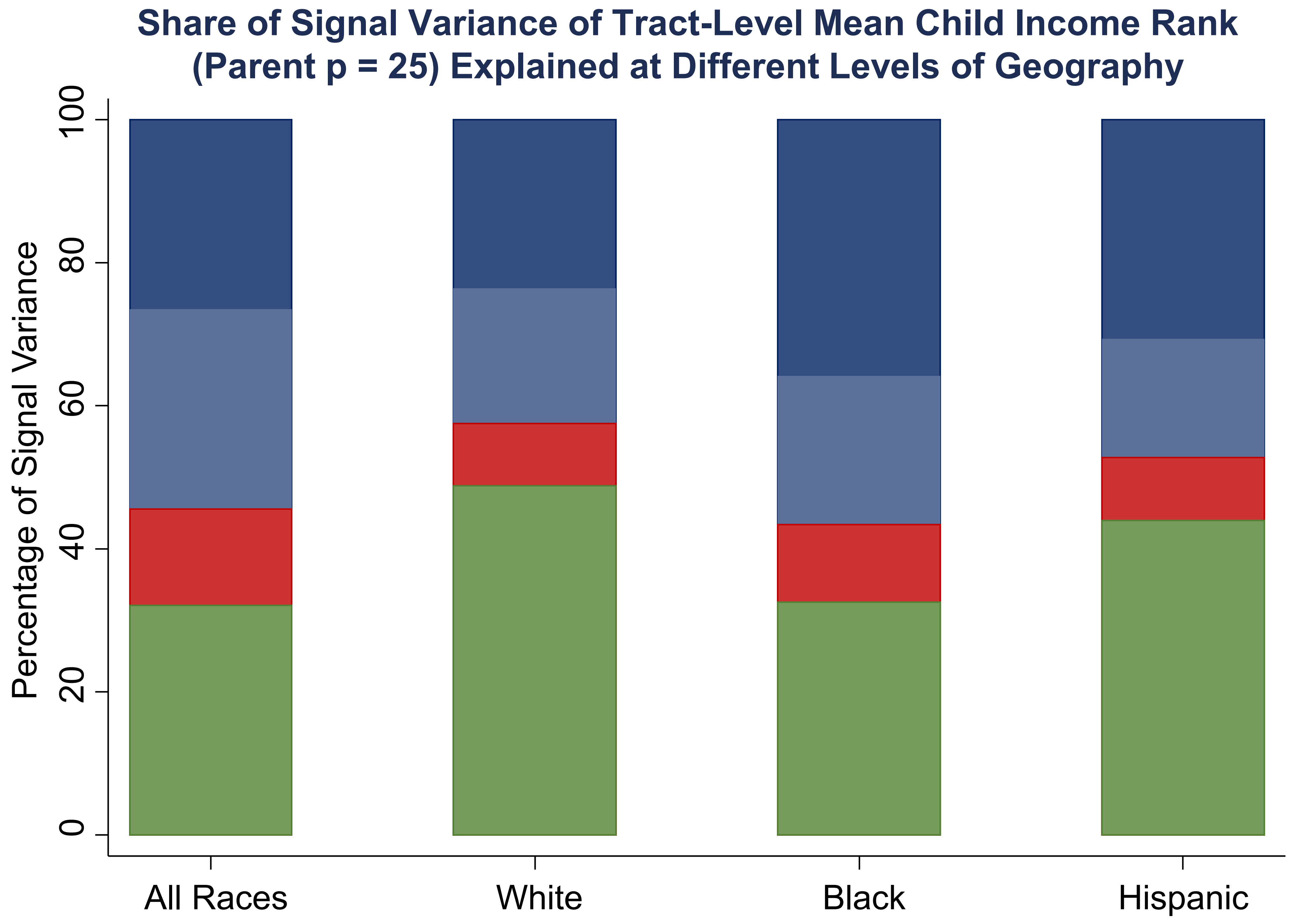
- Example illustrates three general results on targeting:

  1. Children’s outcomes vary widely across nearby tracts → location where children grow up is a useful tag for policy interventions.

Share of Signal Variance of Tract-Level Mean Child Income Rank (Parent p = 25) Explained at Different Levels of Geography




Share of Signal Variance of Tract-Level Mean Child Income Rank
(Parent p = 25) Explained at Different Levels of Geography
Percentage of Signal Variance
0
20
40
60
80
100
Tract
High School
Catchment Area
County
CZ
All Races
White
Black
Hispanic


Share of Signal Variance of Tract-Level Mean Child Income Rank
(Parent p = 25) Explained at Different Levels of Geography
Percentage of Signal Variance
0
20
40
60
80
100
All Races
White
Black
Hispanic

Targeting Place-Based Policies

- Example illustrates three general results on targeting:

  1. Children's outcomes vary widely across nearby tracts → location where children grow up is a useful tag for policy interventions.

  2. Substantial heterogeneity *within* areas across subgroups and outcomes cond. on parent income → neighborhoods not well described by a single-factor model.

Correlations Between Outcomes Across Census Tracts within CZs

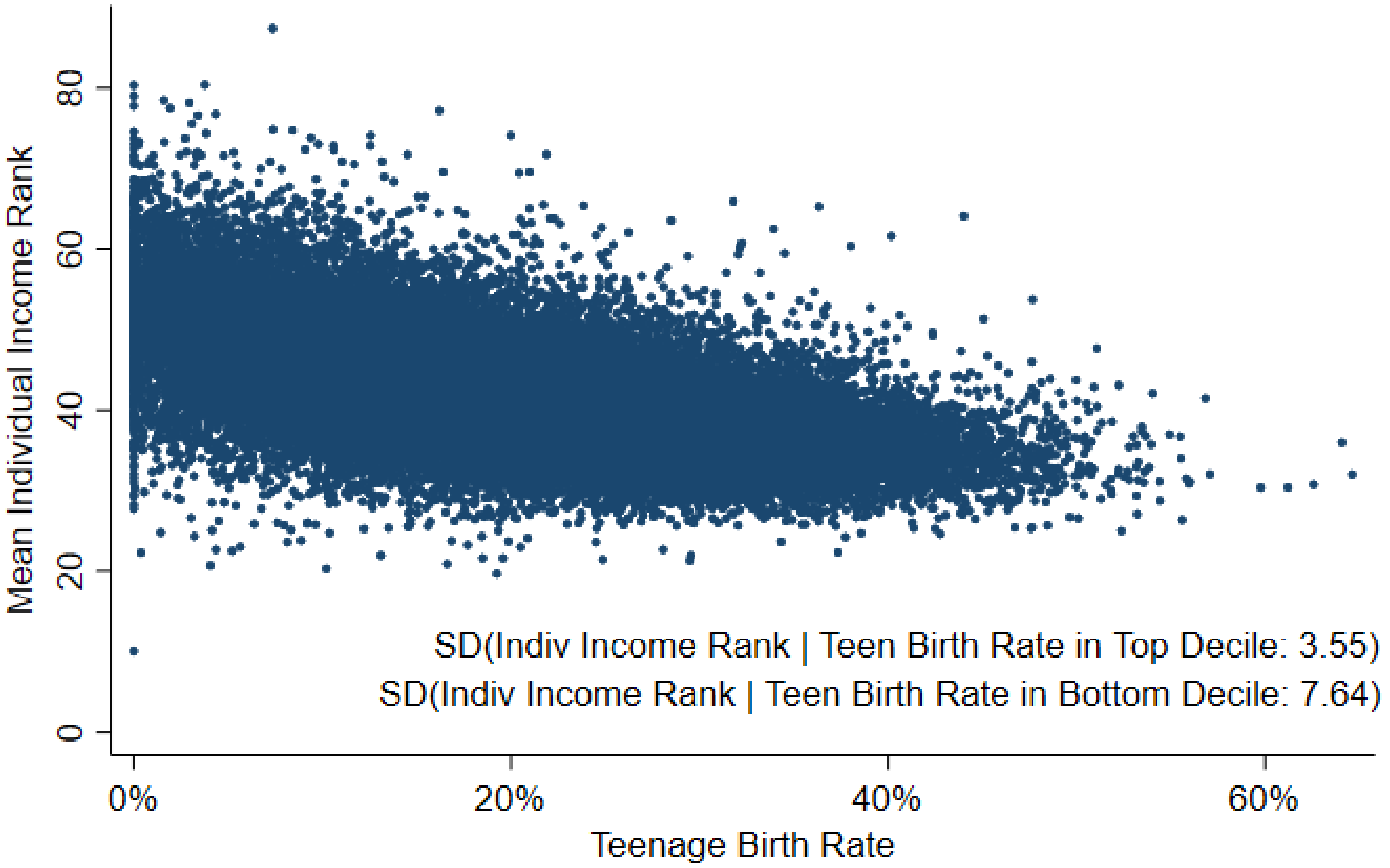
Children with Parents at 25th Percentile, Race-Adjusted

	Household Income Rank	Individual Income Rank	Employment Rate	Incarceration Rate	Teenage Birth Rate
	(1)	(2)	(3)	(4)	(5)
Household Income Rank	1	0.964	0.446	-0.767	-0.870
Individual Income Rank		1	0.559	-0.742	-0.844
Employment Rate			1	-0.334	-0.312
Incarceration Rate				1	0.774
Teenage Birth Rate					1

Note: Correlations estimated by splitting families into two random samples, estimating correlations across the two samples, and adjusting for sampling error

Upward Mobility vs. Teenage Birth Rates Across Tracts

White Women with Parents at 25th Percentile of Income Distribution



Correlation of Mean Income Ranks by Tract Across Racial Groups within CZs

Children with Parents at 25th Percentile

	White	Black	Hispanic	Asian	American Indian & Alaska Natives	Parents at 75th Pctile, Same Race
	(1)	(2)	(3)	(4)	(5)	(6)
White	1	0.573	0.580	0.523	0.636	0.604
Black		1	0.546	0.357	0.436	0.452
Hispanic			1	0.374	0.602	0.352
Asian				1	0.267	0.463
American Indian & Alaska Natives					1	0.356

Note: Signal correlations adjusted for sampling error in the outcome variables

Targeting Place-Based Policies

- Example illustrates three general results on targeting:

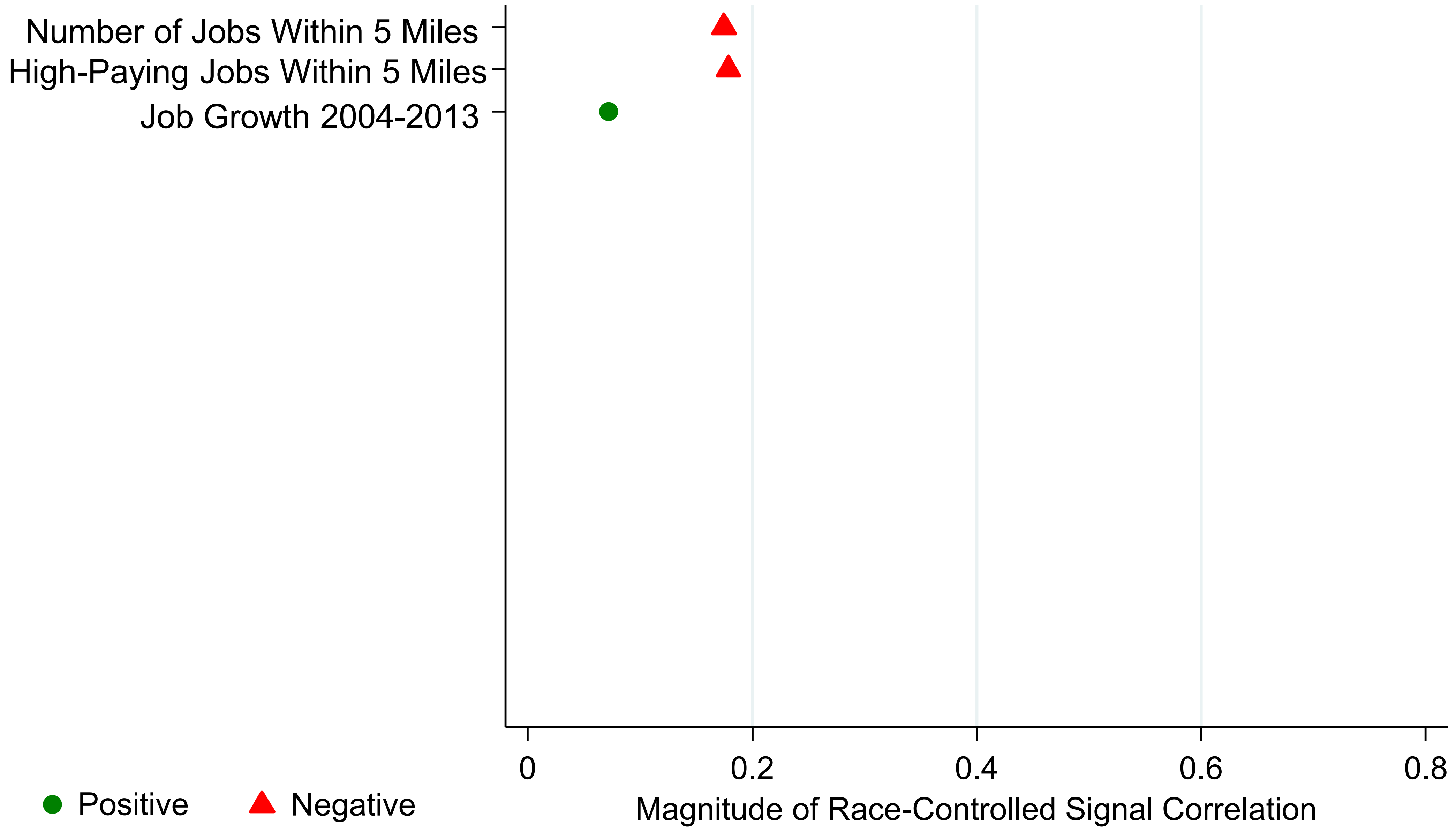
  1. Children’s outcomes vary widely across nearby tracts → location where children grow up is a useful tag for policy interventions.

  2. Substantial heterogeneity *within* areas across subgroups and outcomes cond. on parent income → neighborhoods not well described by a single-factor model.

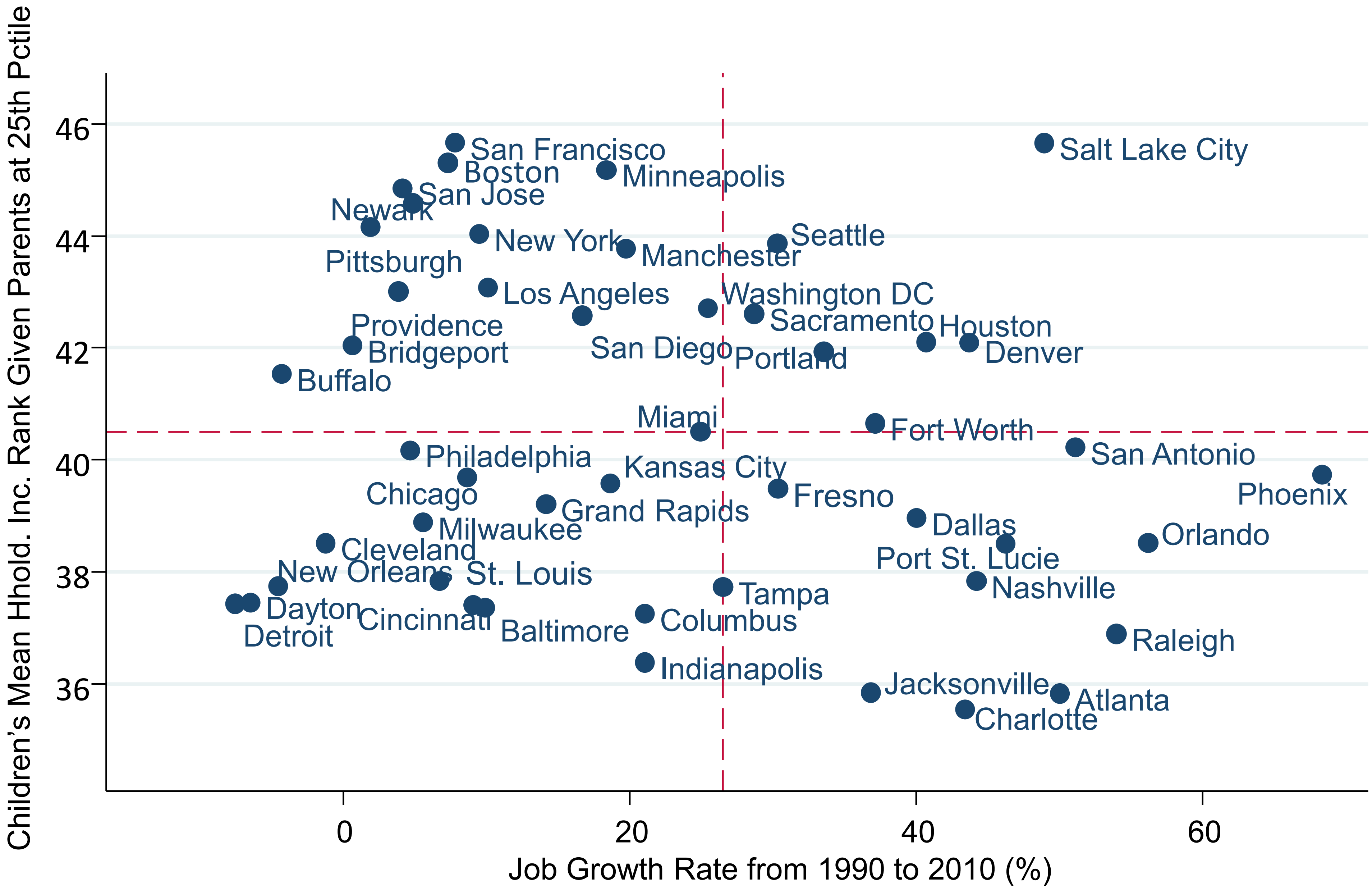
  3. Outcome-based measures contain new information relative to traditional measures used to target policies, such as poverty rates or job growth.

Correlations between Tract-Level Covariates and Household Income Rank

Race-Adjusted, Parent Income at 25th Percentile



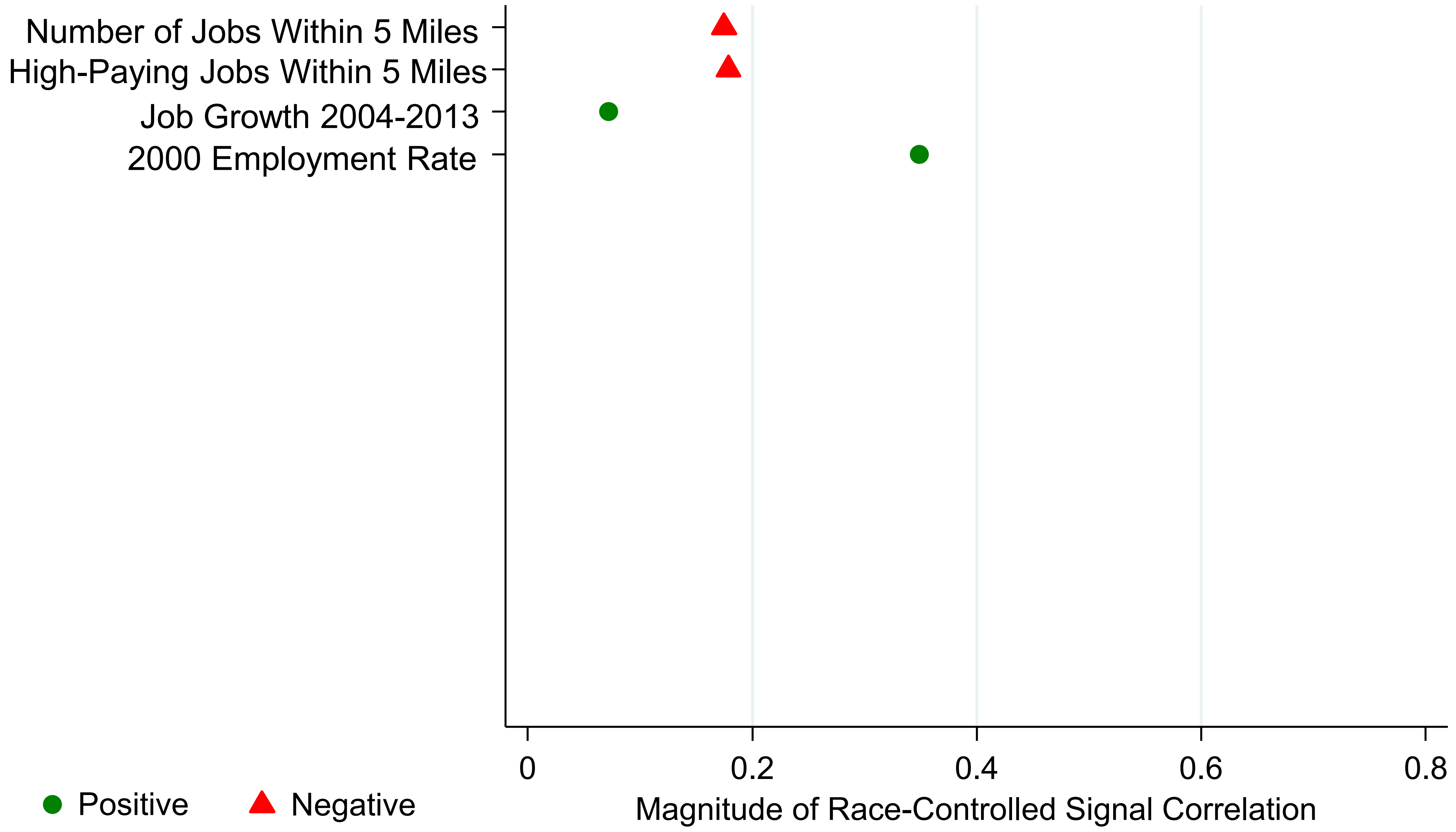
Upward Mobility vs. Job Growth in the 50 Largest Commuting Zones



Correlation (across all CZs): -0.03

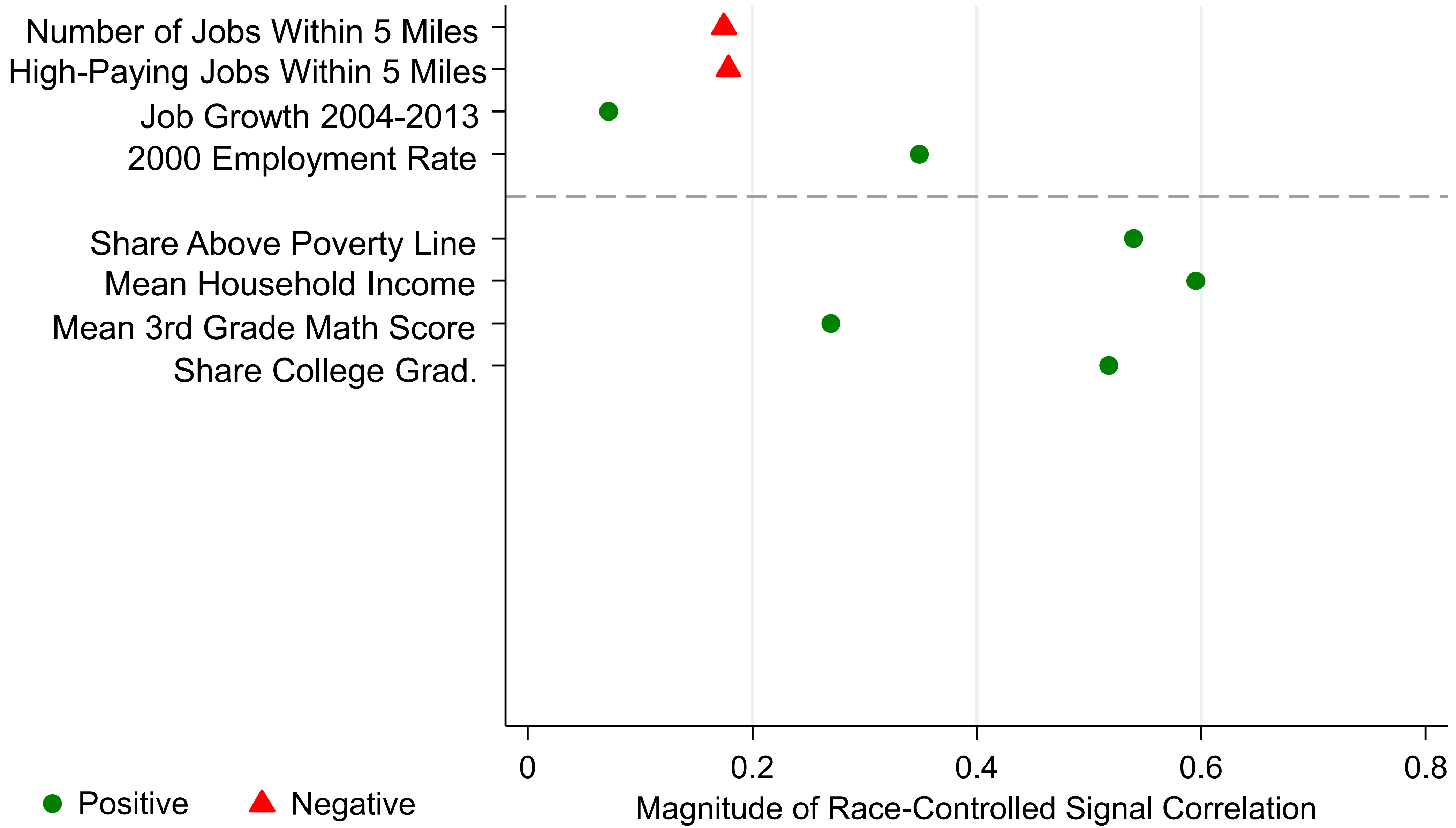
Correlations between Tract-Level Covariates and Household Income Rank

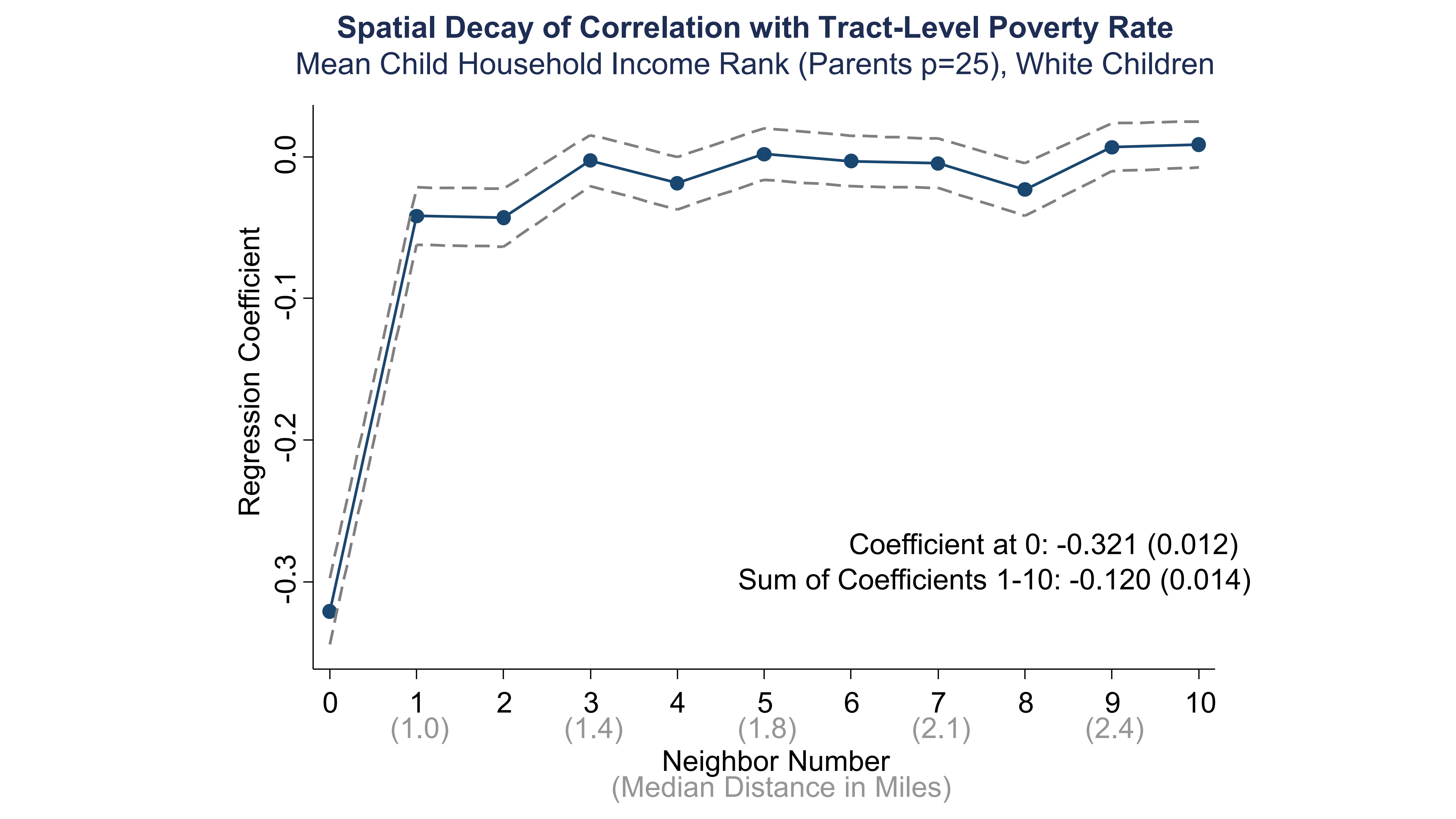
Race-Adjusted, Parent Income at 25th Percentile

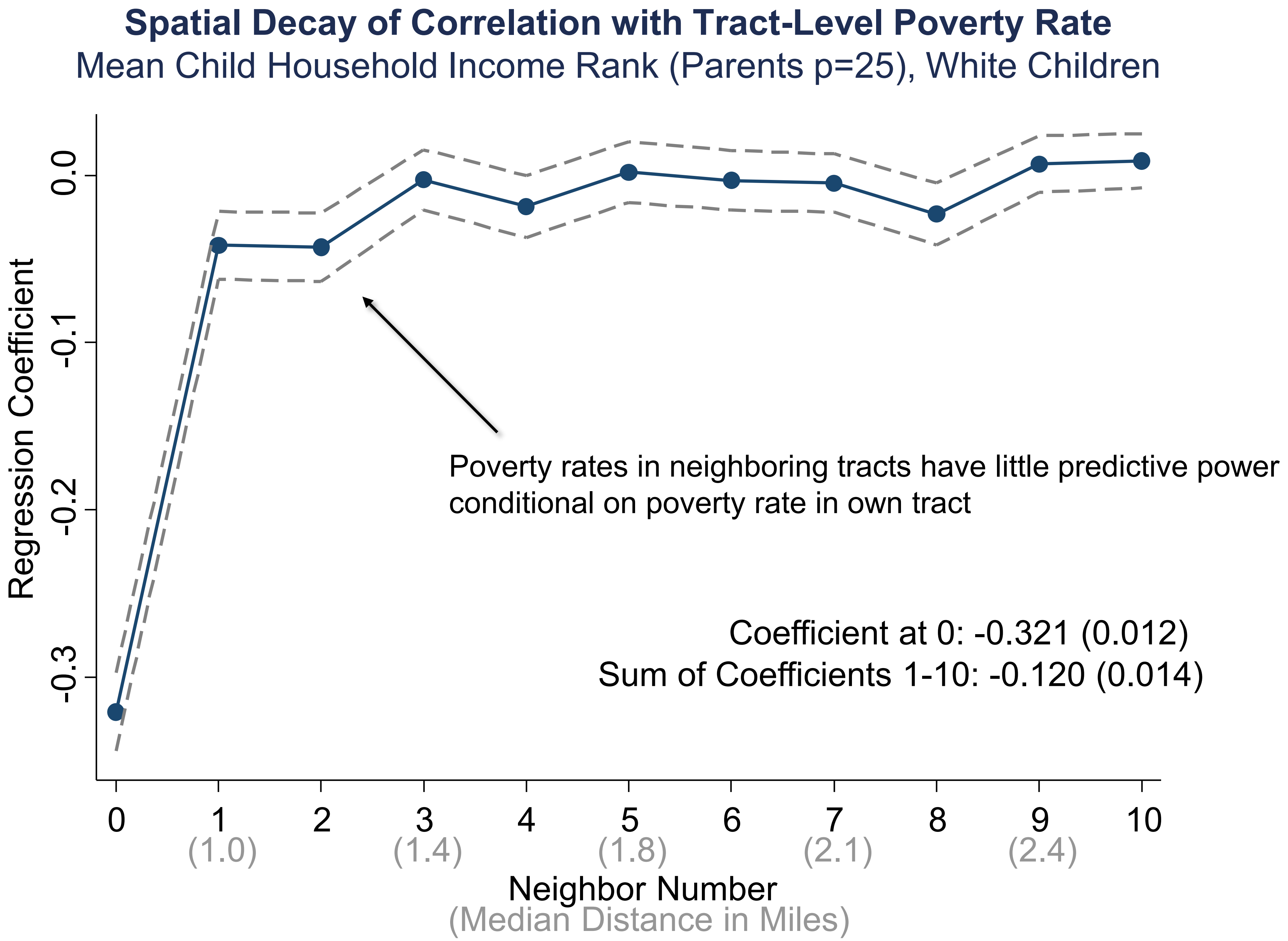


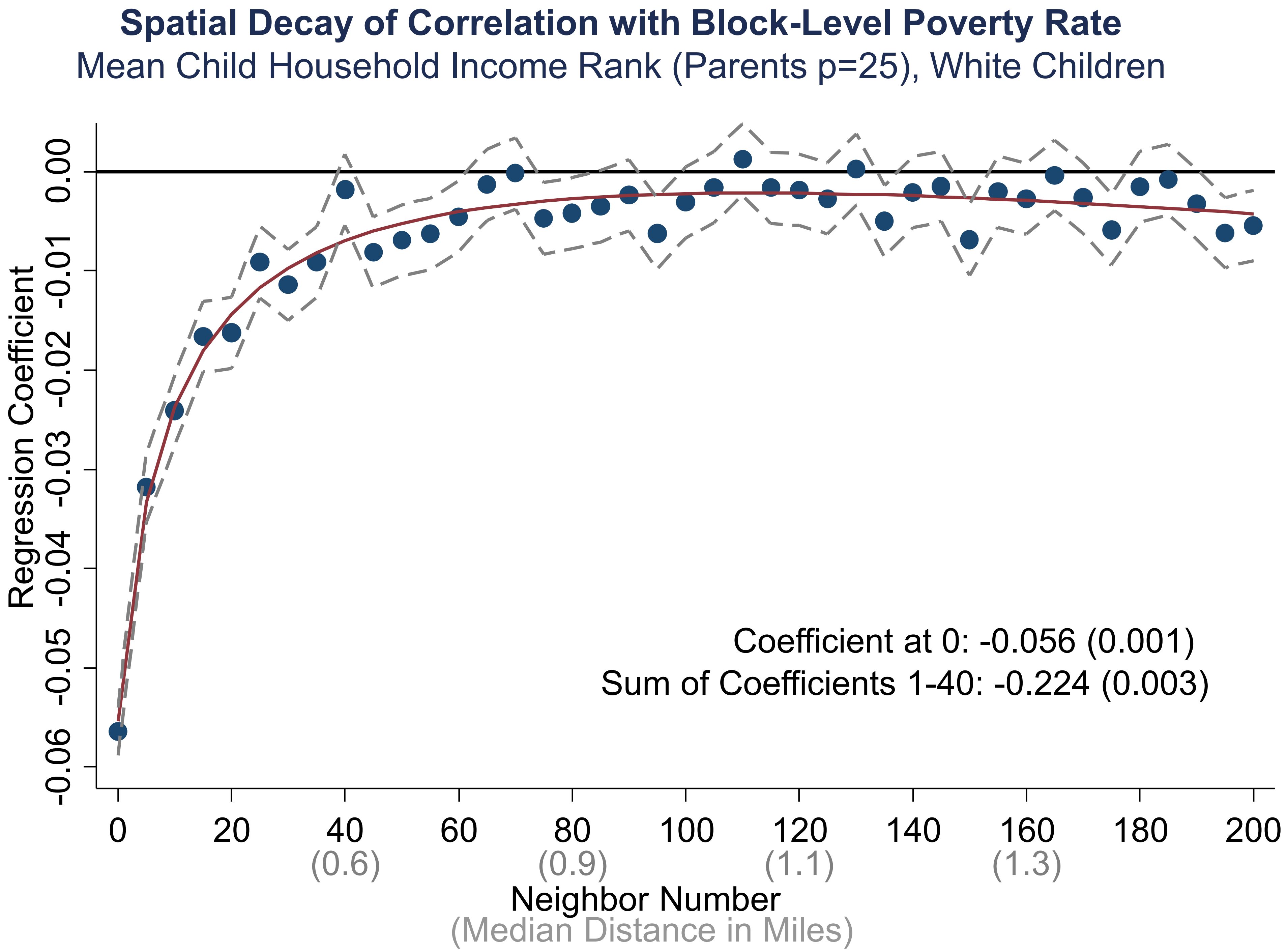
Correlations between Tract-Level Covariates and Household Income Rank

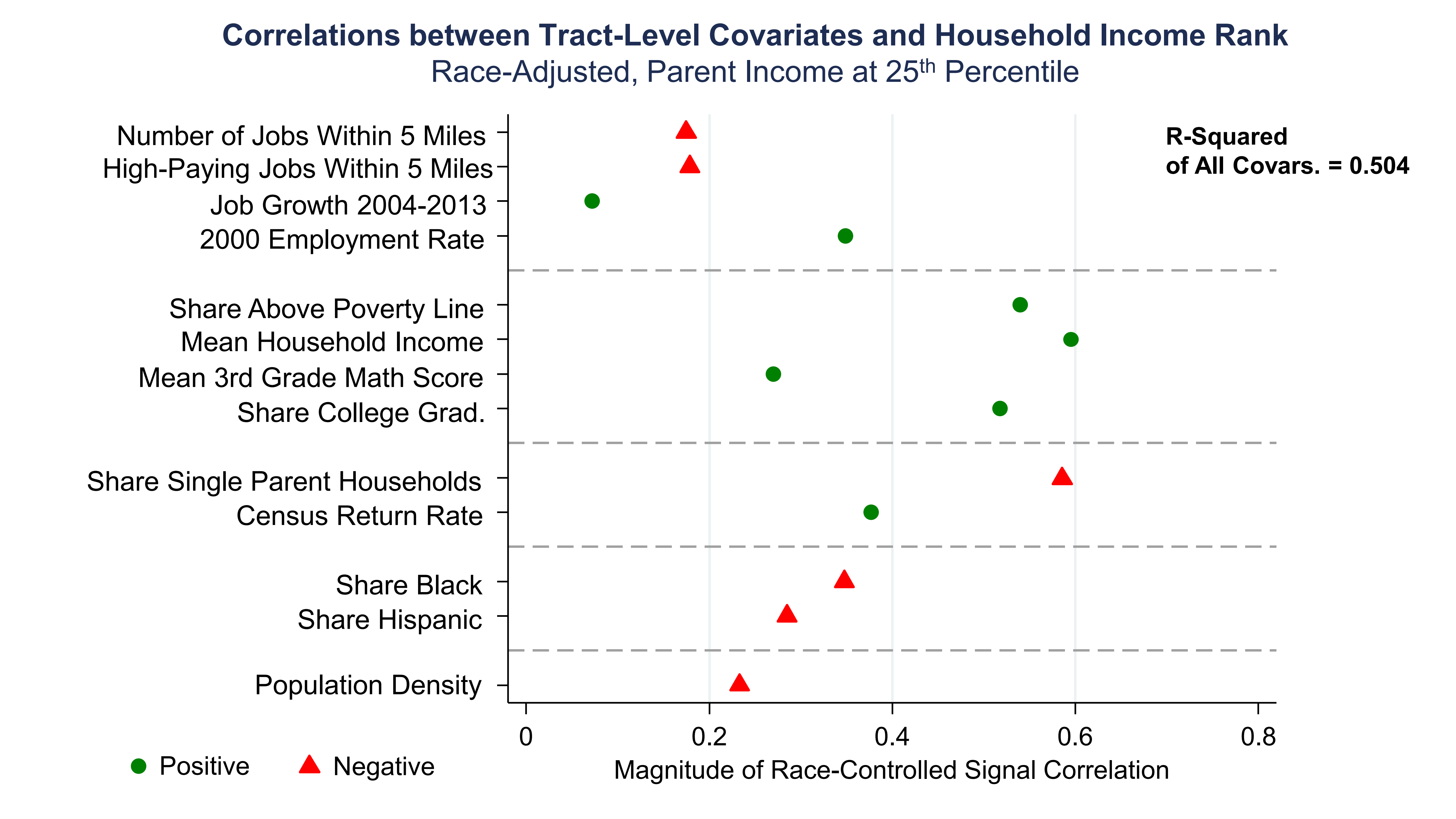
Race-Adjusted, Parent Income at 25th Percentile




Spatial Decay of Correlation with Tract-Level Poverty Rate
Mean Child Household Income Rank (Parents p=25), White Children
Regression Coefficient
0.0
-0.1
-0.2
-0.3
Coefficient at 0: -0.321 (0.012)
Sum of Coefficients 1-10: -0.120 (0.014)
0
1
2
3
4
5
6
7
8
9
10
(1.0)
(1.4)
(1.8)
(2.1)
(2.4)
Neighbor Number
(Median Distance in Miles)


Spatial Decay of Correlation with Tract-Level Poverty Rate
Mean Child Household Income Rank (Parents p=25), White Children
Regression Coefficient
0.0
-0.1
-0.2
-0.3
Poverty rates in neighboring tracts have little predictive power conditional on poverty rate in own tract
Coefficient at 0: -0.321 (0.012)
Sum of Coefficients 1-10: -0.120 (0.014)
0
1
(1.0)
2
3
(1.4)
4
5
(1.8)
6
7
(2.1)
8
9
(2.4)
10
Neighbor Number
(Median Distance in Miles)

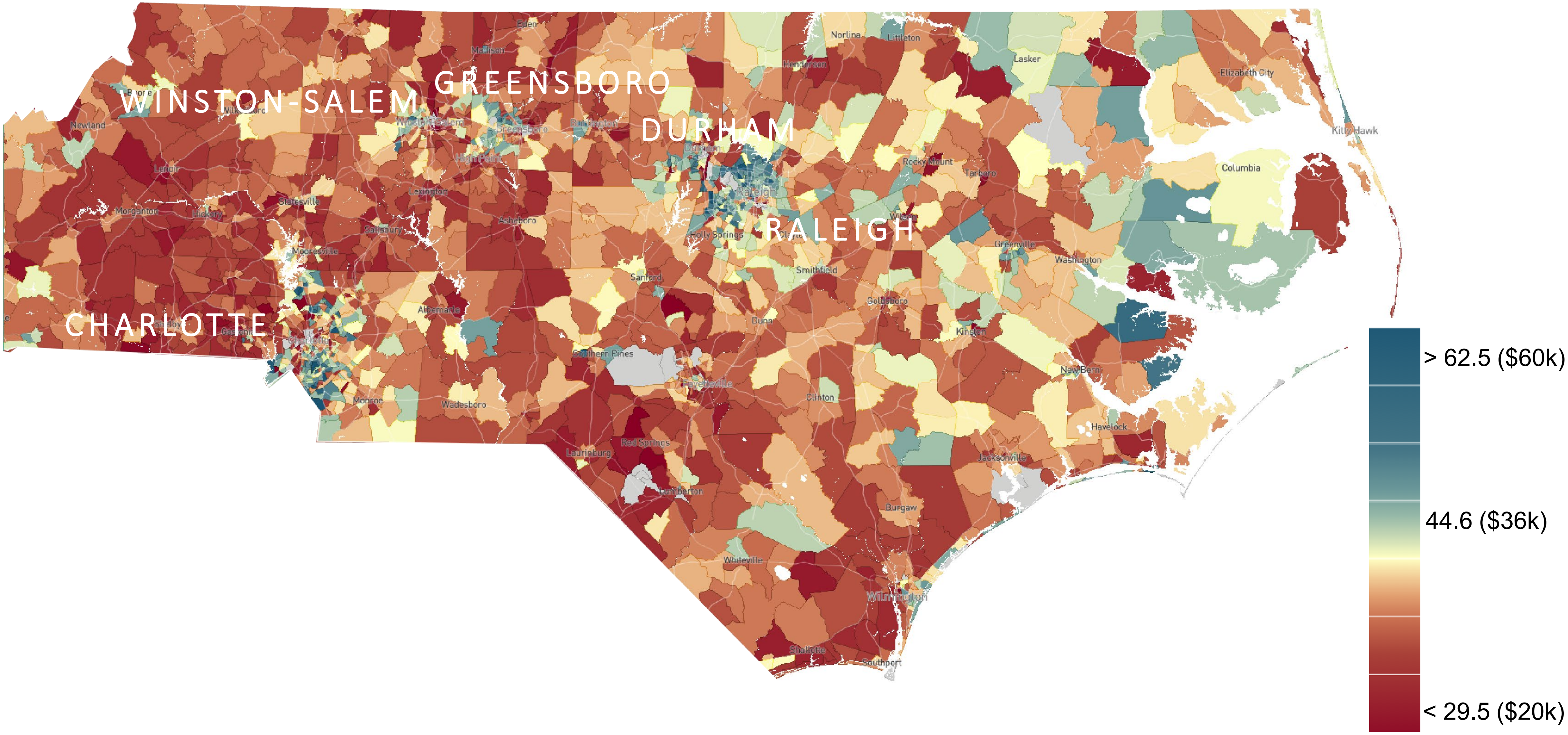

Spatial Decay of Correlation with Block-Level Poverty Rate
Mean Child Household Income Rank (Parents p=25), White Children
Regression Coefficient
0.00
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
Coefficient at 0: -0.056 (0.001)
Sum of Coefficients 1-40: -0.224 (0.003)
0
20
40
60
80
100
120
140
160
180
200
(0.6)
(0.9)
(1.1)
(1.3)
Neighbor Number
(Median Distance in Miles)



Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile
Number of Jobs Within 5 Miles
High-Paying Jobs Within 5 Miles
Job Growth 2004-2013
2000 Employment Rate
Share Above Poverty Line
Mean Household Income
Mean 3rd Grade Math Score
Share College Grad.
Share Single Parent Households
Census Return Rate
Share Black
Share Hispanic
Population Density
R-Squared
of All Covars. = 0.504
0
0.2
0.4
0.6
0.8
Magnitude of Race-Controlled Signal Correlation
Positive
Negative

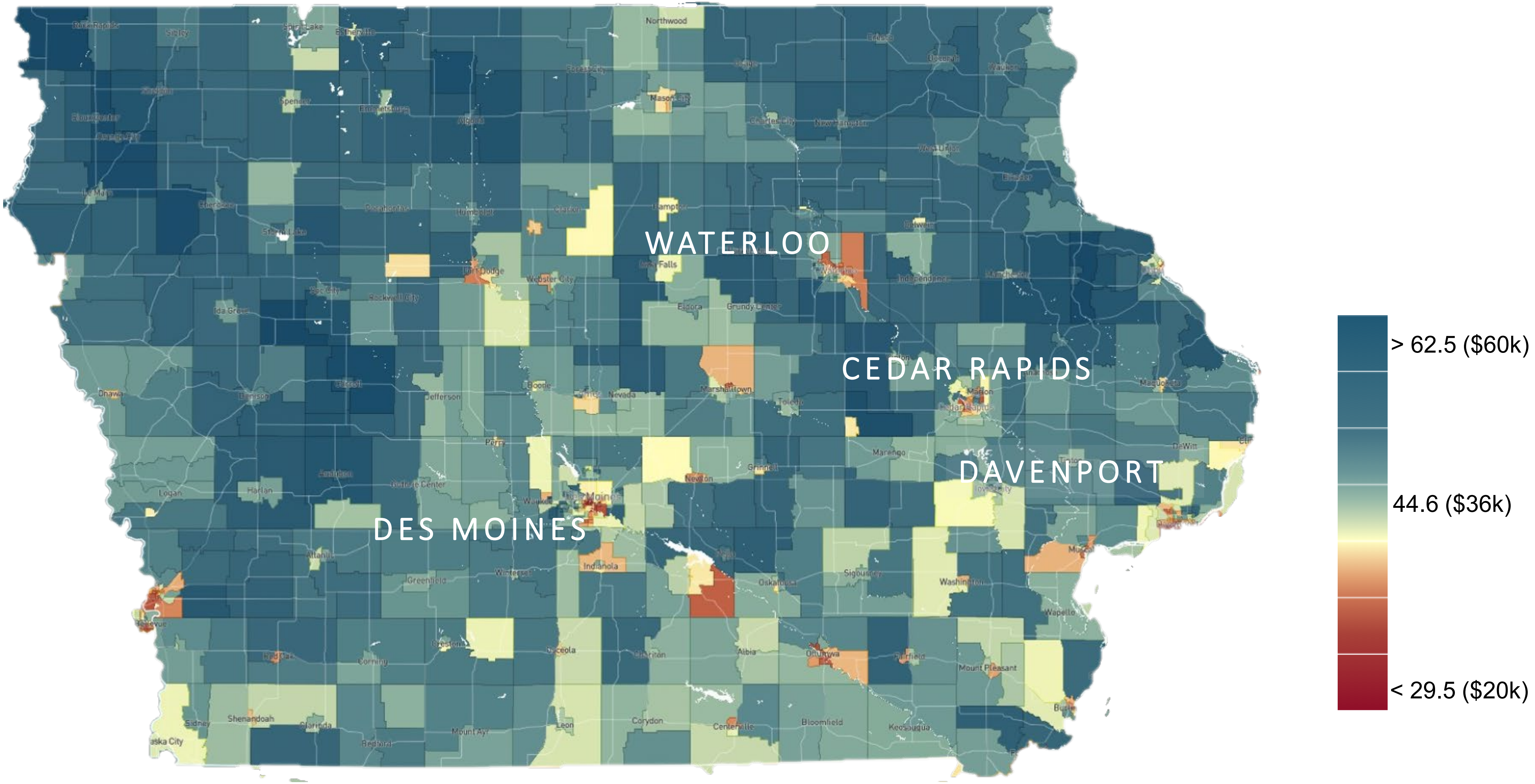
Do Cities Offer Greater Opportunities for Upward Mobility?

Average Income for White Children with Parents Earning $25,000 in North Carolina



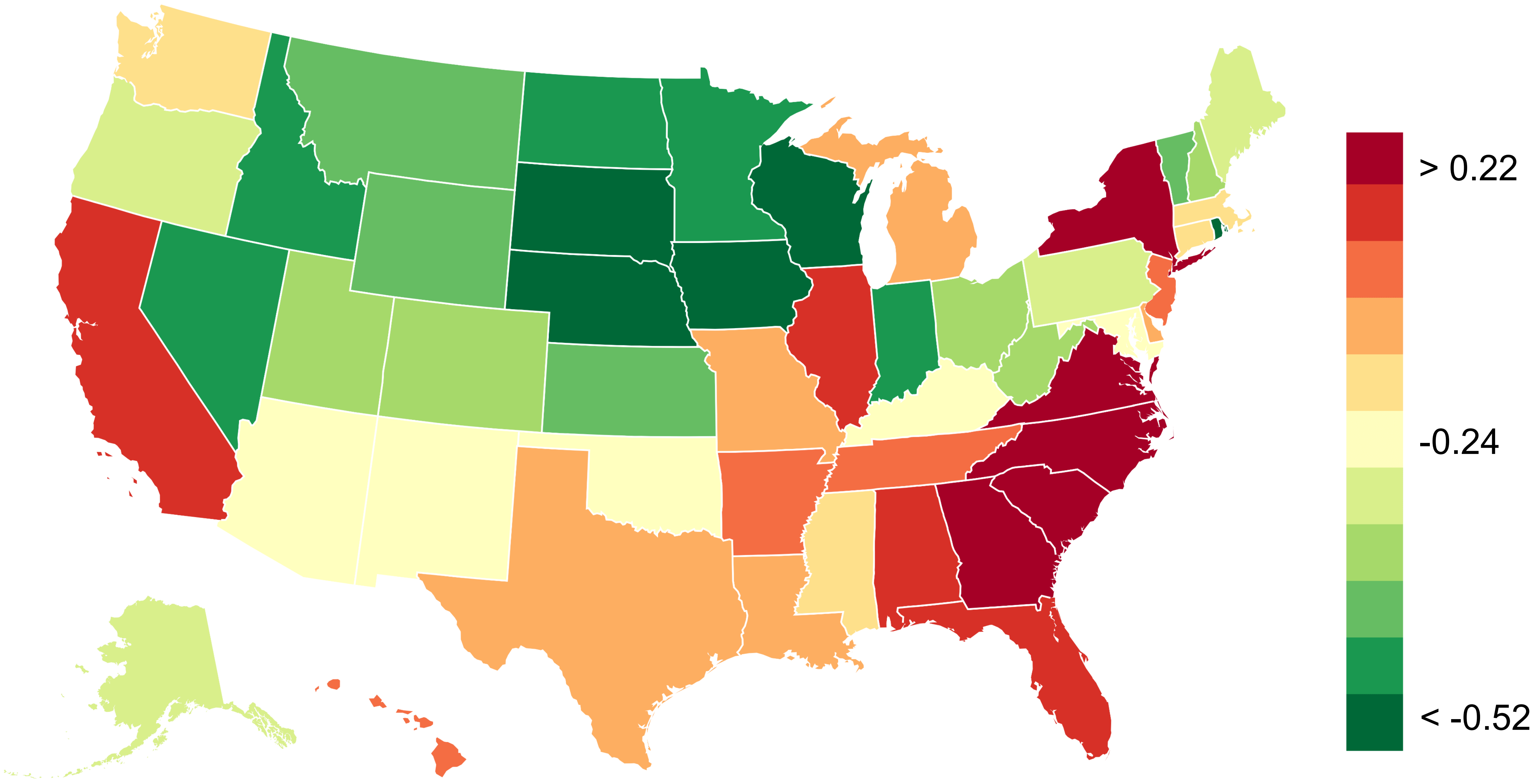
Do Cities Offer Greater Opportunities for Upward Mobility?

Average Income for White Children with Parents Earning $25,000 in Iowa



Correlations between Population Density and Household Income Rank Across Tracts, by State

White Children, Parent Income at 25th Percentile



Using Location as a Tag for Policy

- Tract-level estimates of children’s appear to provide new information that could be helpful in identifying areas where opportunity is most lacking.
- Practical challenge in using these estimates to inform policy: they come with a lag, since one must wait until children grow up to observe their earnings.
- Statistic of interest for policy is rate of social mobility for children today, which is inherently unobservable.
- Key conceptual question: are historical estimates useful predictors of opportunity for current cohorts?

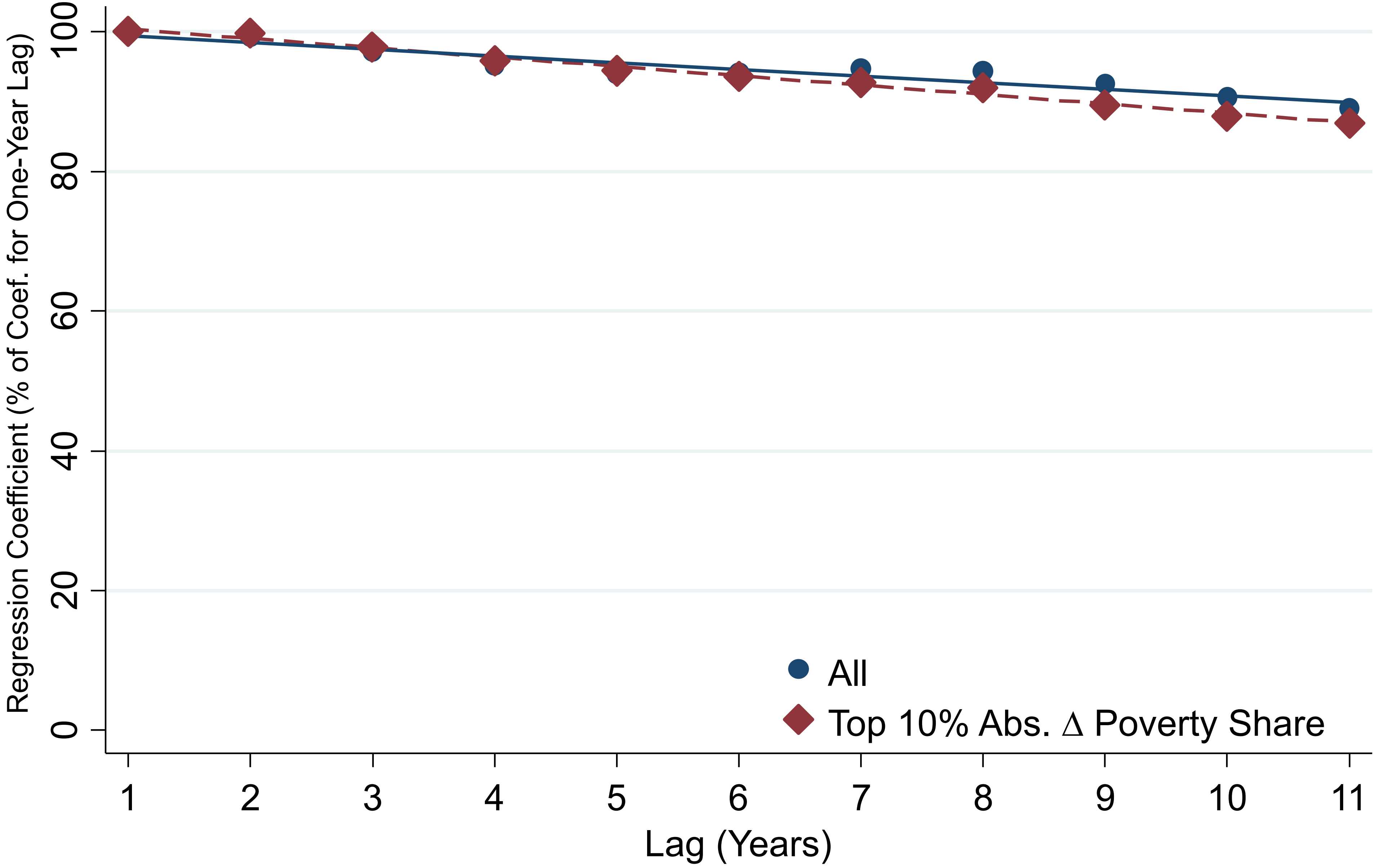
Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

- Assess predictive power of historical estimates in two steps:

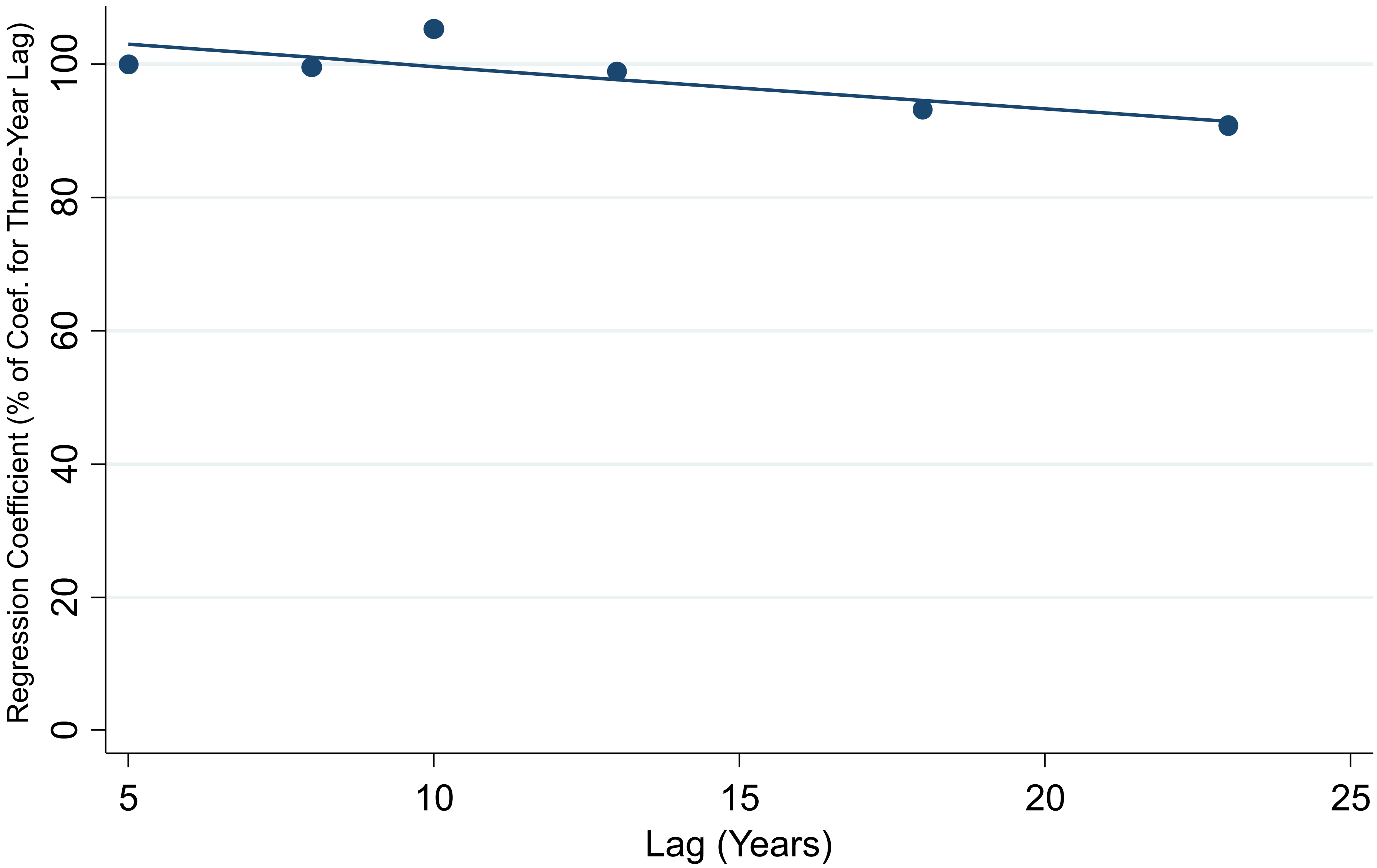
1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power.

Autocovariance of Tract-Level Estimates

Mean Household Income at Age 26 for Children with Parents at p=25



Autocovariance of Tract-Level Poverty Rates Using Publicly Available Census Data



Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

- Assess predictive power of historical estimates in two steps:

1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power.

2. Compare predictive power of historical outcomes to observable characteristics such as poverty rate and single parent share.

   - When predicting upward mobility for 1989 cohort, incremental R-squared of covariates is 20% of the R-squared of upward mobility for 1979 cohort.

   - Correlation of predicted values using models with vs. without neighborhood characteristics exceeds 0.85.

Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

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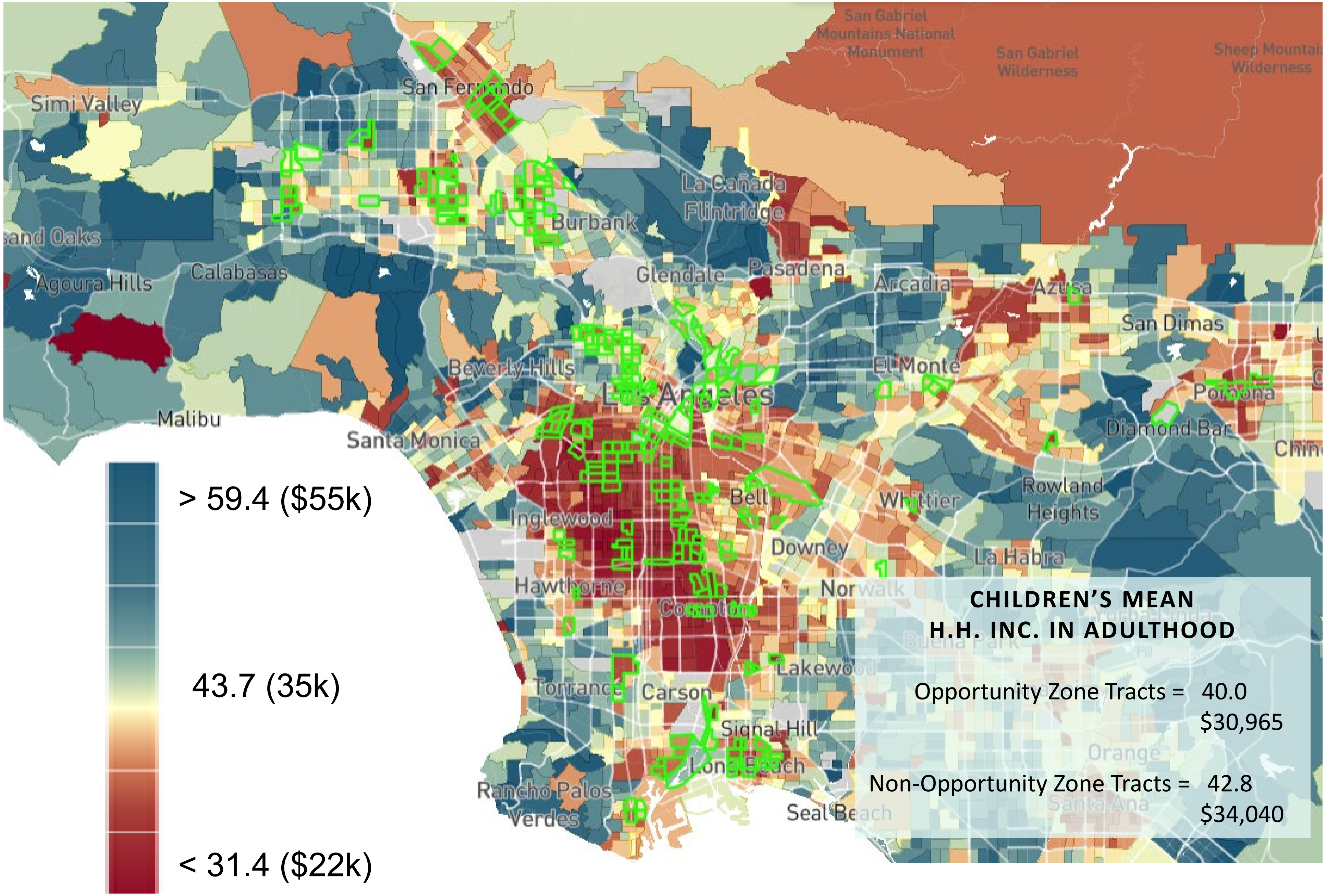
   – When predicting upward mobility for 1989 cohort, incremental R-squared of covariates is 20% of the R-squared of upward mobility for 1979 cohort.

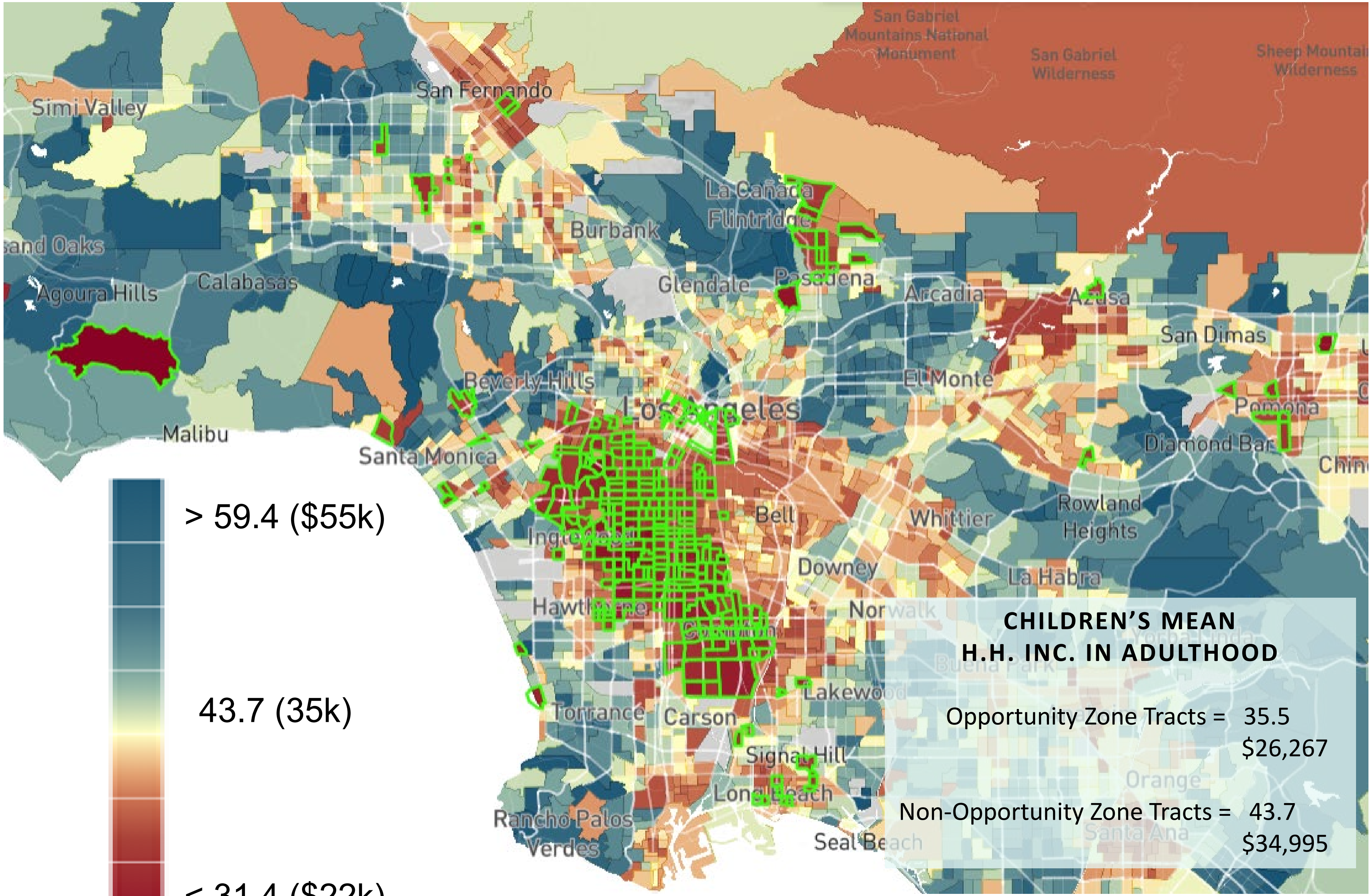
   – Correlation of predicted values using models with vs. without neighborhood characteristics exceeds 0.85.

→ Tract-level estimates of outcomes provide informative (but imperfect) predictors of economic opportunity for children today.

Currently Designated Opportunity Zones in Los Angeles County



Hypothetical Opportunity Zones using Upward Mobility Estimates



> 59.4 ($55k)

43.7 (35k)

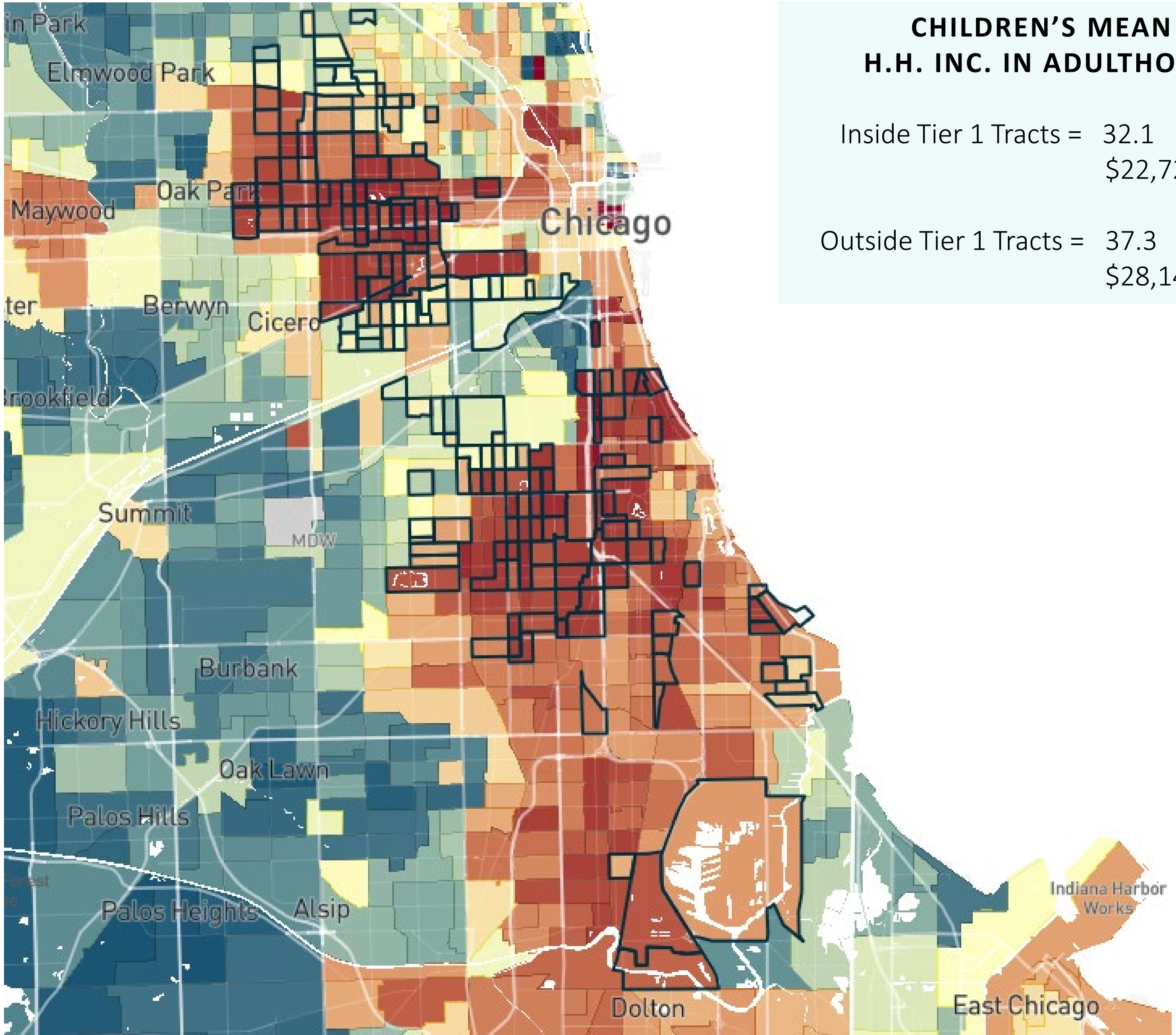
< 31.4 ($22k)

CHILDREN'S MEAN H.H. INC. IN ADULTHOOD

Opportunity Zone Tracts = 35.5 $26,267

Non-Opportunity Zone Tracts = 43.7 $34,995

Preferential Admission Tracts to Selective Chicago Public Schools



CHILDREN'S MEAN H.H. INC. IN ADULTHOOD

Inside Tier 1 Tracts = 32.1
$22,720

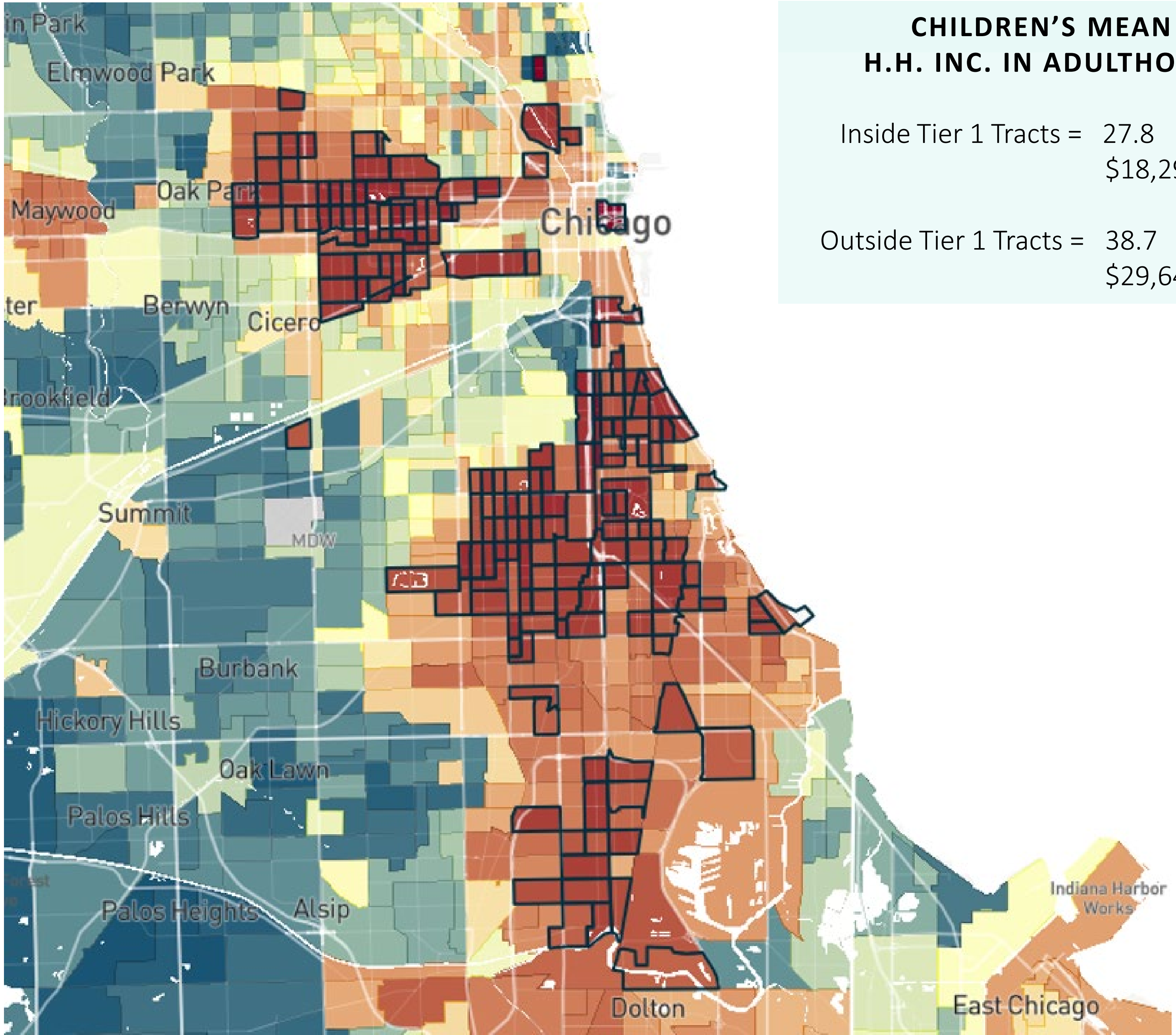
Outside Tier 1 Tracts = 37.3
$28,143

> 59.4 ($55k)

43.7 (35k)

< 19.5 ($9.9k)

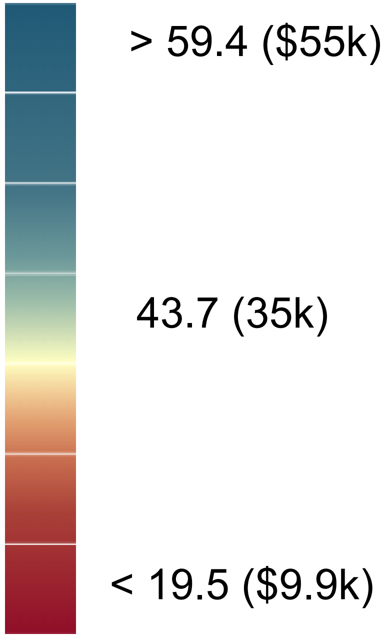
Hypothetical Admission Tracts using Upward Mobility Estimates



CHILDREN'S MEAN H.H. INC. IN ADULTHOOD

Inside Tier 1 Tracts = 27.8
$18,298

Outside Tier 1 Tracts = 38.7
$29,649



1 Data

2 Methods to Construct Tract-Level Estimates

3 Observational Variation and Targeting

4 Causal Effects and Neighborhood Choice

Neighborhood Choice and Causal Effects of Place

- Where should a family seeking to improve their children's outcomes live?

- Answer matters both to individual families and potentially for policy design.

  – Ex: Many affordable housing programs (e.g., Housing Choice Vouchers) have explicit goal of helping low-income families access "higher opportunity" areas.

- For these questions, critical to understand whether observational variation is driven by **causal effects** of place or selection.

Identifying Causal Effects of Place

- Identify causal effects using two research designs:

  1. Moving-to-Opportunity (MTO) Experiment: Compare observational predictions to treatment effects of MTO experiment on children's earnings.

  2. Movers Quasi-Experiment: Analyze outcomes of children who move at different ages across all tracts.

Moving to Opportunity Experiment

- 4,600 families at 5 sites from 1994-98: Baltimore, Boston, Chicago, LA, New York.

- Families randomly assigned to one of three groups:

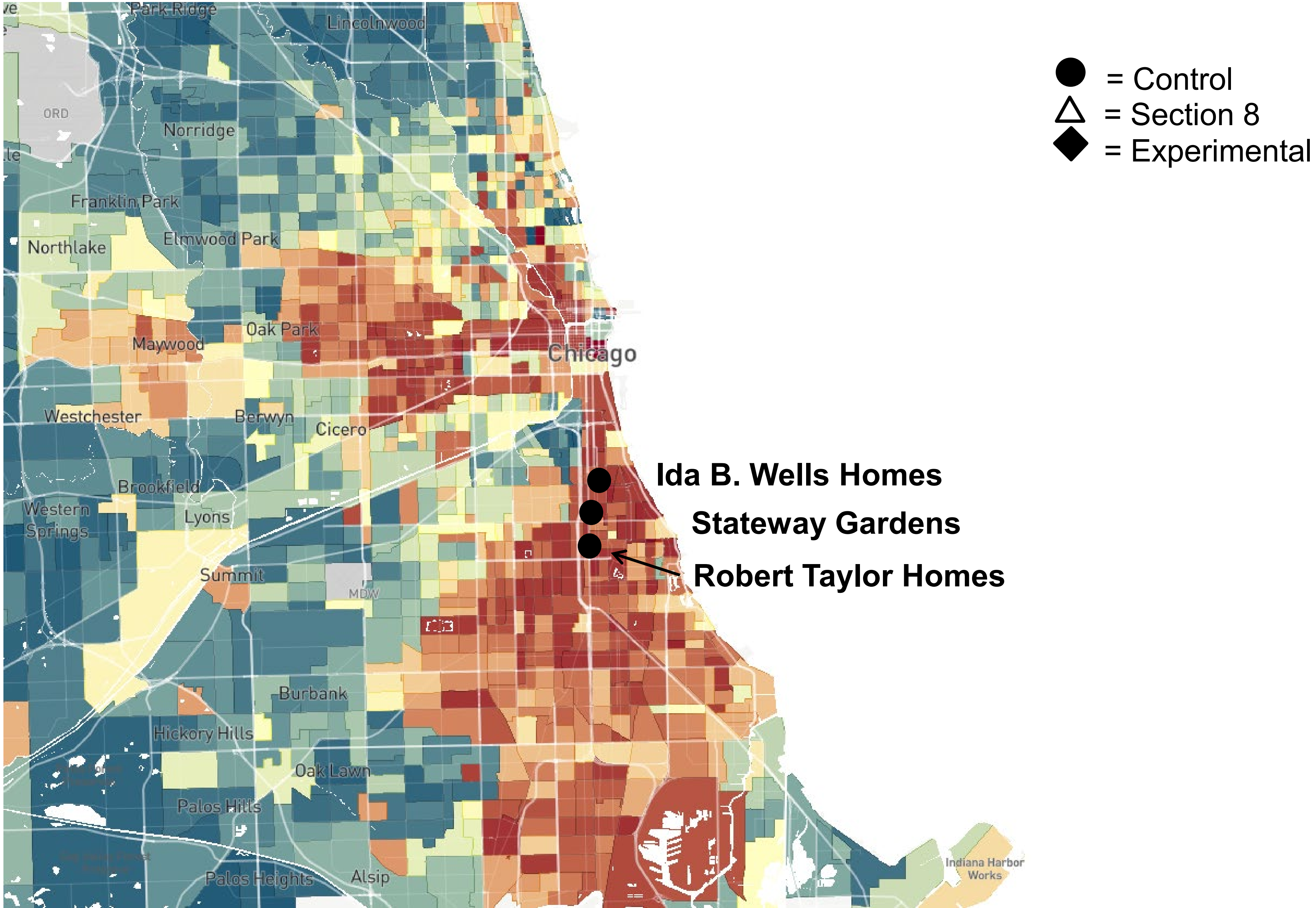
  1. Control: public housing in high-poverty (50% at baseline) areas.

  2. Section 8: conventional housing vouchers, no restrictions.

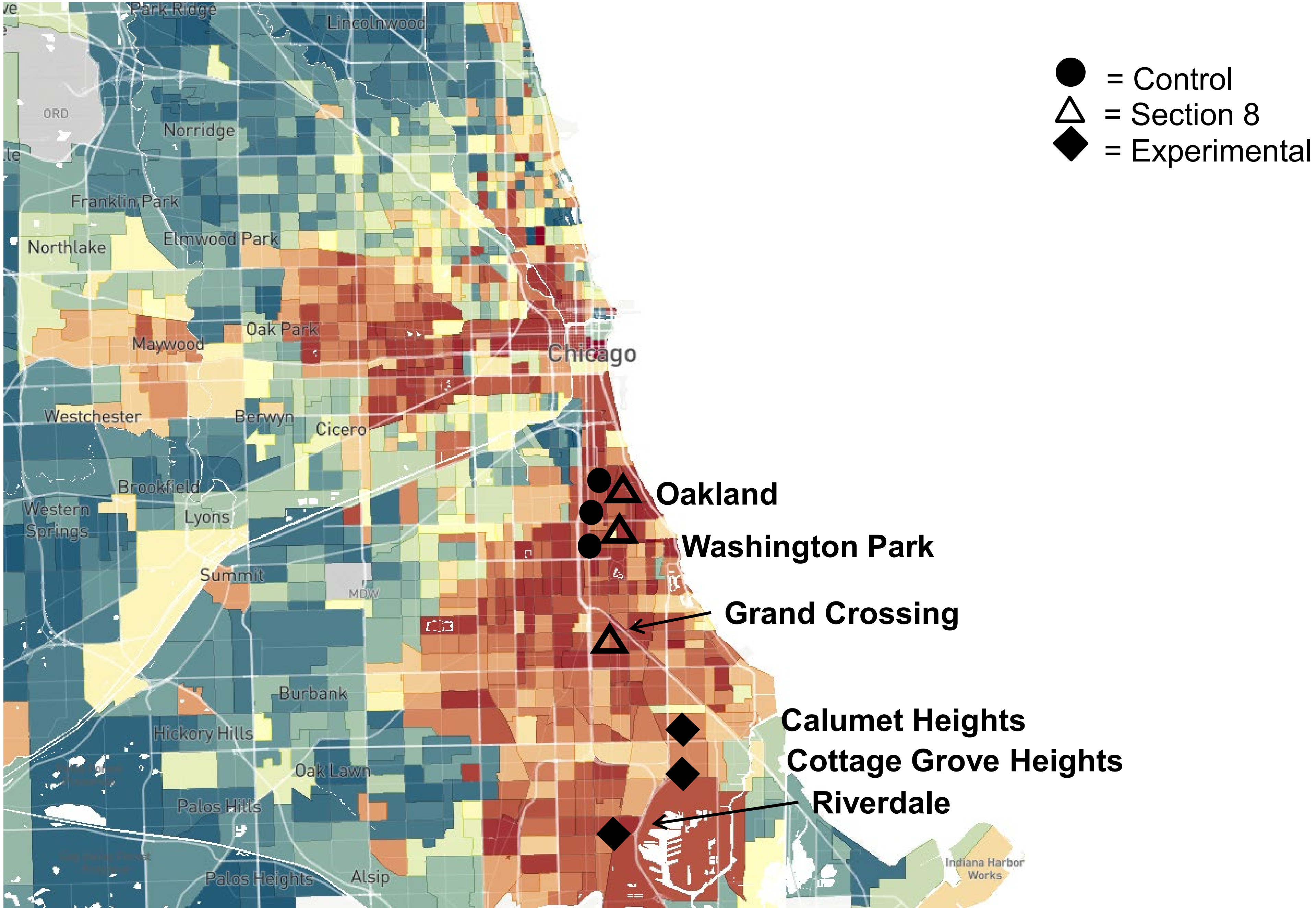
  3. Experimental: housing vouchers restricted to low-poverty (<10%) Census tracts.

- Chetty, Hendren, and Katz (2016) show that children who moved using vouchers **when young** (<age 13) earn more; those who move at older ages do not.

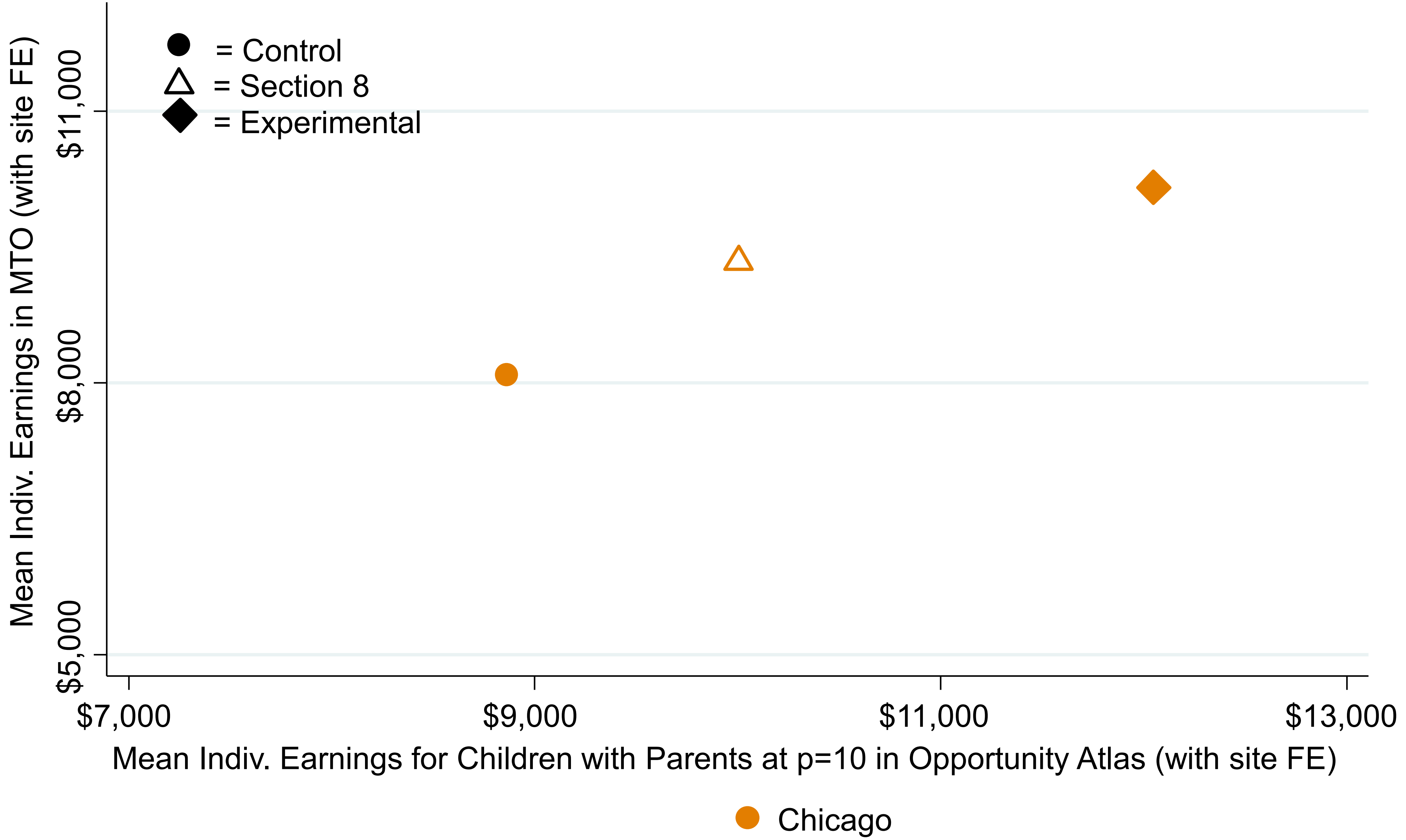
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago



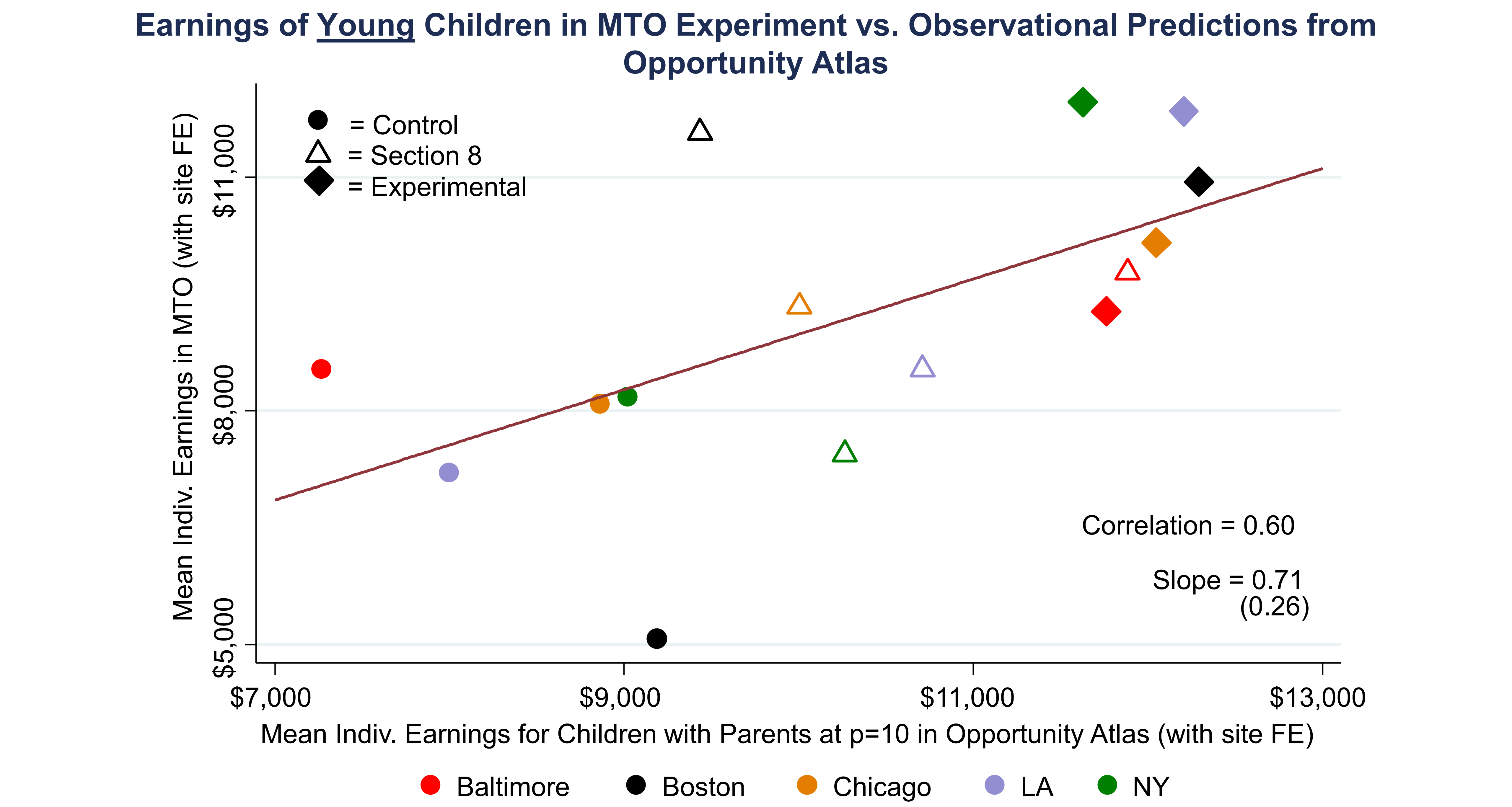
Moving To Opportunity Experiment: Origin and Destination Locations in Chicago



Earnings of Young Children in MTO Experiment vs. Observational Predictions from Opportunity Atlas



Chetty, Hendren, and Katz (2016, Online Appendix Table 7, Panel B)



Chetty, Hendren, and Katz (2016, Online Appendix Table 7, Panel B)

Quasi-Experimental Estimates

- MTO experiment shows that observational estimates predict causal effects of moving in a small set of neighborhoods.

- Now extend this approach to all areas using a quasi-experimental design in observational data, following Chetty and Hendren (2018a).

  - Much larger sample size permits a more precise characterization of how neighborhoods affect outcomes.

  - Briefly summarize key results here.

Estimating Exposure Effects in Observational Data

- To begin, consider families who move when their child is exactly 5 years old.

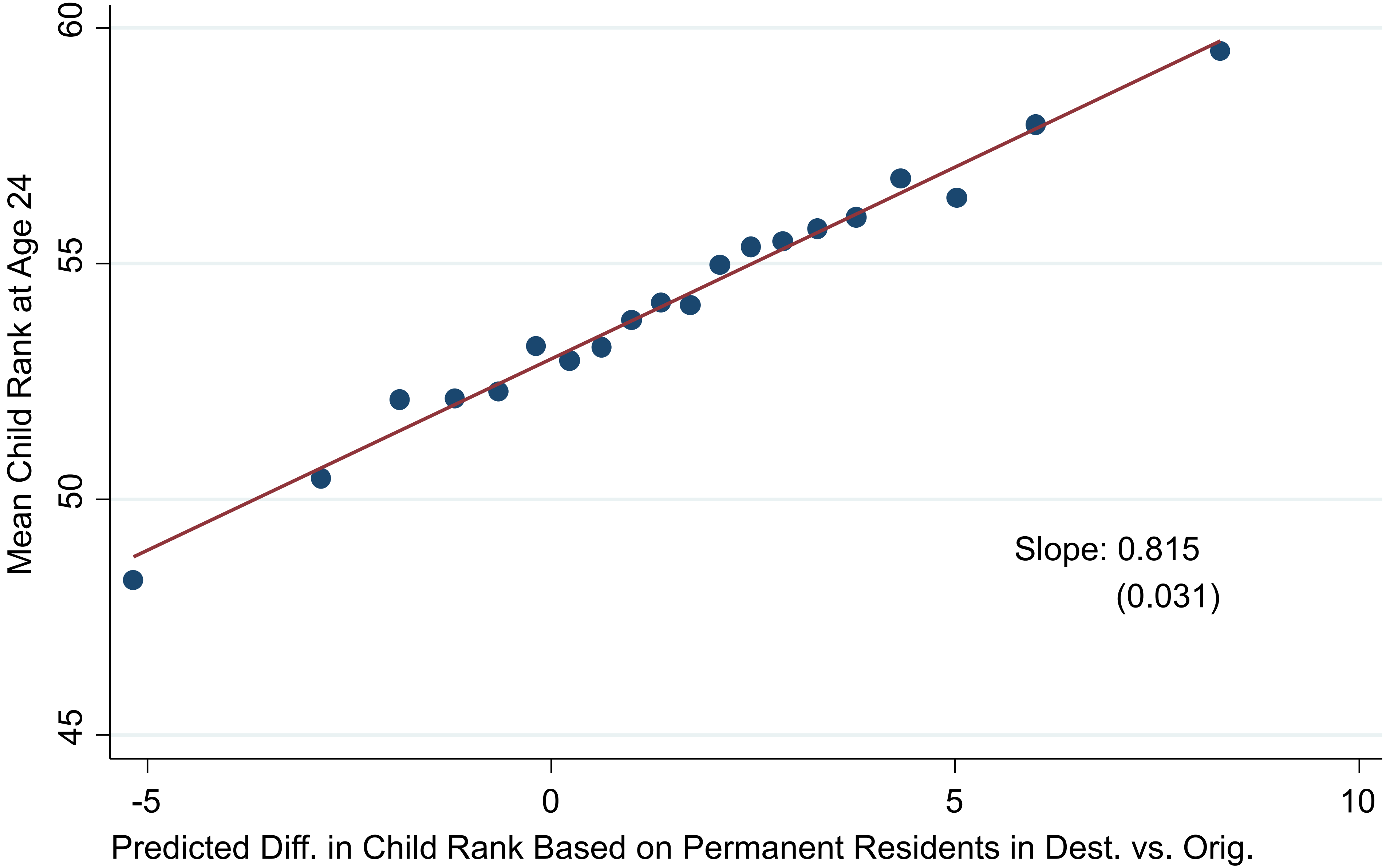
- Regress child's income rank in adulthood (y_i) on mean rank of children with same parental income level in destination:

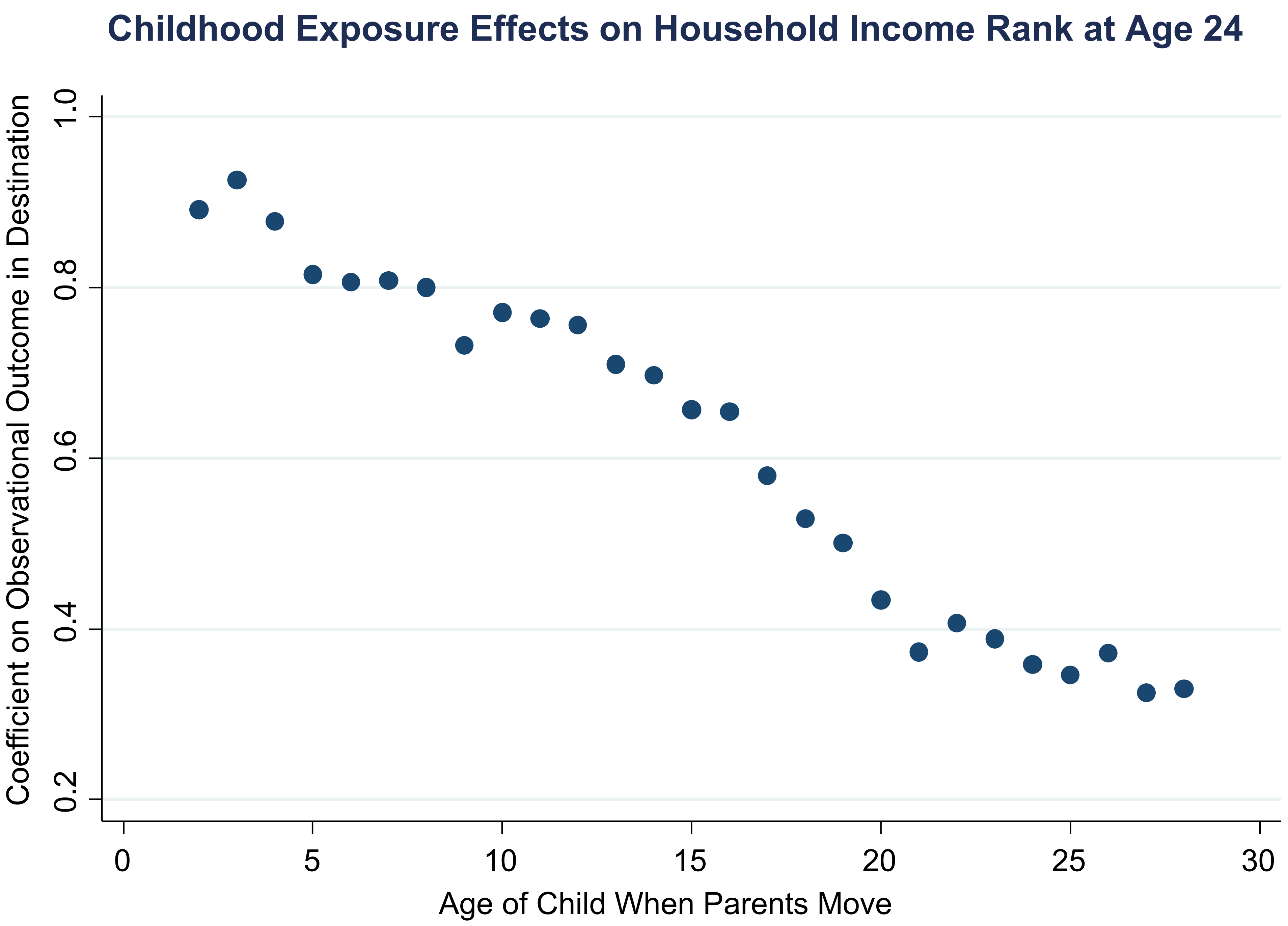
$$y_i = \alpha_{qo} + b_m \bar{y}_{pd} + \eta_i$$

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

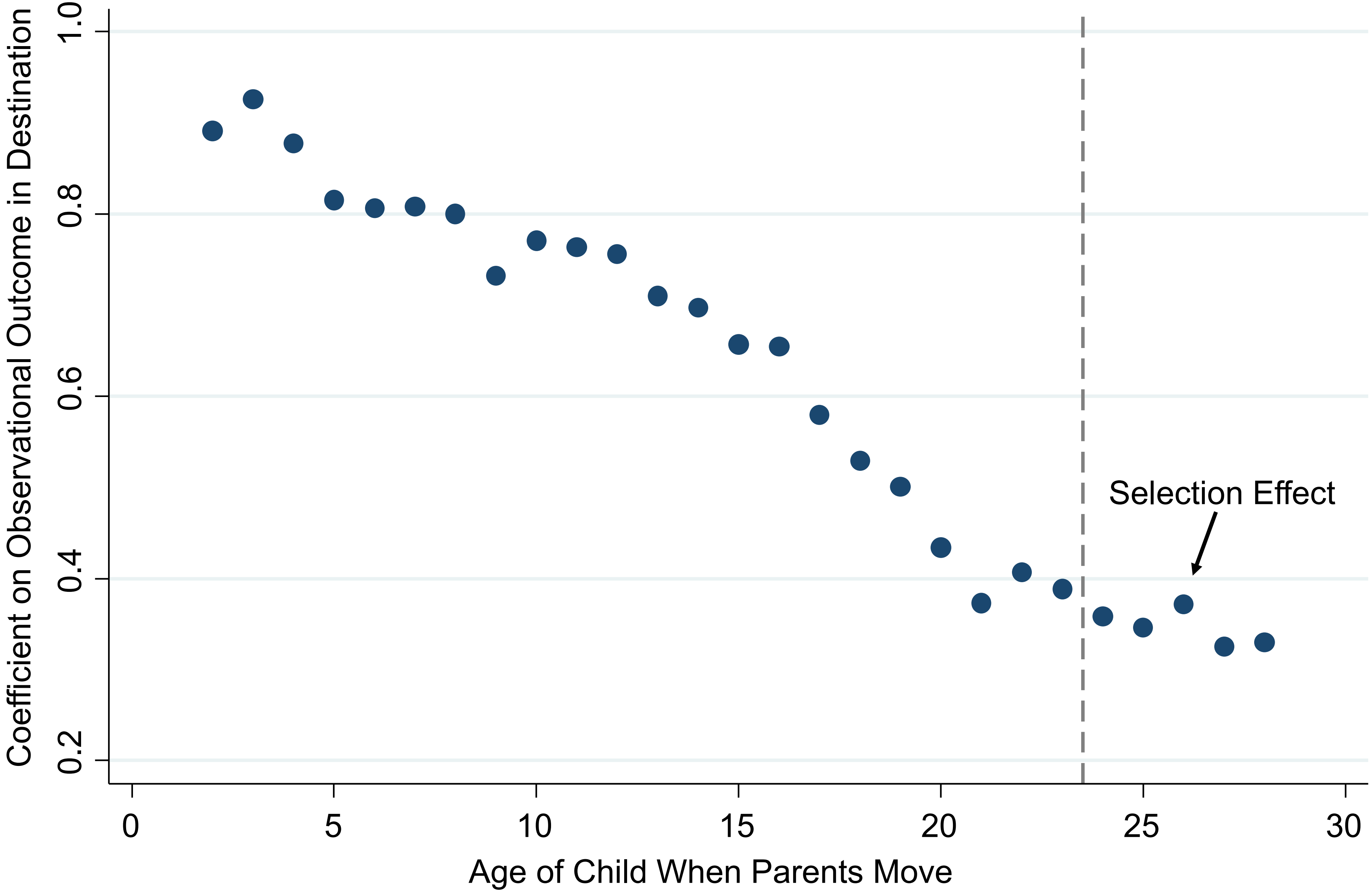
Movers' Income Ranks vs. Mean Ranks of Children in Destination

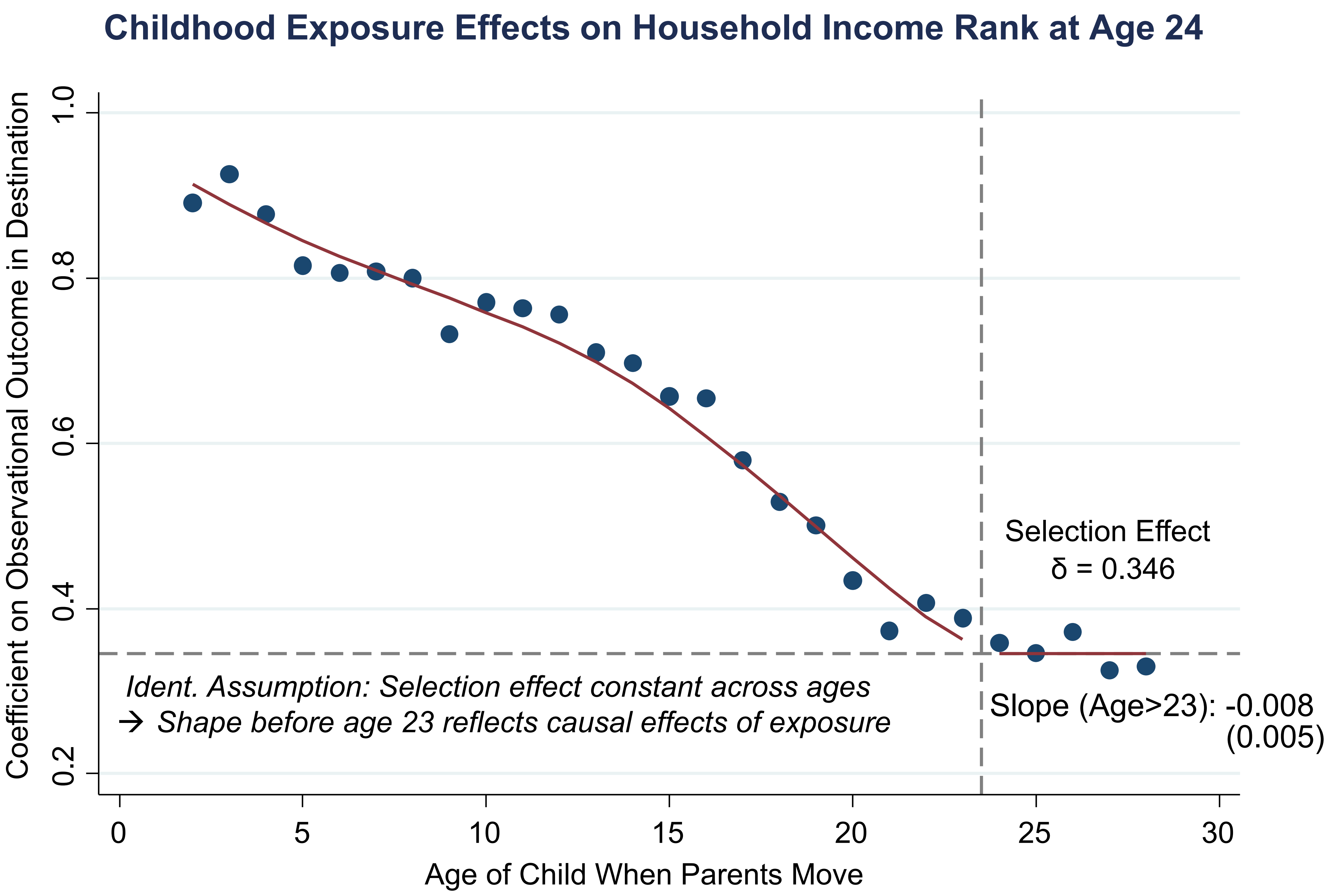
For Children Who Move at Age 5



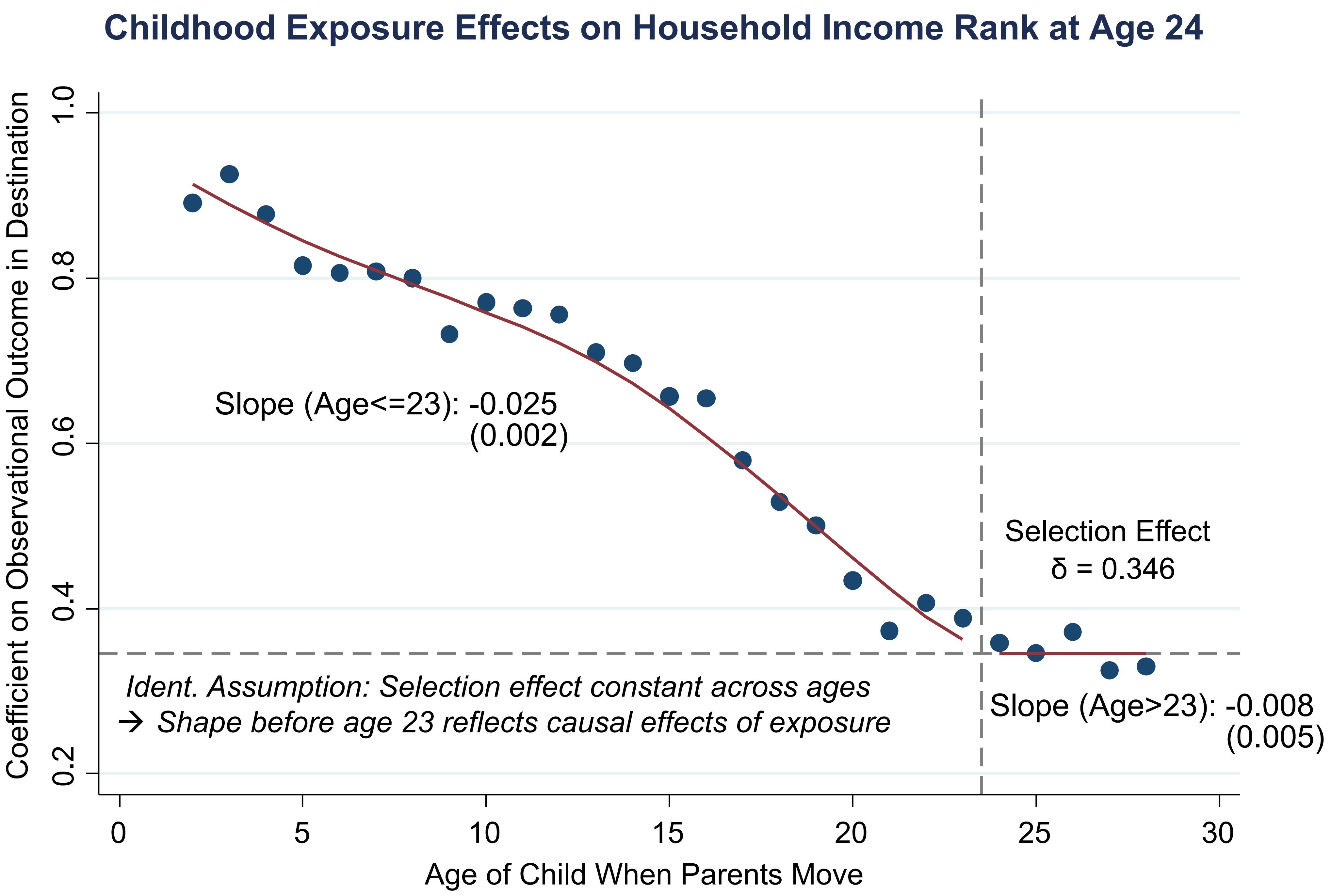

Childhood Exposure Effects on Household Income Rank at Age 24
Coefficient on Observational Outcome in Destination
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30
Age of Child When Parents Move

Childhood Exposure Effects on Household Income Rank at Age 24





Childhood Exposure Effects on Household Income Rank at Age 24
Coefficient on Observational Outcome in Destination
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
Age of Child When Parents Move
Selection Effect
δ = 0.346
Ident. Assumption: Selection effect constant across ages
→ Shape before age 23 reflects causal effects of exposure
Slope (Age>23): -0.008
(0.005)


Childhood Exposure Effects on Household Income Rank at Age 24
Coefficient on Observational Outcome in Destination
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
Age of Child When Parents Move
Slope (Age<=23): -0.025
(0.002)
Selection Effect
δ = 0.346
Slope (Age>23): -0.008
(0.005)
Ident. Assumption: Selection effect constant across ages
→ Shape before age 23 reflects causal effects of exposure

Identifying Causal Exposure Effects

- Use two approaches to evaluate validity of key assumption, following Chetty and Hendren (2018a):

  1. Sibling comparisons to control for family fixed effects.

Childhood Exposure Effects on Household Income Rank at Age 24

Regression Estimates Based on One-Time Movers Across Tracts

	Baseline	No Age Interactions	Family FEs
	(1)	(2)	(3)
Age <= 23	-0.027	-0.026	**-0.021**
	(0.001)	(0.001)	(0.002)
Age > 23	-0.008	-0.004	-0.004
	(0.009)	(0.008)	(0.009)
Num. of Obs.	2,814,000	2,814,000	2,814,000

Note: Standard errors in parentheses

Identifying Causal Exposure Effects

- Use two approaches to evaluate validity of key assumption, following Chetty and Hendren (2018a):

  1. Sibling comparisons to control for family fixed effects

  2. Outcome-based placebo tests exploiting heterogeneity in place effects by gender, quantile, and outcome.

     – Ex: moving to a place where boys have high earnings → son improves in proportion to exposure but daughter does not.

Gender-Specific Childhood Exposure Effects on Household Income Rank

Regression Estimates Based on One-Time Movers Across Tracts

Outcome:	**Child Household Income Rank at Age 24**	
	Males	**Females**
	(1)	(2)
Prediction for Males	**-0.024**	-0.003
	(0.002)	(0.002)
Prediction for Females	-0.001	**-0.027**
	(0.003)	(0.003)
Num. of Obs.	1,146,000	1,082,000

Note: Standard errors in parentheses

Childhood Exposure Effects on Other Outcomes

For Male Children of All Races

	Income Rank at 24	Married at 30	Incarceration
	(1)	(2)	(3)
Mean Income Rank at 24	**-0.024**	-0.005	0.001
	(0.002)	(0.006)	(0.002)
Frac. Married at 30	0.000	**-0.022**	0.000
	(0.001)	(0.003)	(0.001)
Incarceration Rate	-0.001	-0.009	**-0.032**
	(0.007)	(0.016)	(0.005)
Num. of Obs.	1,132,000	824,000	734,000

Note: Standard errors in parentheses

Childhood Exposure Effects on Other Outcomes

For Female Children of All Races

	Income Rank at 24	Married at 30	Teen Birth
	(1)	(2)	(3)
Mean Income Rank at 24	**-0.032**	0.002	-0.003
	(0.003)	(0.007)	(0.003)
Frac. Married at 30	-0.003	**-0.029**	0.004
	(0.001)	(0.002)	(0.001)
Teen Birth	-0.005	-0.010	**-0.026**
	(0.002)	(0.004)	(0.002)
Num. of Obs.	1,068,000	776,000	1,347,000

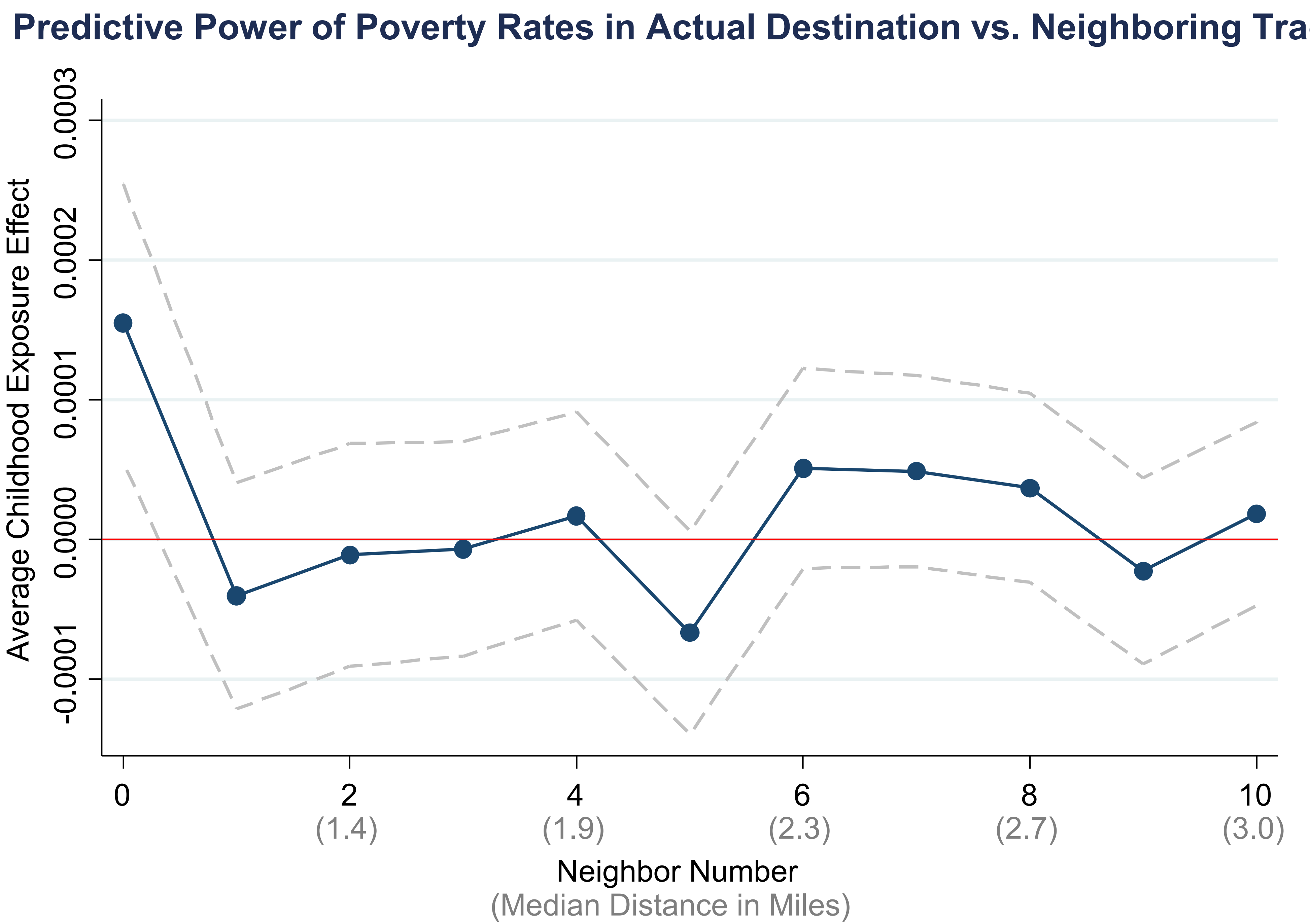
Note: Standard errors in parentheses

Childhood Exposure Effects on Household Income Rank at Age 24

Regression Estimates Based on One-Time Movers Across Tracts

	Baseline	Good and Bad Moves	Large Moves	Observed Components of Opportunity	Unobserved Components of Opportunity
	(1)	(2)	(3)	(4)	(5)
Age <= 23	-0.027 (0.001)		-0.046 (0.017)	-0.020 (0.001)	-0.025 (0.003)
Age <= 23, Good Moves		-0.031 (0.002)			
Age <= 23, Bad Moves		-0.027 (0.002)			
Num. of Obs.	2,814,000	2,814,000	22,500	2,692,000	2,692,000

Note: Standard errors in parentheses



Predictive Power of Poverty Rates in Actual Destination vs. Neighboring Tracts
Average Childhood Exposure Effect
0.0003
0.0002
0.0001
0.0000
-0.0001
0
2
(1.4)
4
(1.9)
6
(2.3)
8
(2.7)
10
(3.0)
Neighbor Number
(Median Distance in Miles)

The Price of Opportunity

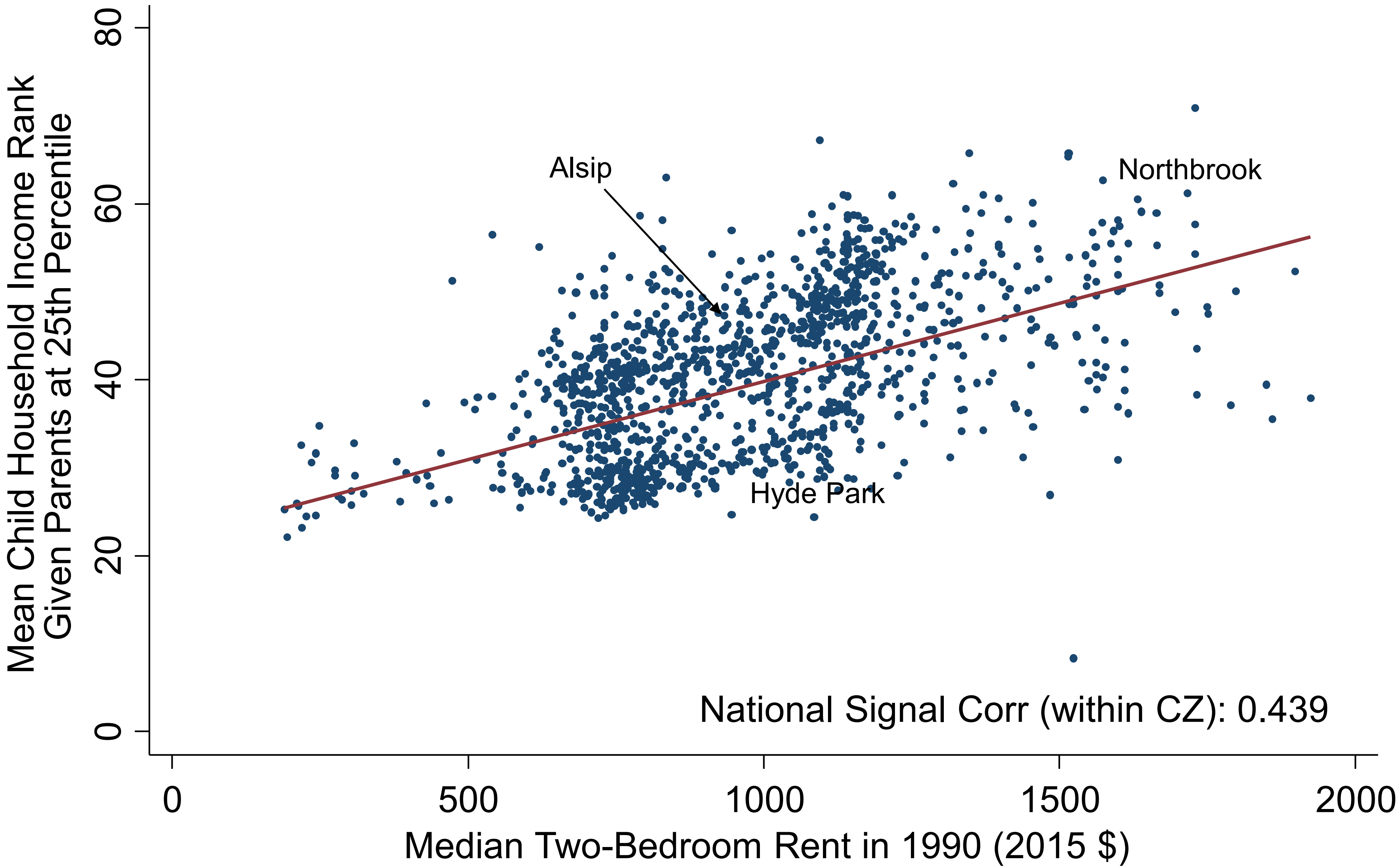
- Moving at birth from tract at 25th percentile of distribution of upward mobility to a tract at 75th percentile within county → $198,000 gain in lifetime earnings.

- Feasibility of such moves relies on being able to find affordable housing in high-opportunity neighborhoods.

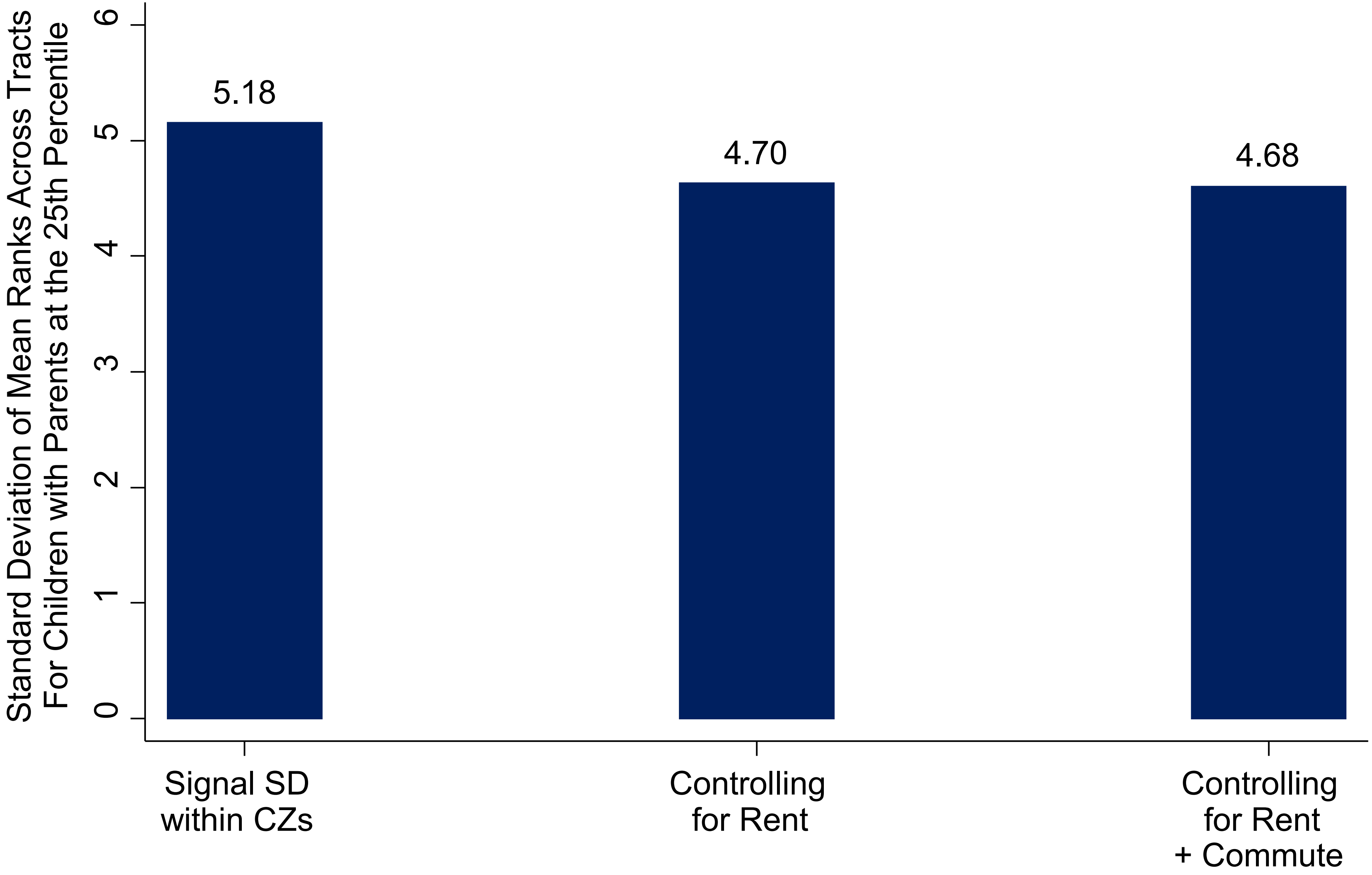
- How does the housing market price the amenity of better outcomes for children?

Children's Mean Income Ranks in Adulthood vs. Median Rents in Chicago, by Tract

Children with Parents at 25th Percentile



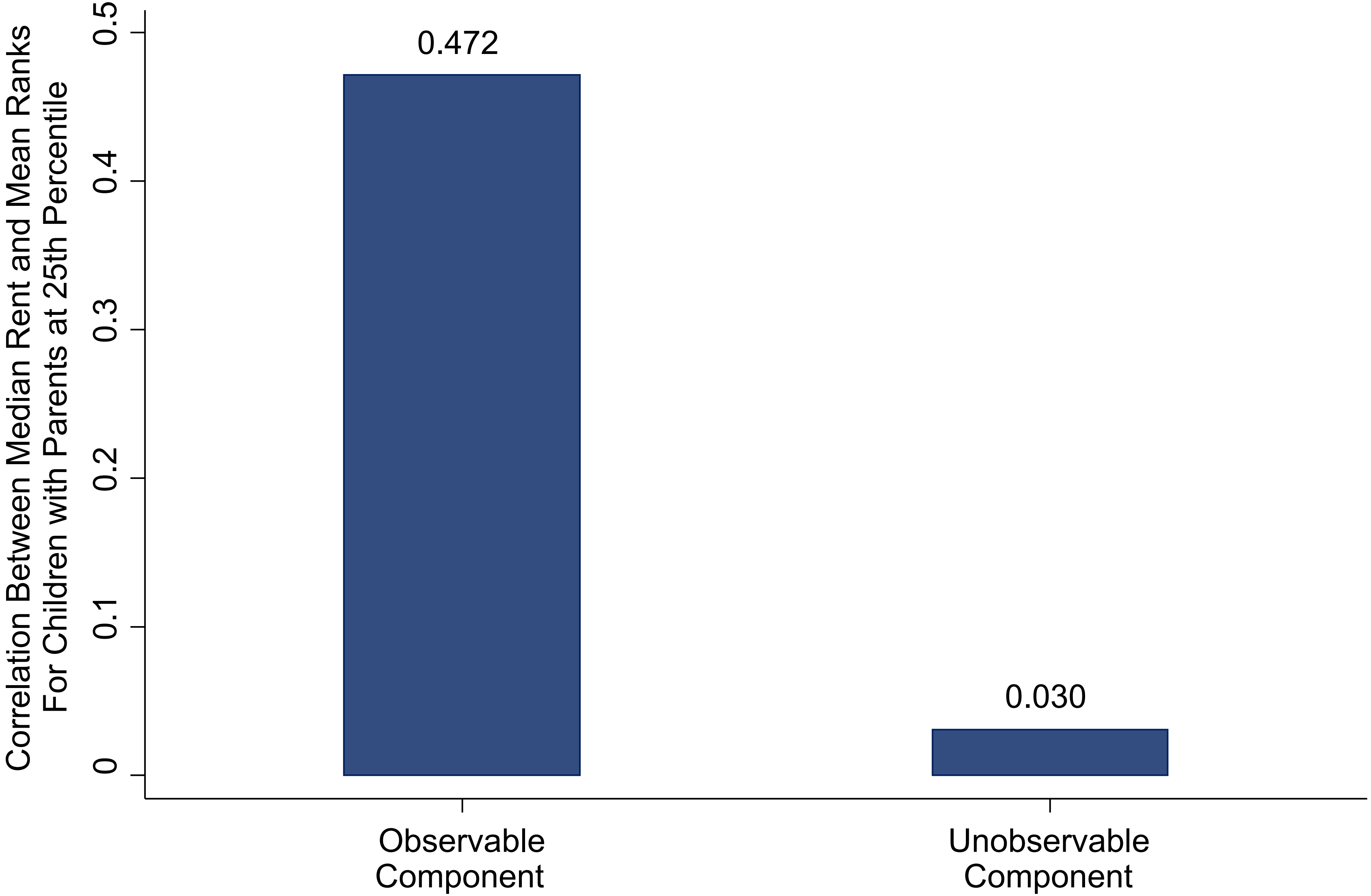
Residual Standard Deviation of Mean Ranks Across Tracts Within CZs
Controlling for Rent and Commute Time



The Price of Opportunity

- What explains the existence of areas that offer good outcomes for children but have low rents in spatial equilibrium?
  - One explanation: these areas have other disamenities.
  - Alternative explanation: lack of information or barriers such as discrimination.
    [DeLuca et al 2019, Christensen and Timmins 2018]

Correlation Between Rents and Observable vs. Unobservable Component of Outcomes



Opportunity Bargains

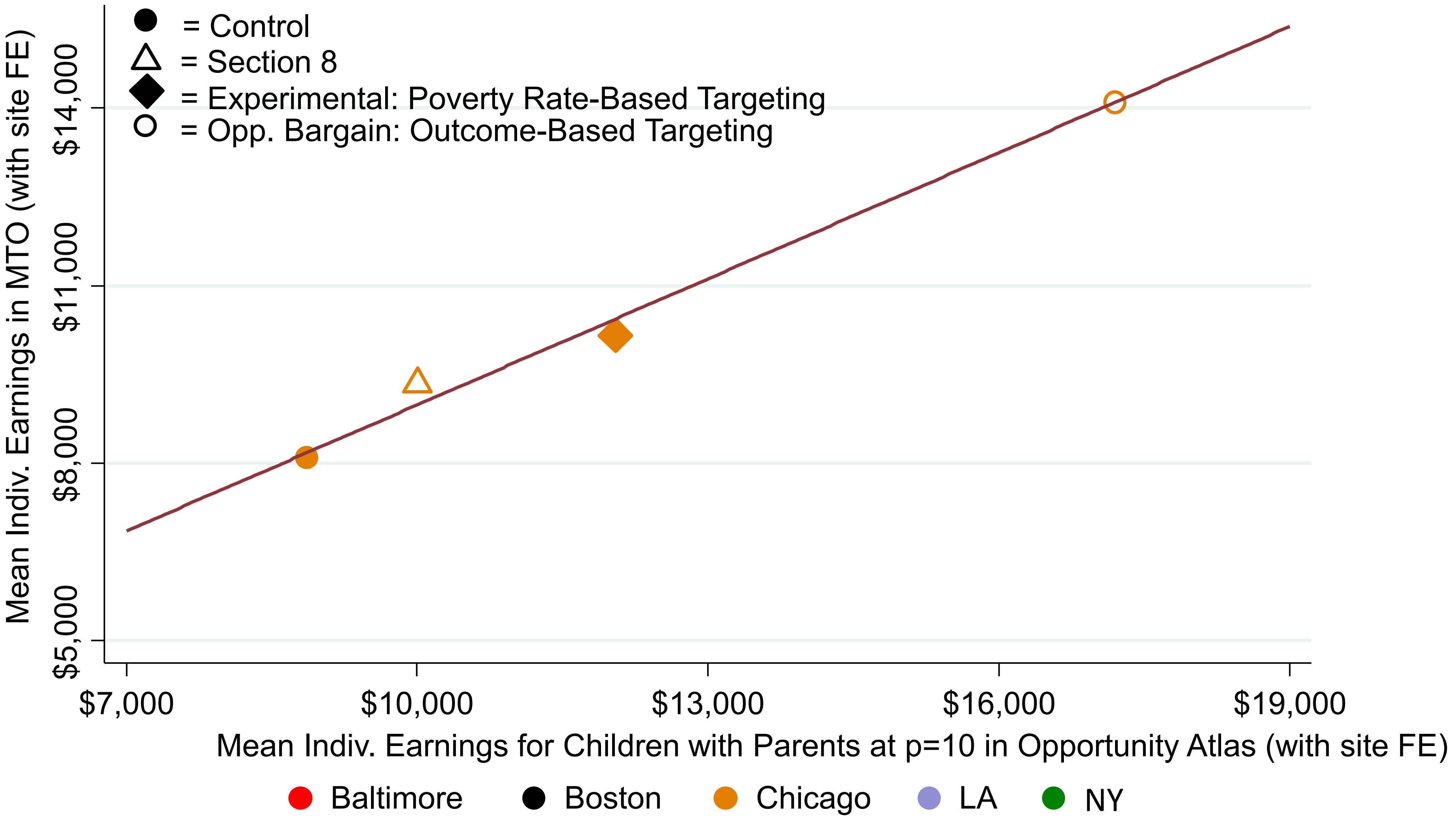
- Potential scope to improve outcomes by helping low-income families with young children move to higher opportunity areas.

- Could also benefit taxpayers:

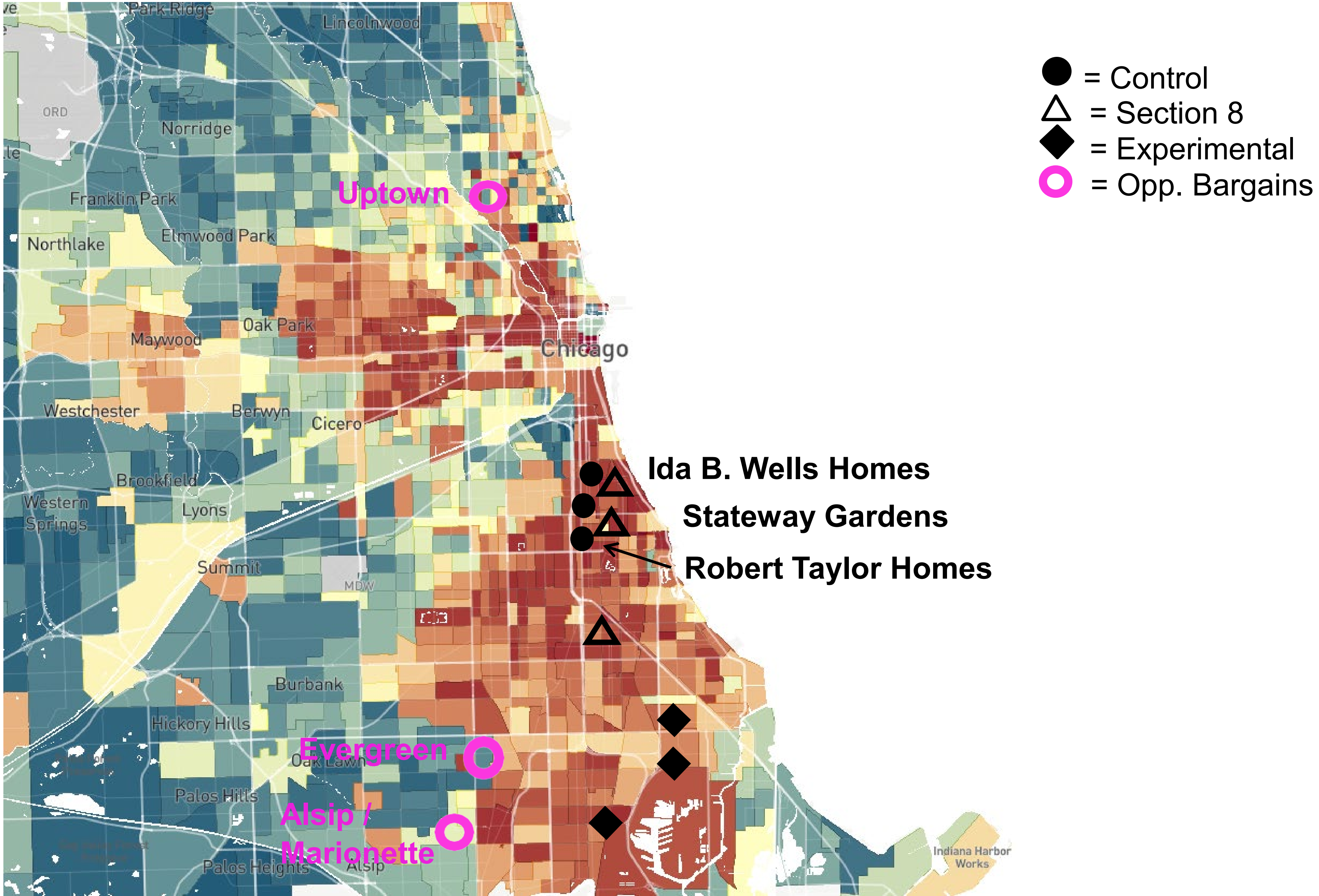
  – If a child were to grow up in an above-average tract instead of a below-average tract in terms of observed earnings, taxpayers would gain ~$40,000.

- Illustrate how we can identify such areas by looking for “opportunity bargains” in Moving to Opportunity data.

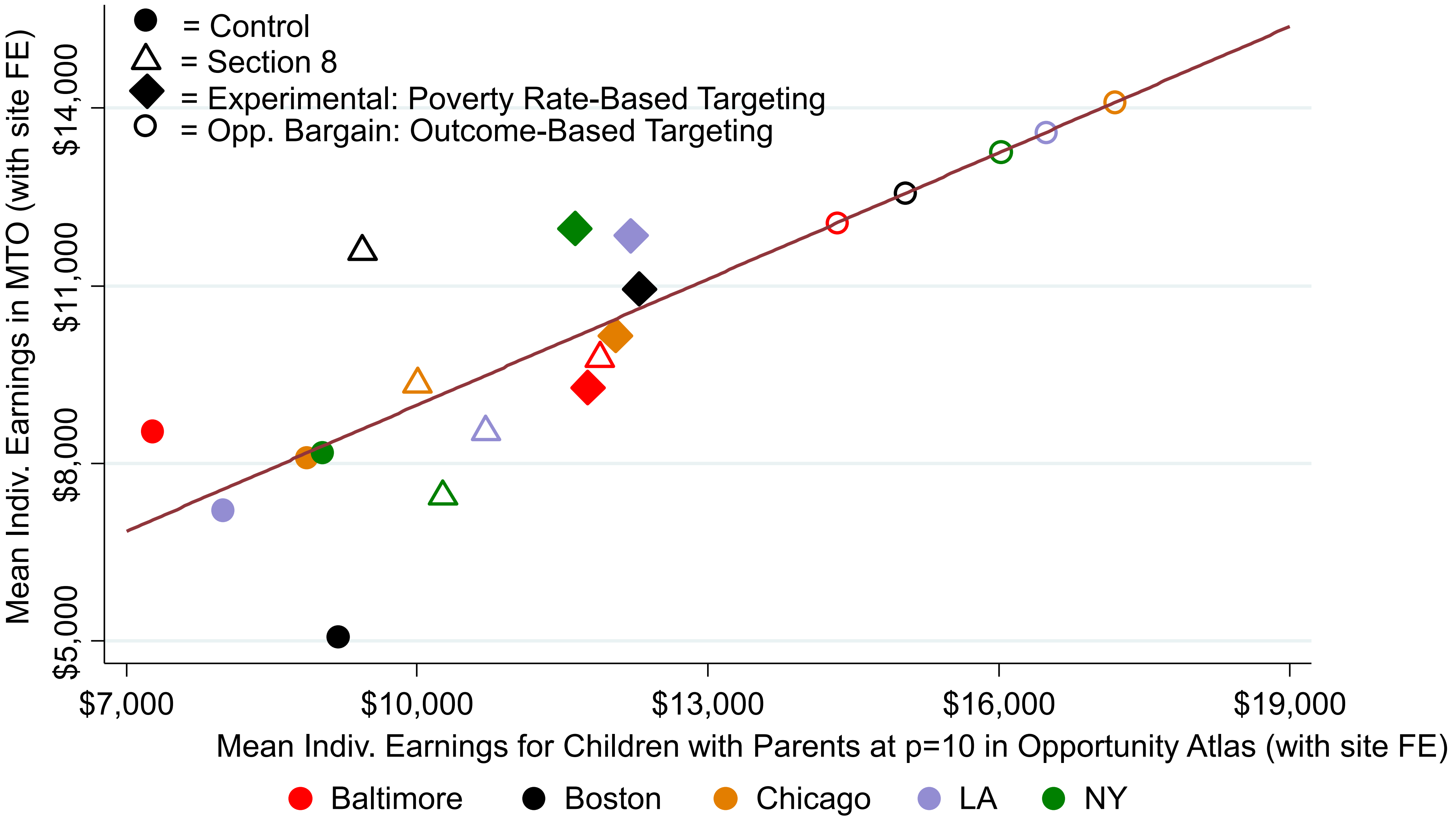
Predicted Impacts of Moving to "Opportunity Bargain" Areas in MTO Cities



Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago



Predicted Impacts of Moving to "Opportunity Bargain" Areas in MTO Cities

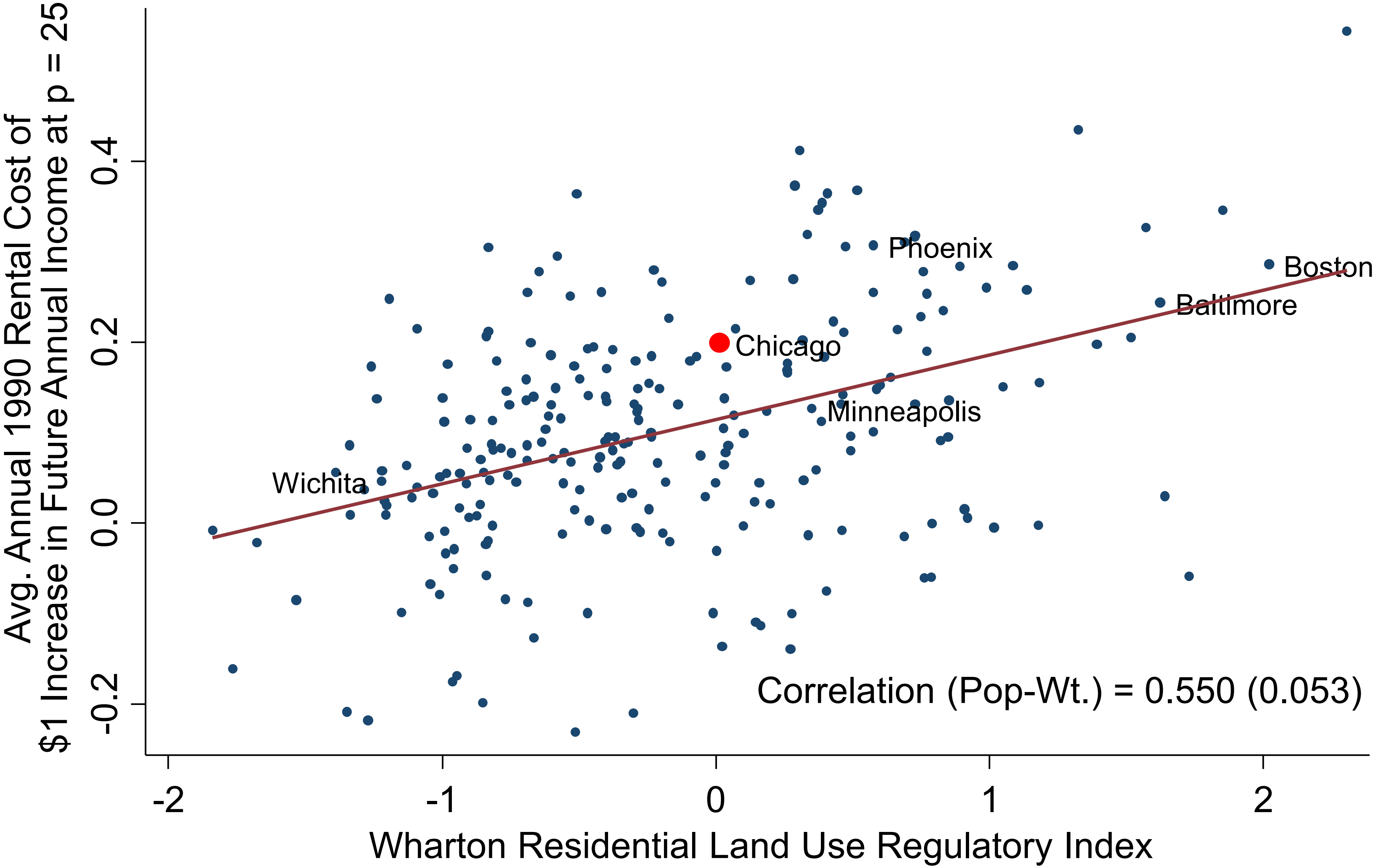


Heterogeneity in the Price of Opportunity

- Price of opportunity itself is highly heterogeneous across metro areas and subgroups.

- Policies such as land use regulation may play a role in determining this price in equilibrium…

Relationship Between Land Regulation and the Price of Opportunity



Note: figure excludes Statesboro and Colby for scaling purposes

Conclusions and Future Work

- Children’s outcomes vary sharply across neighborhoods, and we can now measure and potentially address these differences with greater precision.

- Two directions for future work that we hope will be facilitated by these publicly available data:

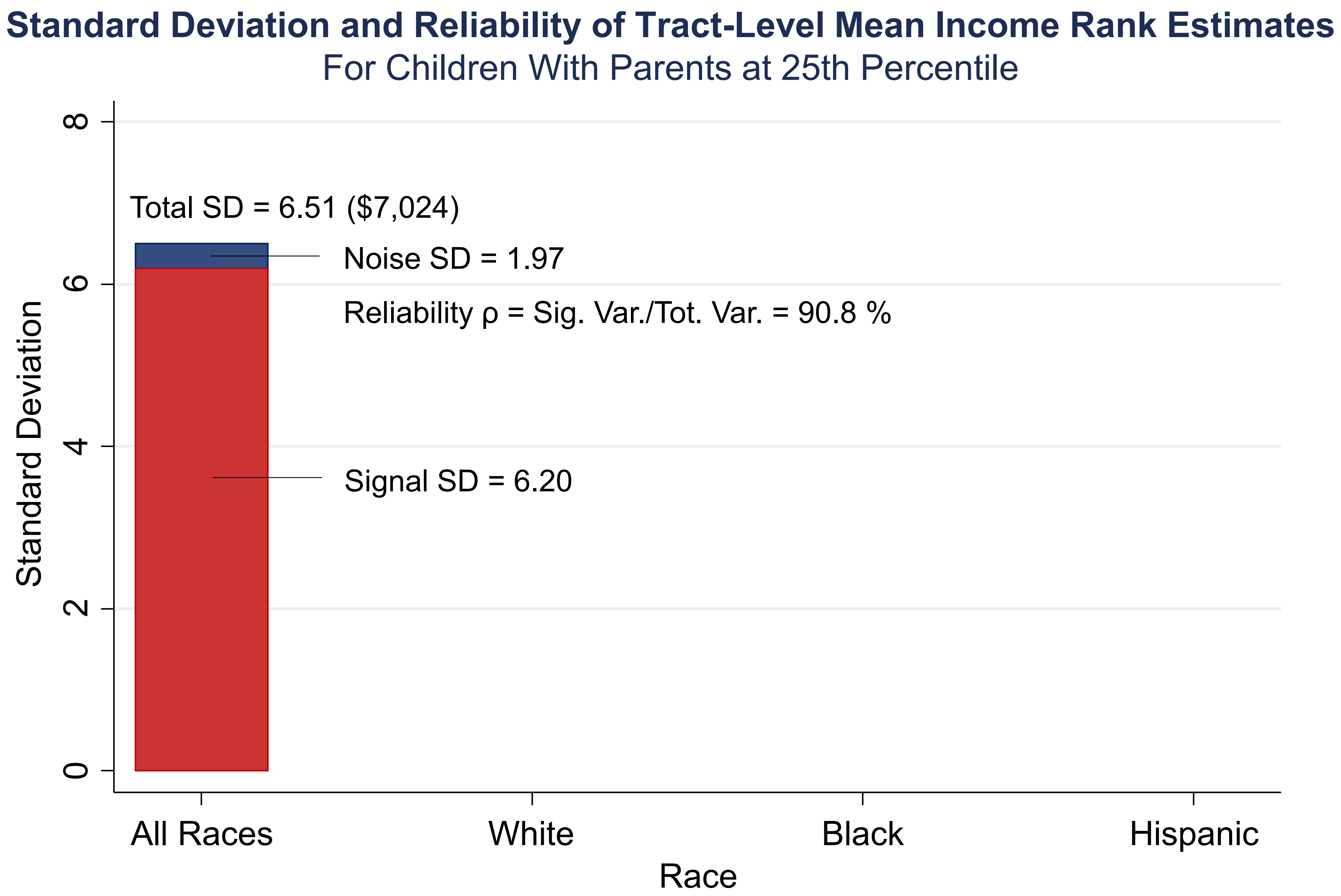
  1. Understanding the causal mechanisms that produce differences in neighborhood quality in spatial equilibrium.

  2. Supporting policy interventions to improve economic opportunity at a local level.

Supplementary Results

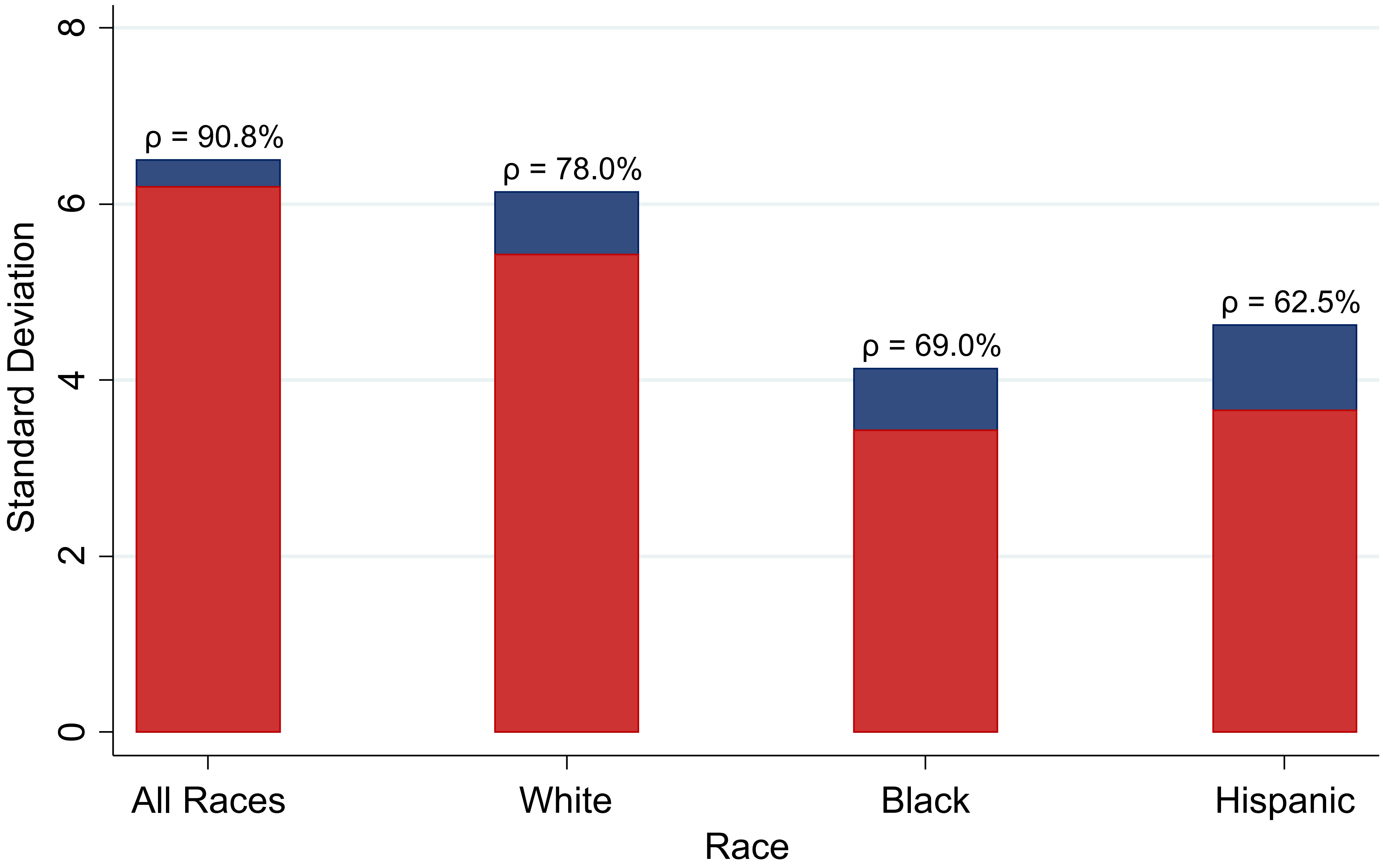
Reliability of Tract-Level Estimates

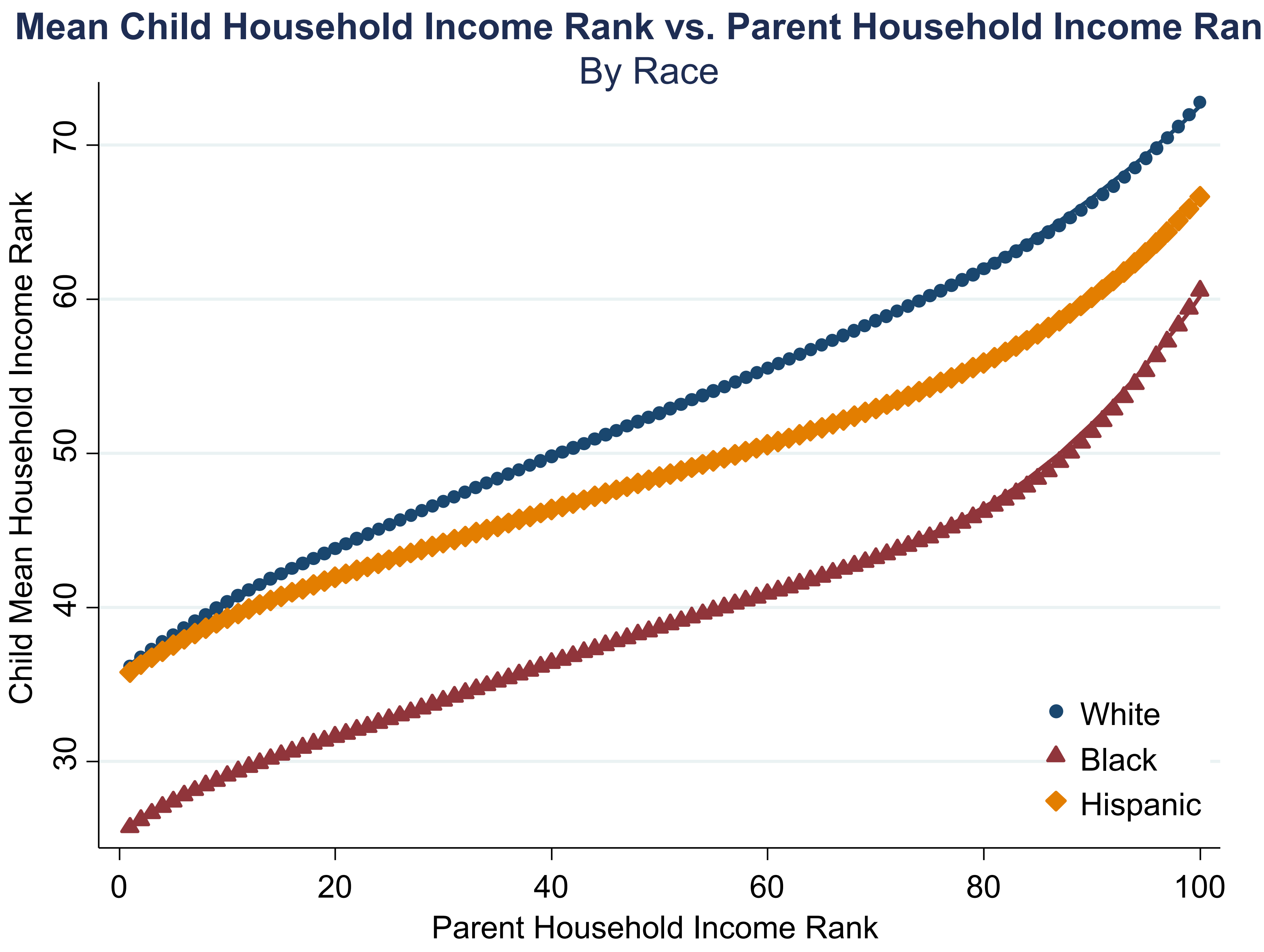
- Each tract typically contains about 300 children in the cohorts we examine.
- Some of the variation across tracts therefore reflects sampling error rather than signal.
- Assess relative importance of signal vs. noise by examining reliability of the estimates.
- As a benchmark to gauge significance of differences in maps that follow:
  - Average standard errors on mean ranks are typically 2 percentiles (~$2K) in pooled data and 3-4 percentiles in subgroups ($3K-$4K).
  - Average standard errors for incarceration rates are 3-4 pp.

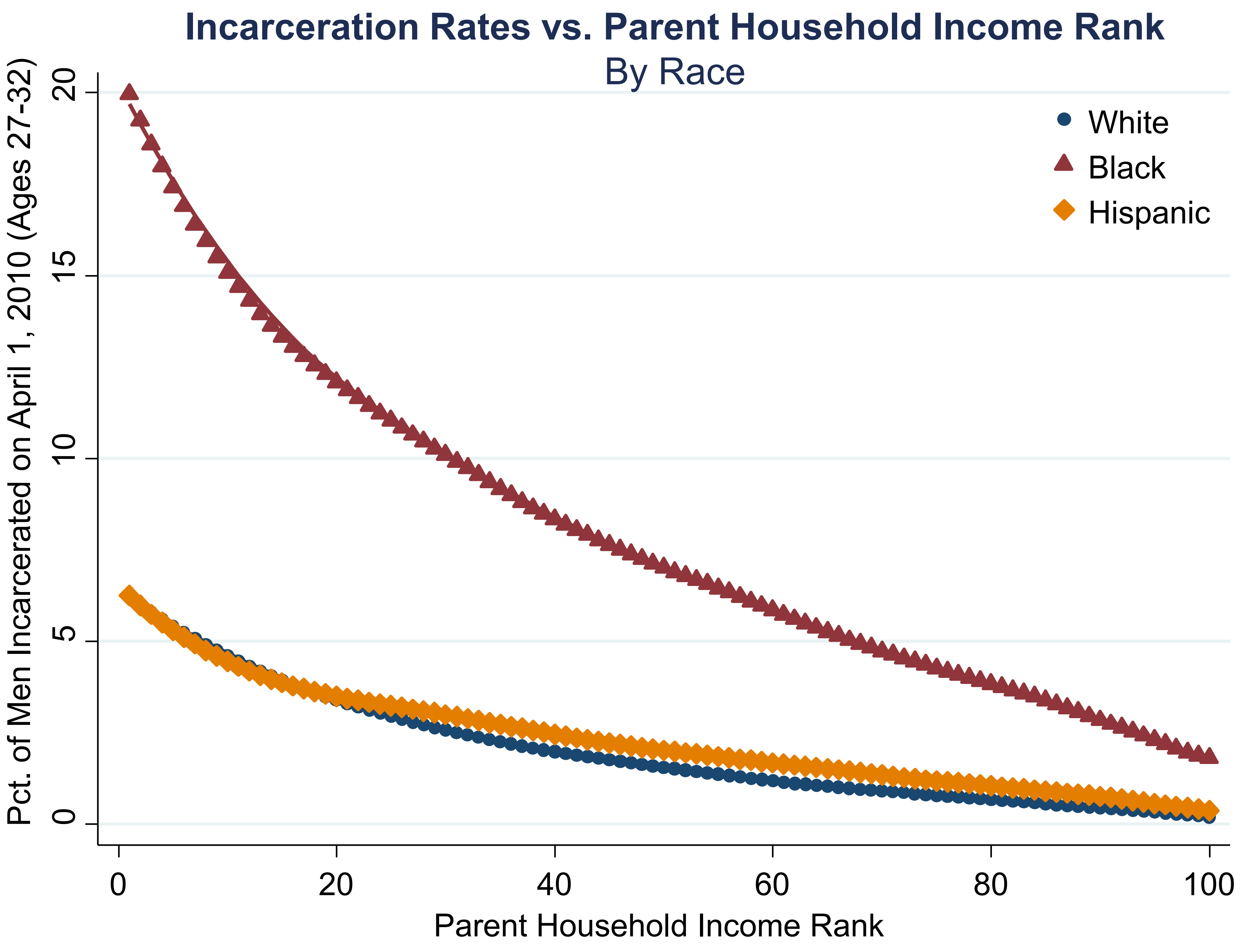

Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates
For Children With Parents at 25th Percentile
Total SD = 6.51 ($7,024)
Noise SD = 1.97
Reliability ρ = Sig. Var./Tot. Var. = 90.8 %
Signal SD = 6.20
Standard Deviation
0
2
4
6
8
All Races
White
Black
Hispanic
Race

Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates

For Children With Parents at 25th Percentile

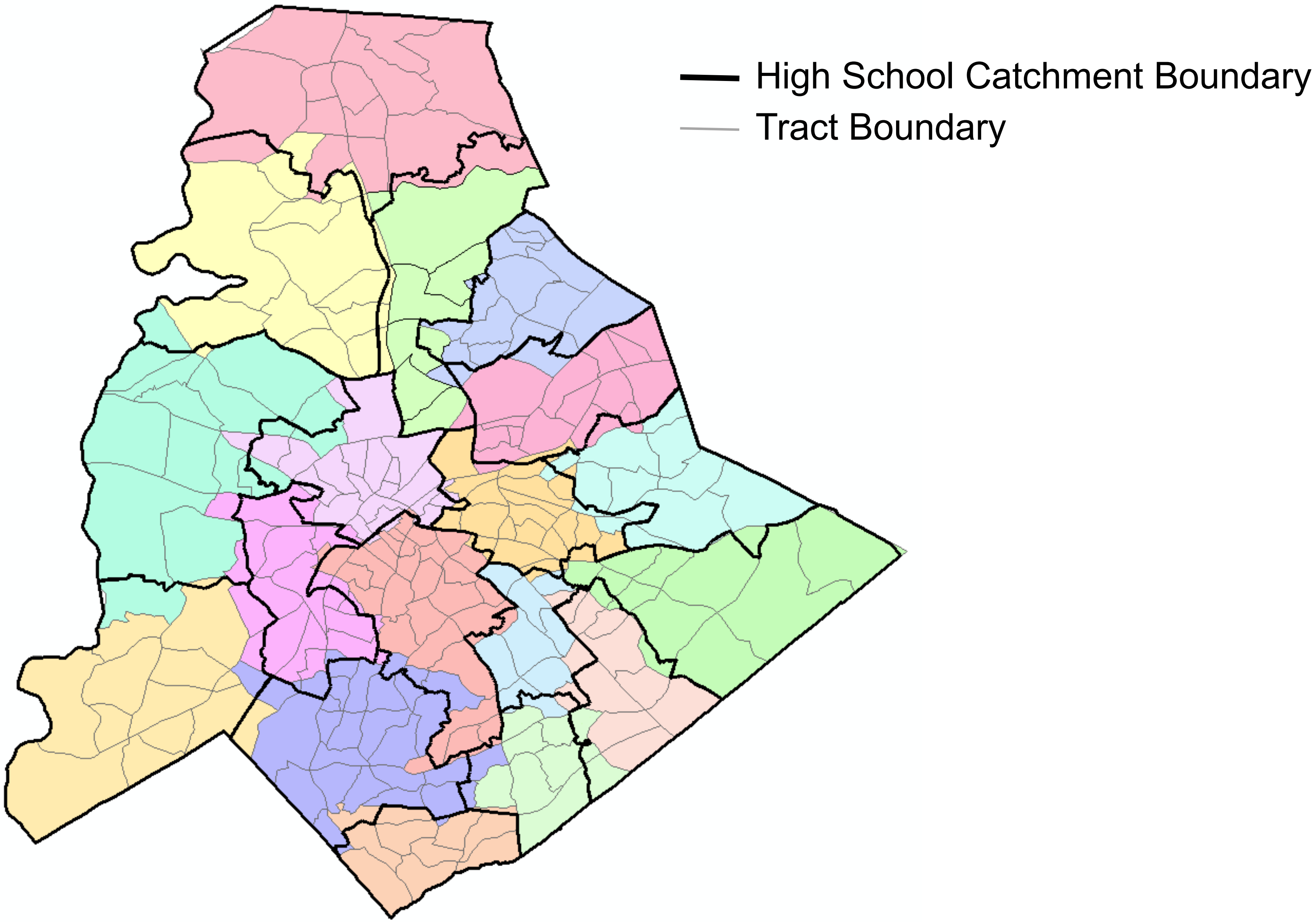


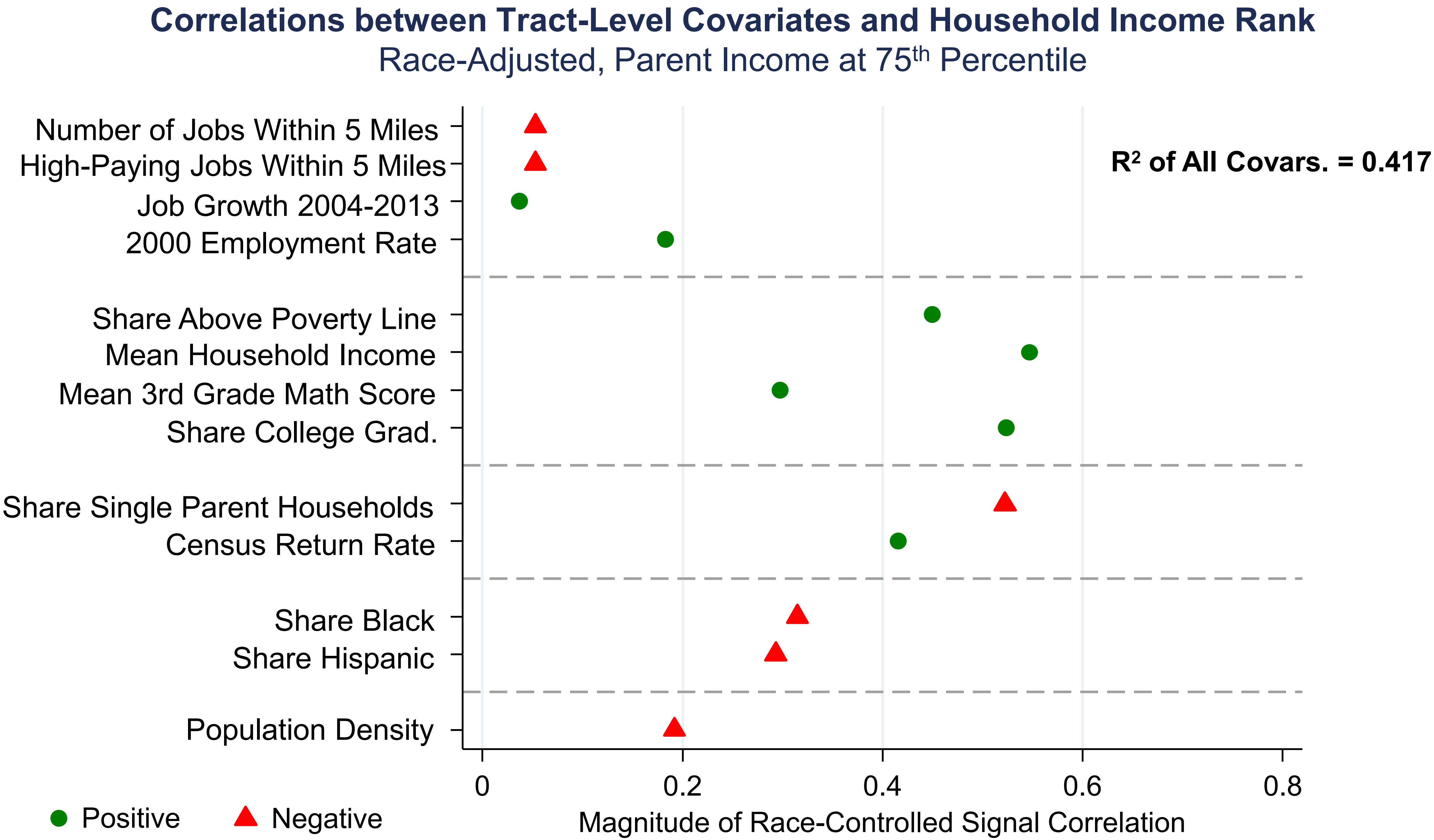

Mean Child Household Income Rank vs. Parent Household Income Rank
By Race
Child Mean Household Income Rank
30
40
50
60
70
0
20
40
60
80
100
Parent Household Income Rank
White
Black
Hispanic



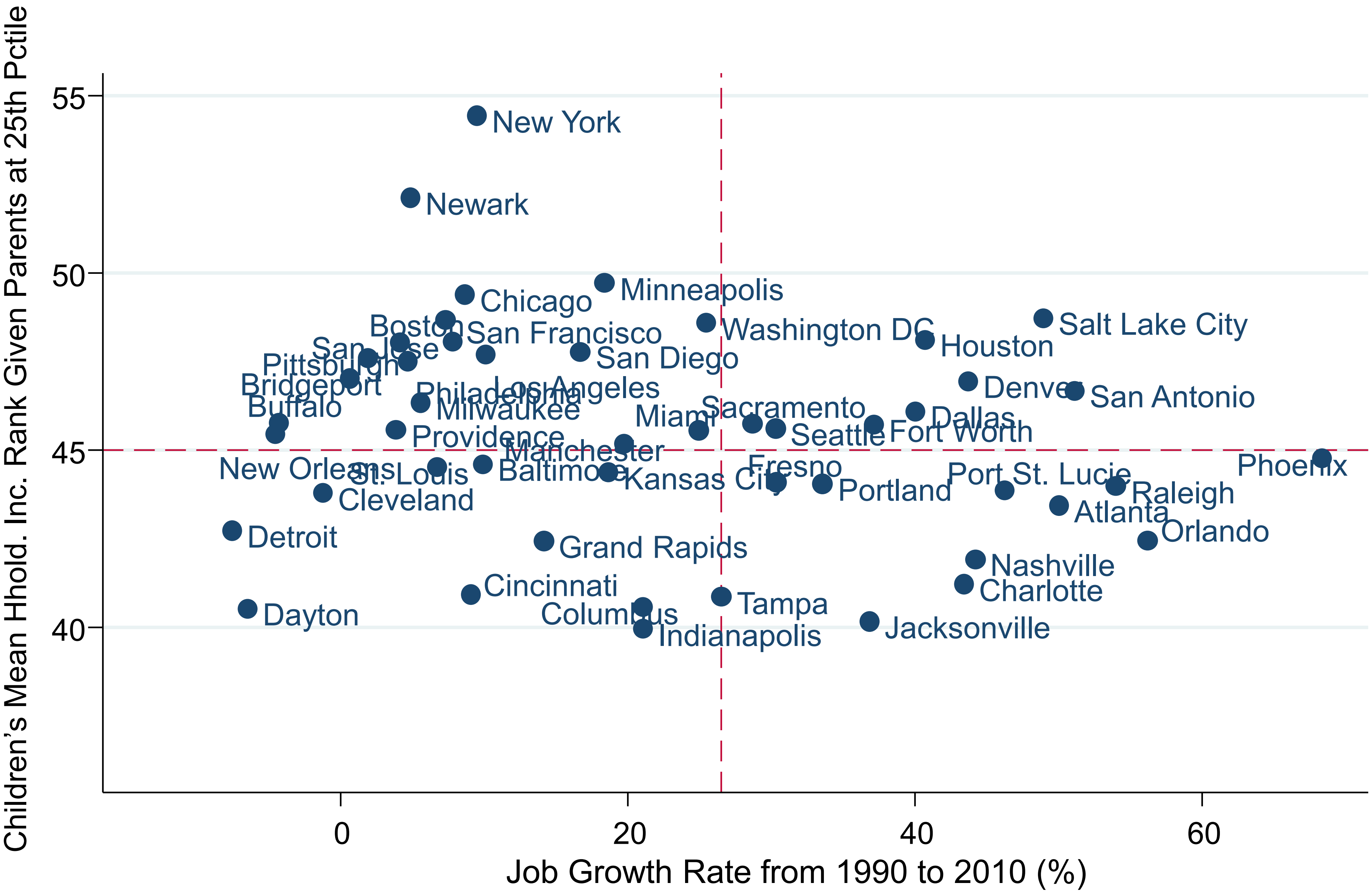
Incarceration Rates vs. Parent Household Income Rank
By Race
White
Black
Hispanic
Pct. of Men Incarcerated on April 1, 2010 (Ages 27-32)
0
5
10
15
20
0
20
40
60
80
100
Parent Household Income Rank

School Catchment Zones in Mecklenburg County: Boundaries vs. Assignment of Tracts to Catchment Zones

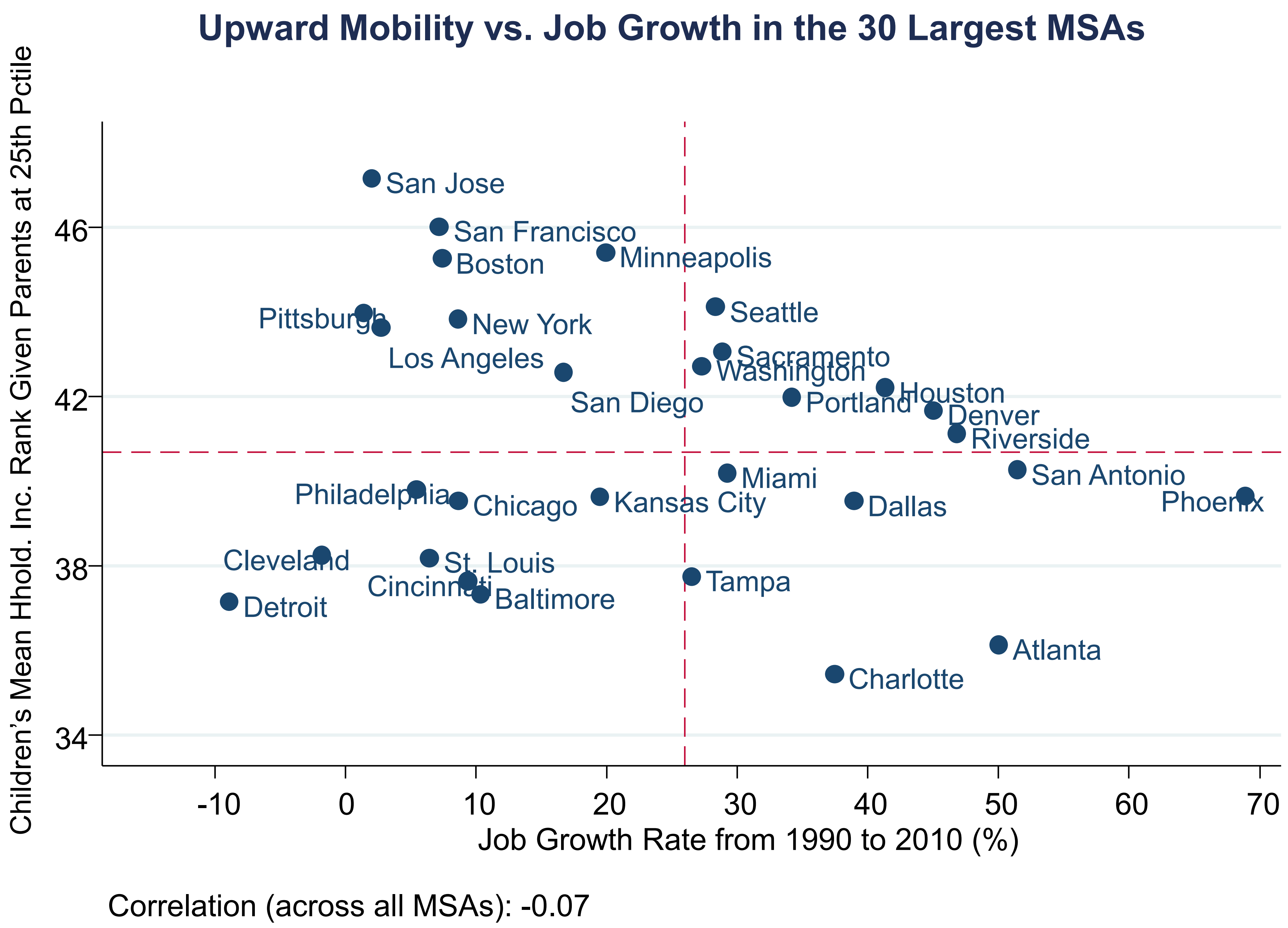



Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 75th Percentile
R² of All Covars. = 0.417
Number of Jobs Within 5 Miles
High-Paying Jobs Within 5 Miles
Job Growth 2004-2013
2000 Employment Rate
Share Above Poverty Line
Mean Household Income
Mean 3rd Grade Math Score
Share College Grad.
Share Single Parent Households
Census Return Rate
Share Black
Share Hispanic
Population Density
0
0.2
0.4
0.6
0.8
Magnitude of Race-Controlled Signal Correlation
Positive
Negative

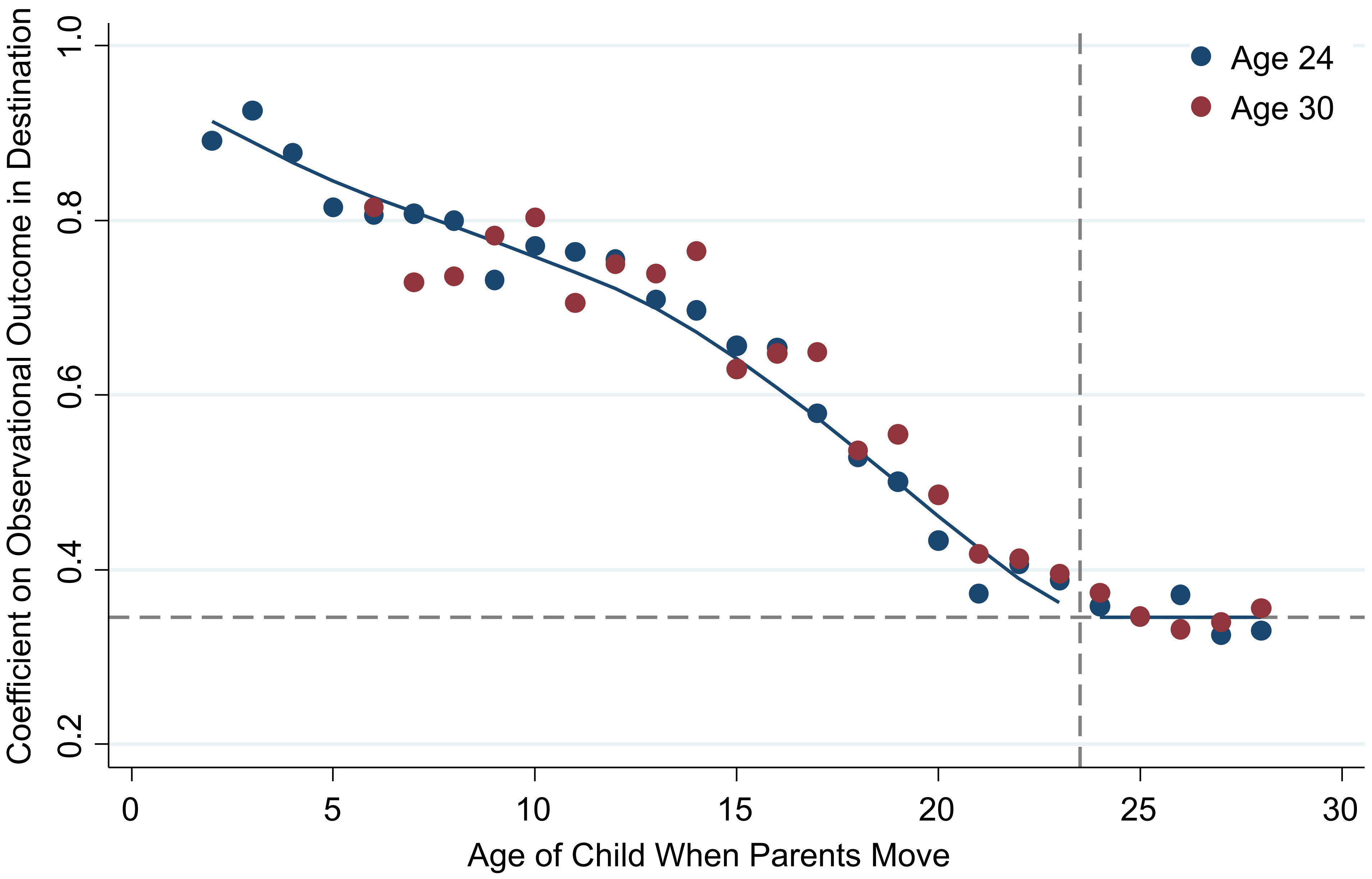
Upward Mobility for Whites vs. Job Growth in the 50 Largest Commuting Zones

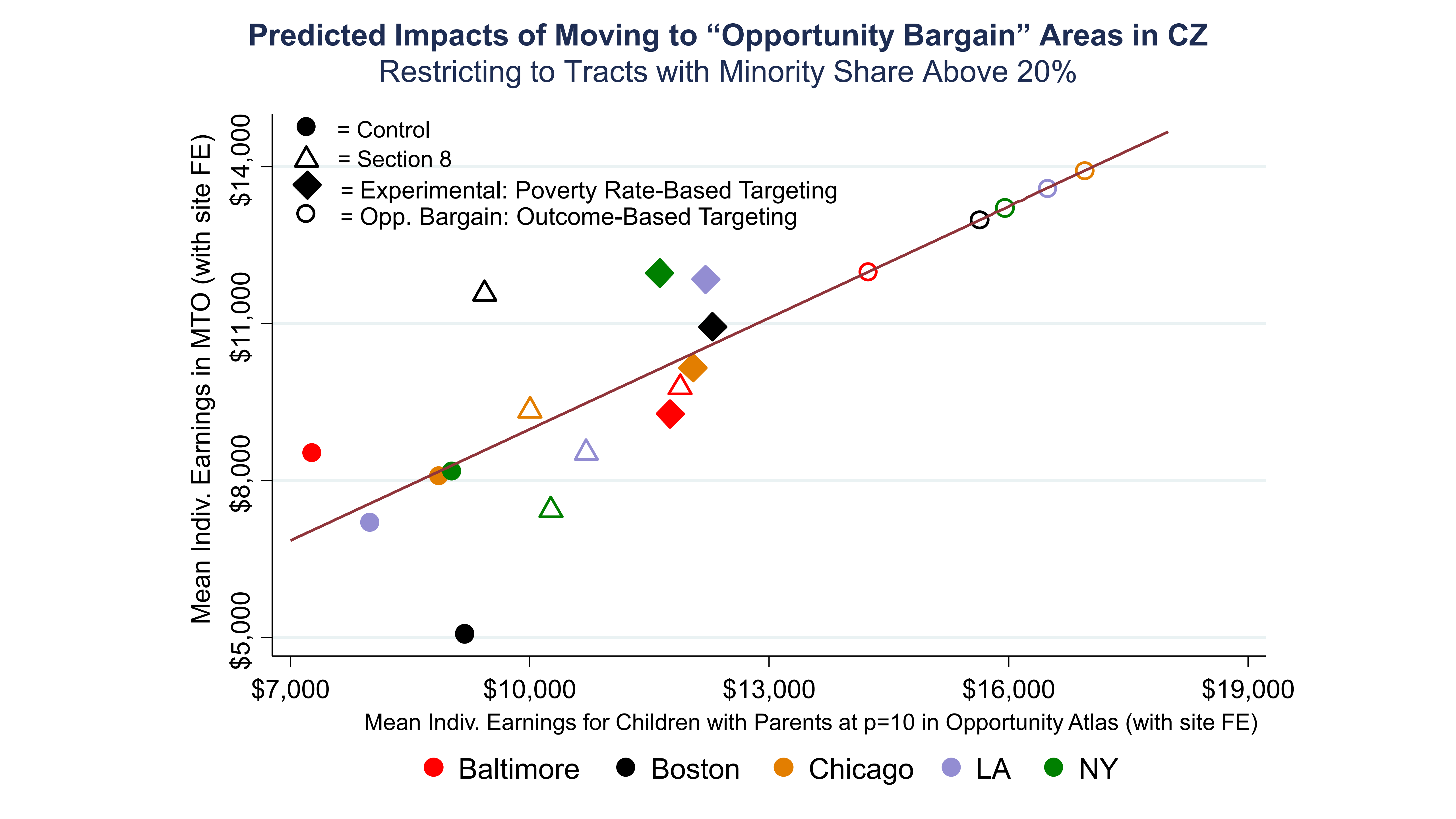


Correlation (across all CZs): 0.02


Upward Mobility vs. Job Growth in the 30 Largest MSAs
Children's Mean Hhold. Inc. Rank Given Parents at 25th Pctile
Job Growth Rate from 1990 to 2010 (%)
46
42
38
34
-10
0
10
20
30
40
50
60
70
San Jose
San Francisco
Boston
Minneapolis
Pittsburgh
New York
Seattle
Los Angeles
Sacramento
Washington
San Diego
Portland
Houston
Denver
Riverside
San Antonio
Miami
Philadelphia
Chicago
Kansas City
Dallas
Phoenix
Cleveland
St. Louis
Cincinnati
Baltimore
Tampa
Detroit
Atlanta
Charlotte
Correlation (across all MSAs): -0.07

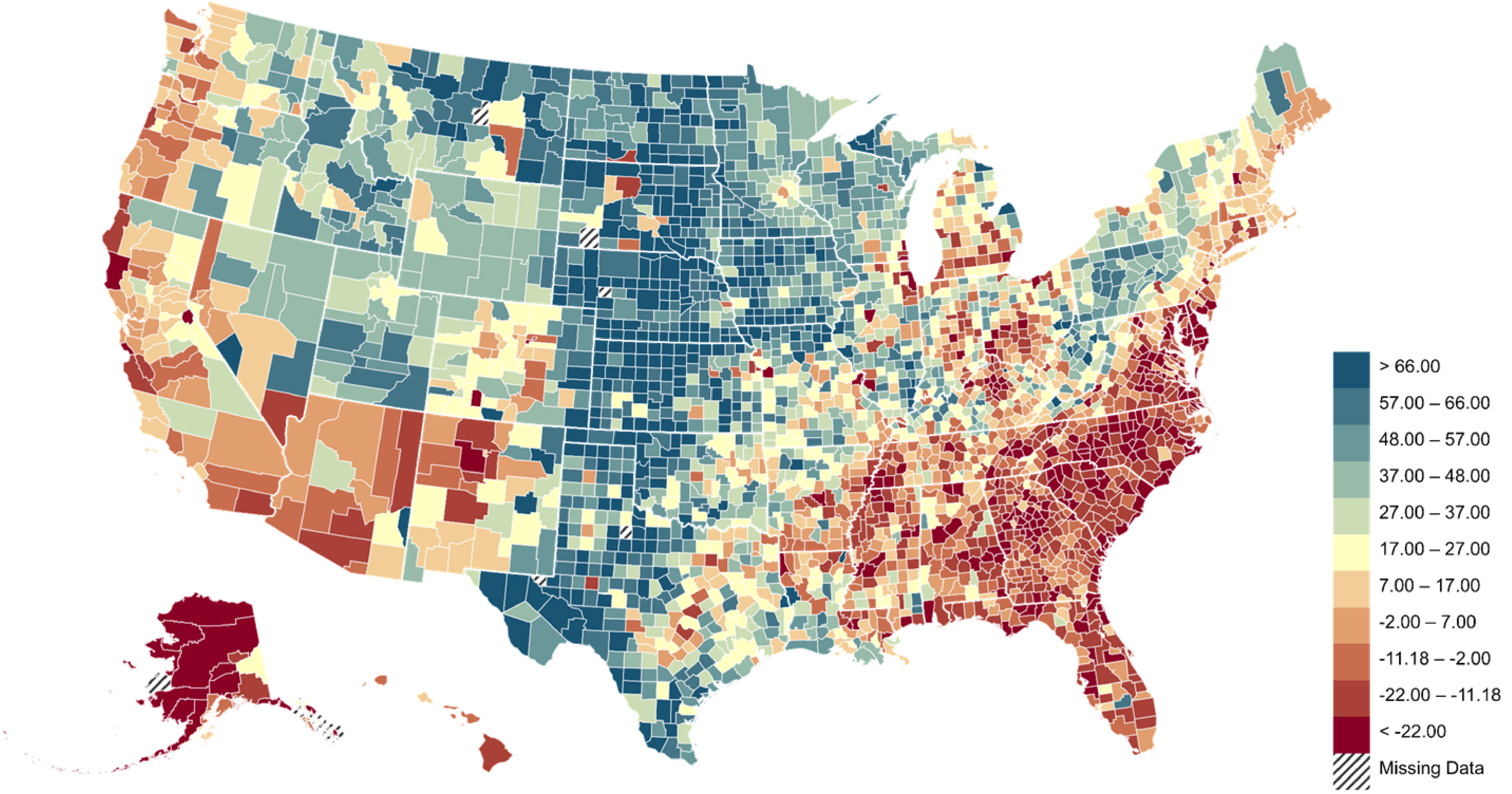
Childhood Exposure Effects on Household Income Ranks at Ages 24 and 30





Predicted Impacts of Moving to "Opportunity Bargain" Areas in CZ
Restricting to Tracts with Minority Share Above 20%
= Control
= Section 8
= Experimental: Poverty Rate-Based Targeting
= Opp. Bargain: Outcome-Based Targeting
Mean Indiv. Earnings in MTO (with site FE)
$5,000
$8,000
$11,000
$14,000
$7,000
$10,000
$13,000
$16,000
$19,000
Mean Indiv. Earnings for Children with Parents at p=10 in Opportunity Atlas (with site FE)
Baltimore
Boston
Chicago
LA
NY

Percentile Difference Between Opportunity Atlas Measures of Mean Child Income in Adulthood And Area Deprivation Index Measure of Neighborhood Quality



Note: Blue = areas where Opportunity Atlas ranking is higher than Area Deprivation Index (Singh 2003); red is the converse