

The Opportunity Atlas

Mapping the Childhood Roots of Social Mobility

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Disclaimer: Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The statistical summaries reported in these slides have been cleared by the Census Bureau's Disclosure Review Board release authorization number CBDRB-FY18-319. All values in the tables and figures that appear in this presentation have been rounded to four significant digits as part of the disclosure avoidance protocol. Unless otherwise noted, source for all tables and figures: authors calculations based on Census 2000 and 2010, tax returns, and American Community Surveys 2005-2015.

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 2018; Chyn 2018; Deutscher 2018; Laliberte 2018 building on Wilson 1987, Case & 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; 4,200 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 2013, 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

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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



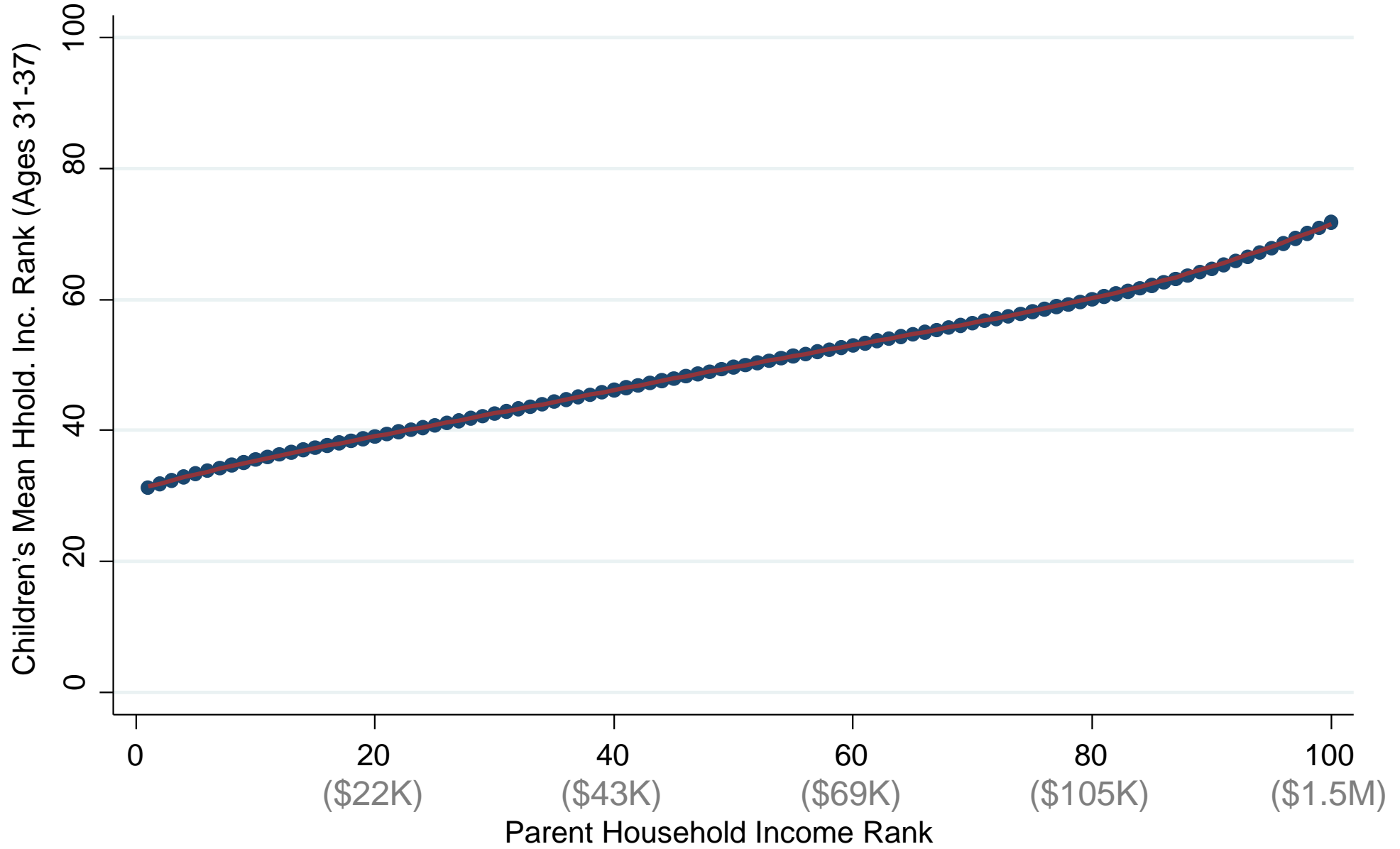
Estimating Mean Outcomes by Tract

- 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

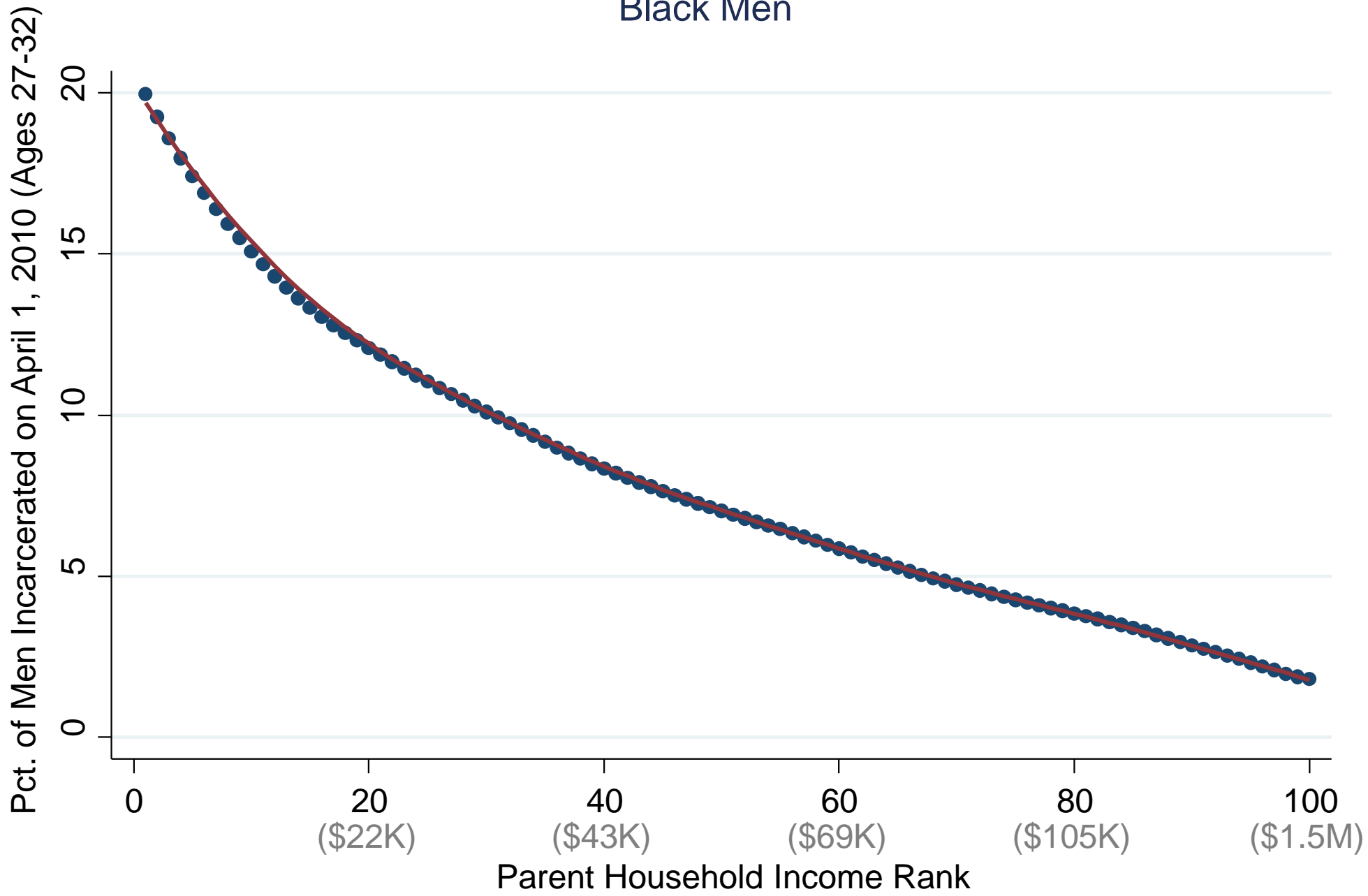
Mean Child Household Income Rank vs. Parent Household Income Rank





Incarceration Rates vs. Parent Household Income Rank

Black Men



Estimating Mean Outcomes by Tract

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- 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
- In practice, 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 at age 34 for ease of interpretation

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3 **Observational Variation and Targeting**

4 Causal Effects and Neighborhood Choice

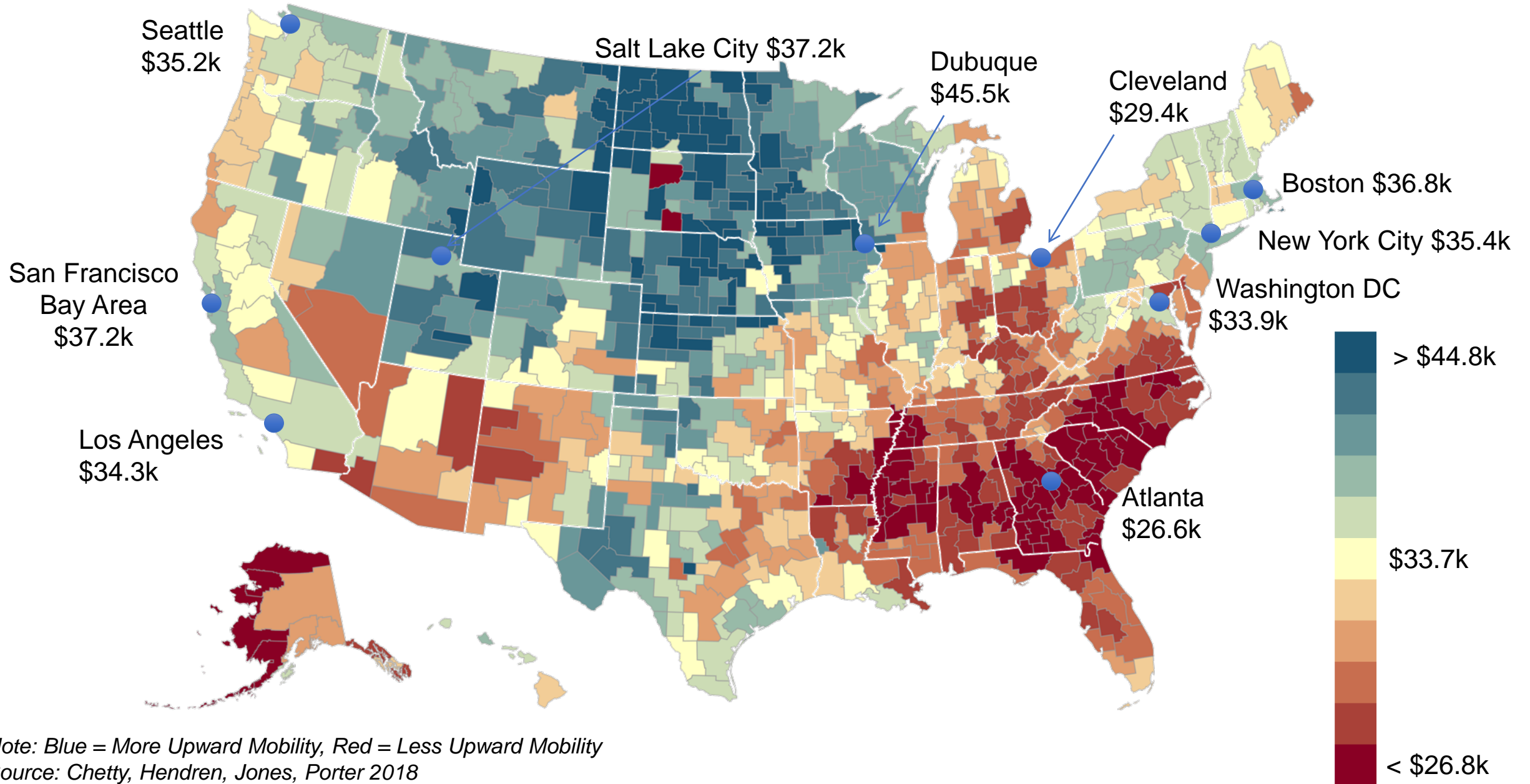
Observational Variation and Targeting

- 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



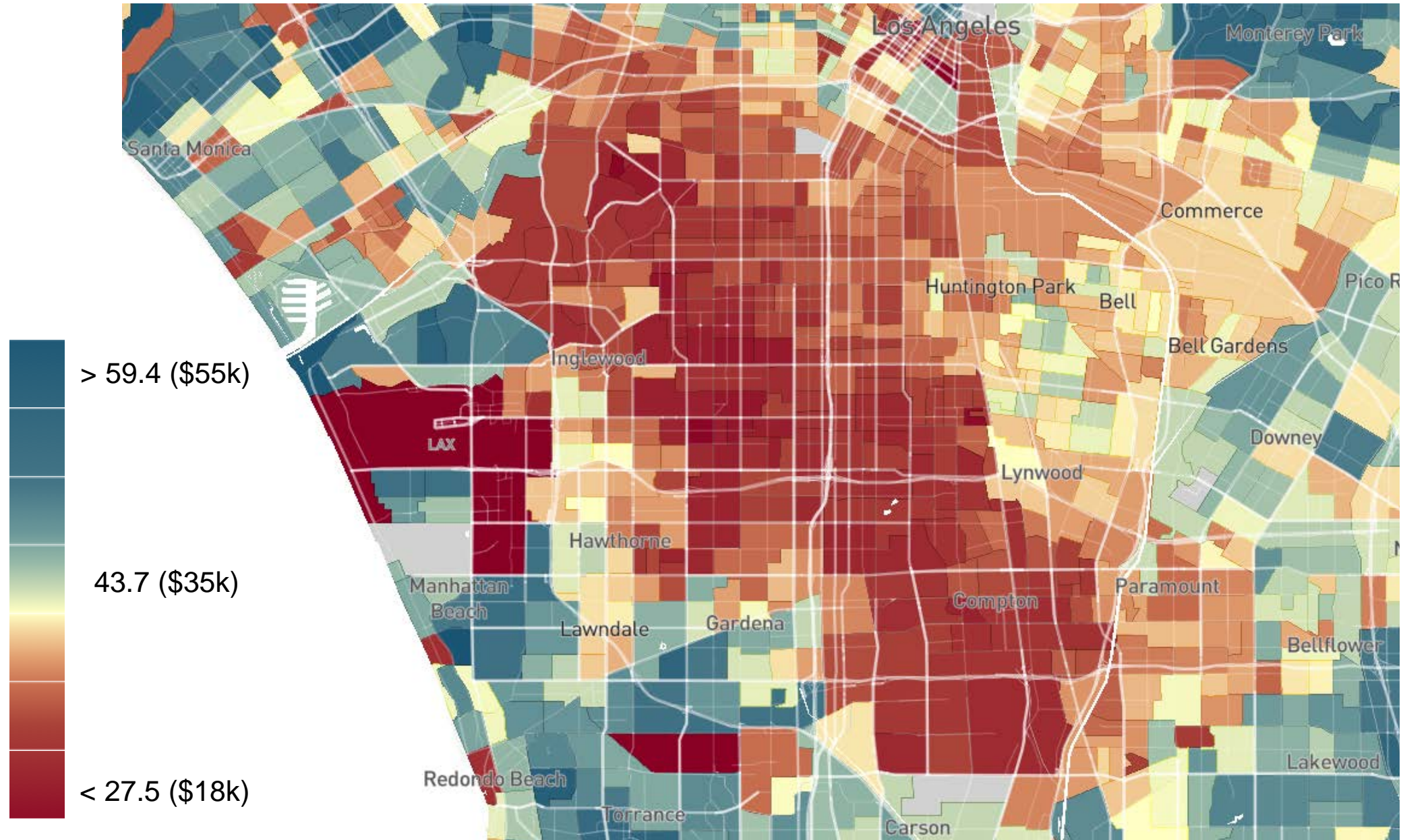
The Geography of Upward Mobility in the United States

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

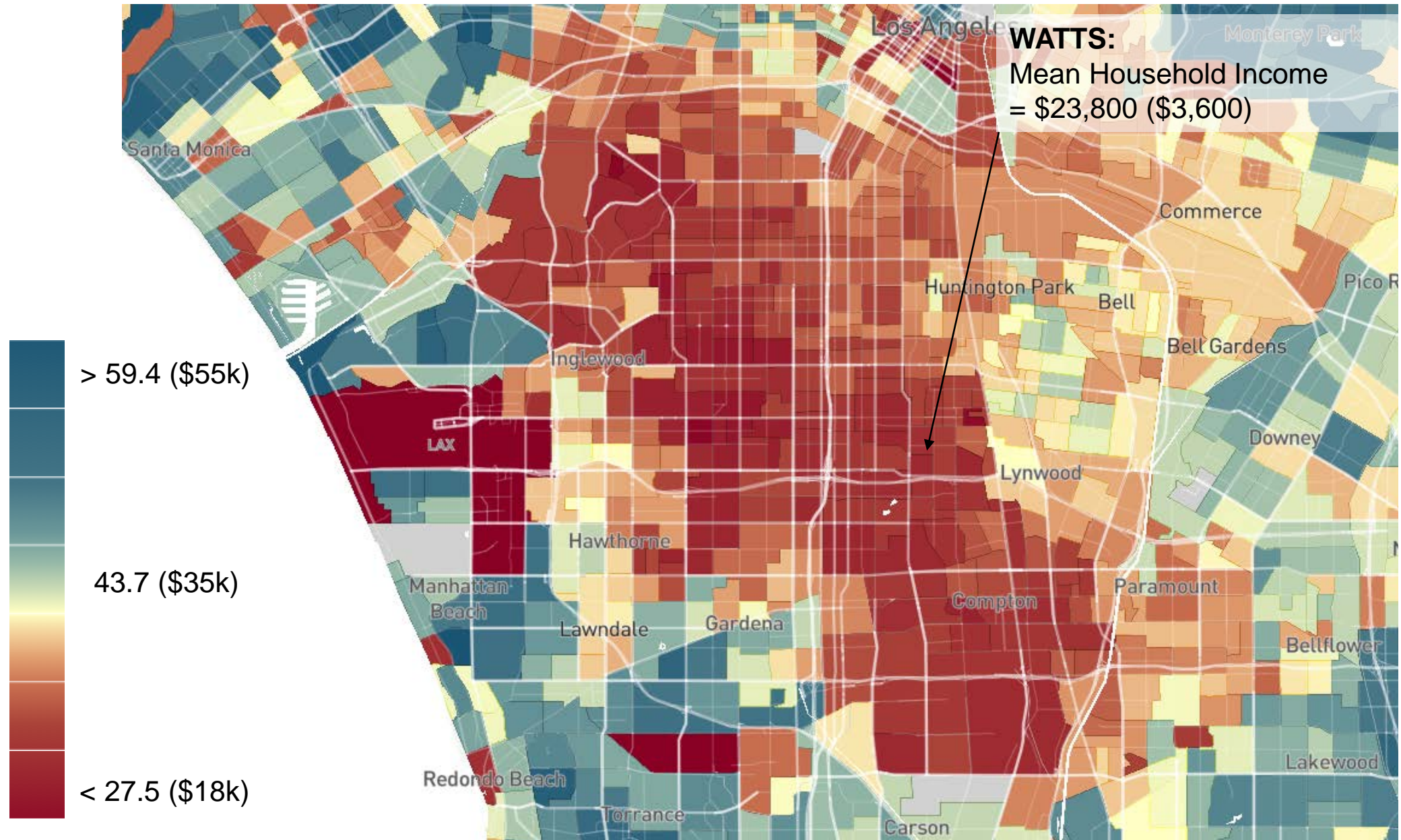


Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: Chetty, Hendren, Jones, Porter 2018

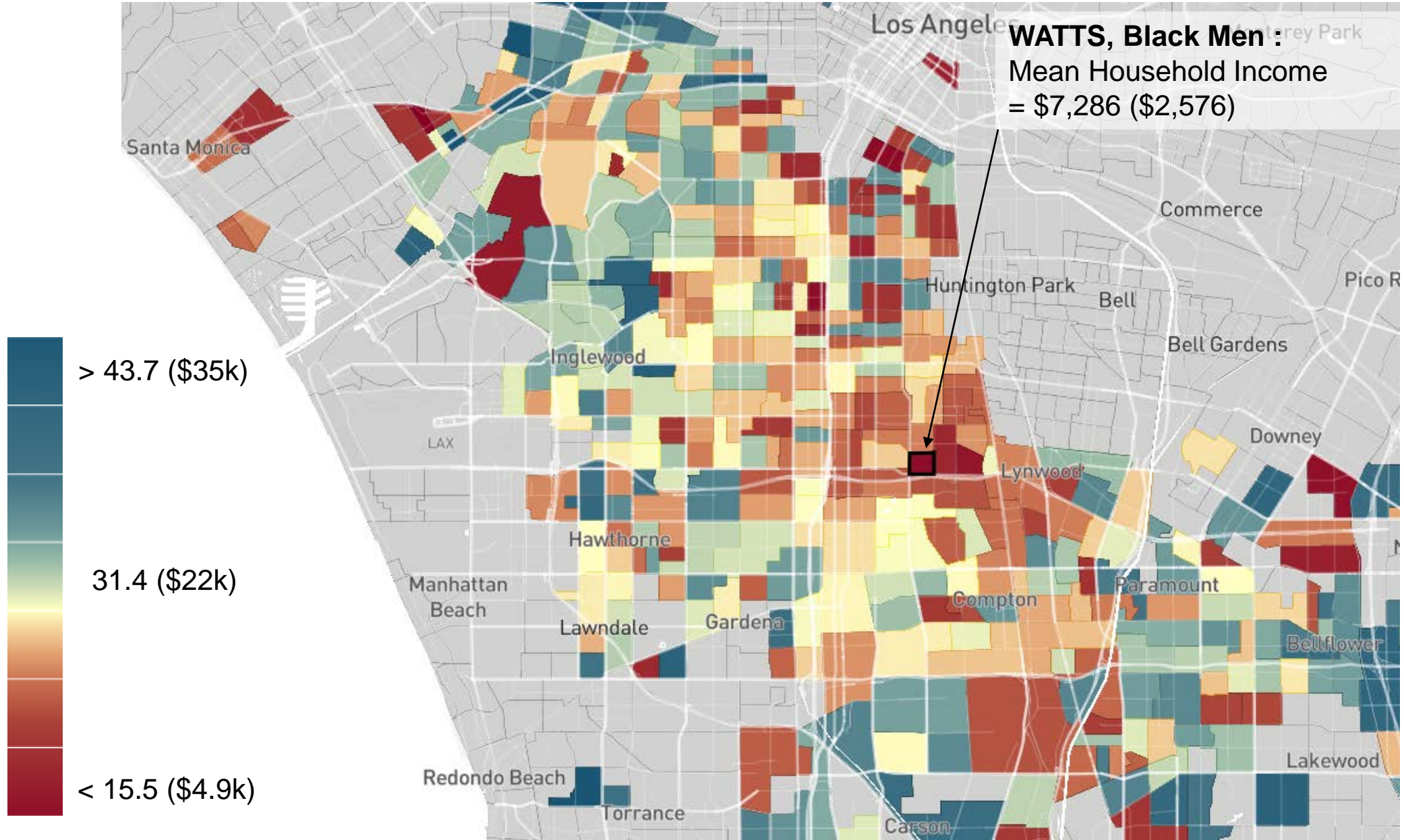
Mean Household Income for Children in Los Angeles with Parents Earning \$27,000 (25th percentile)



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

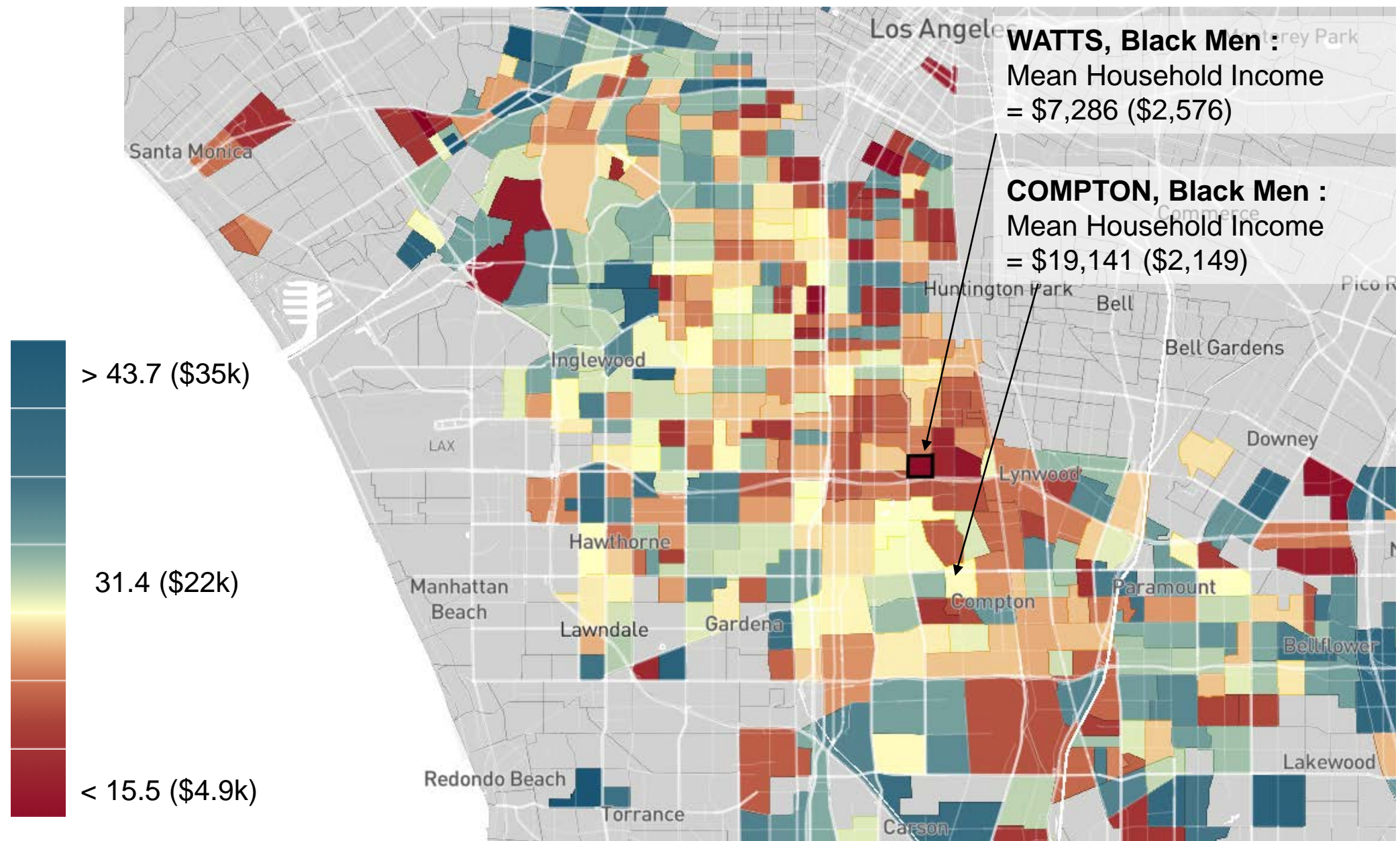


Mean Household Income for Black Men in Los Angeles with Parents Earning \$27,000 (25th percentile)



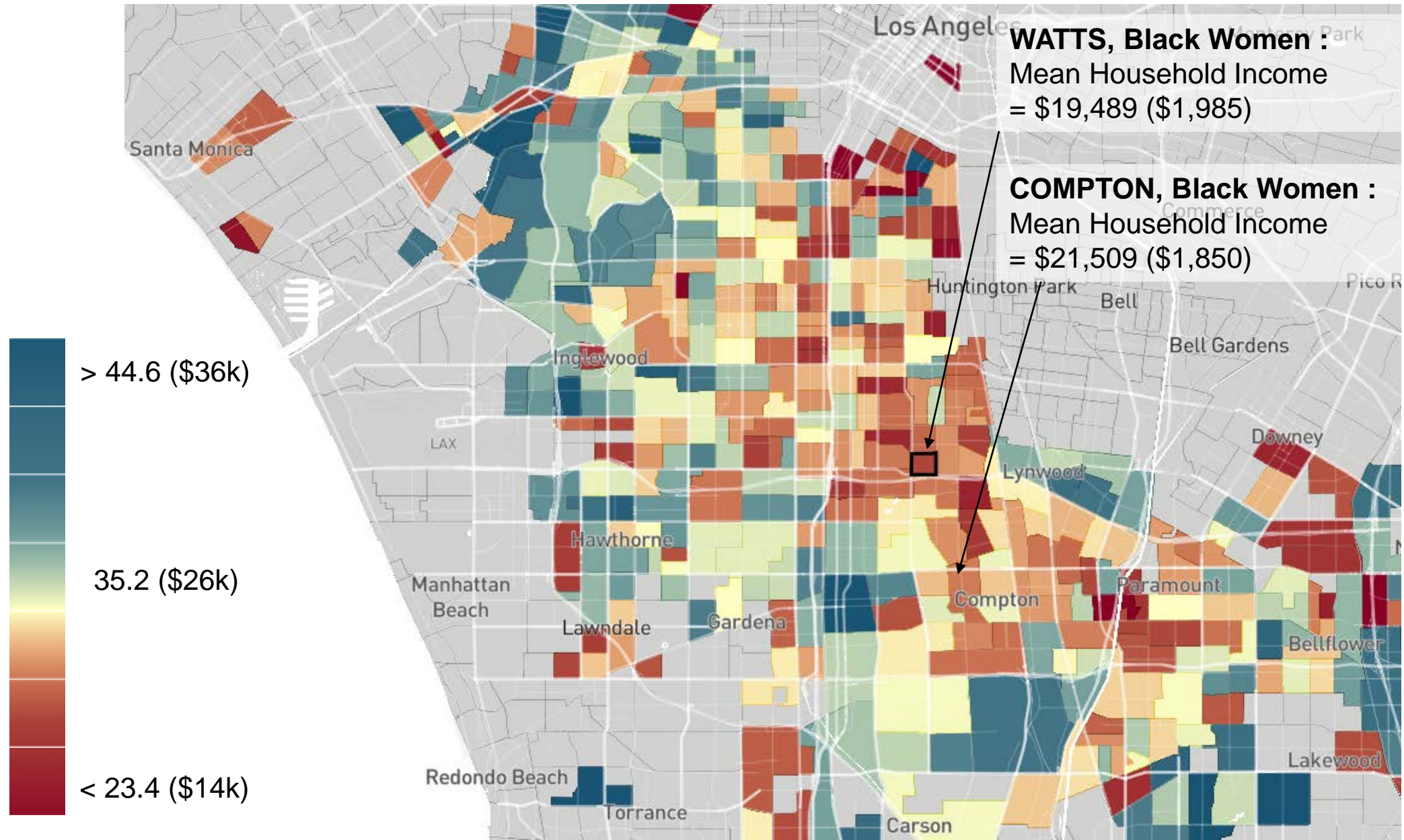


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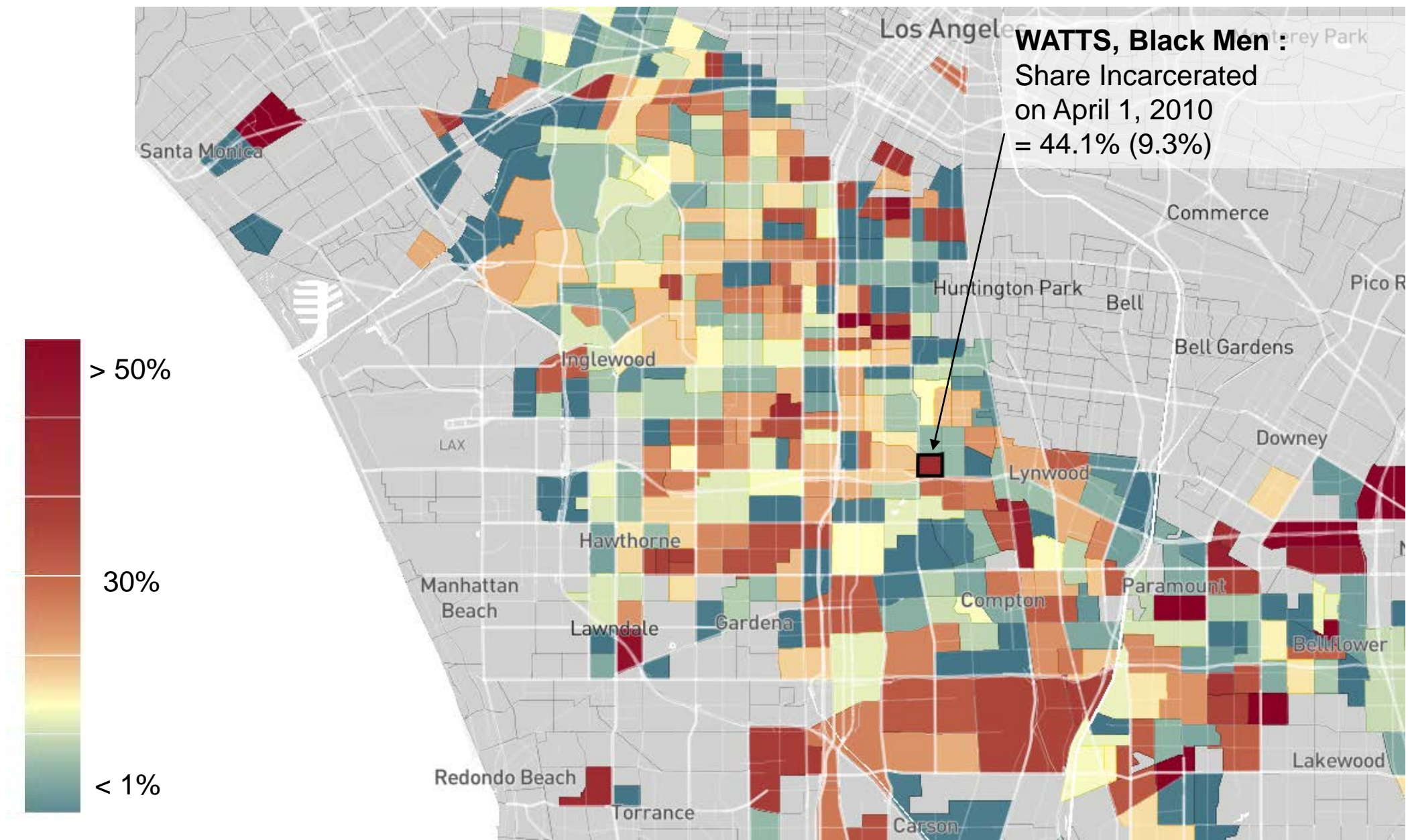




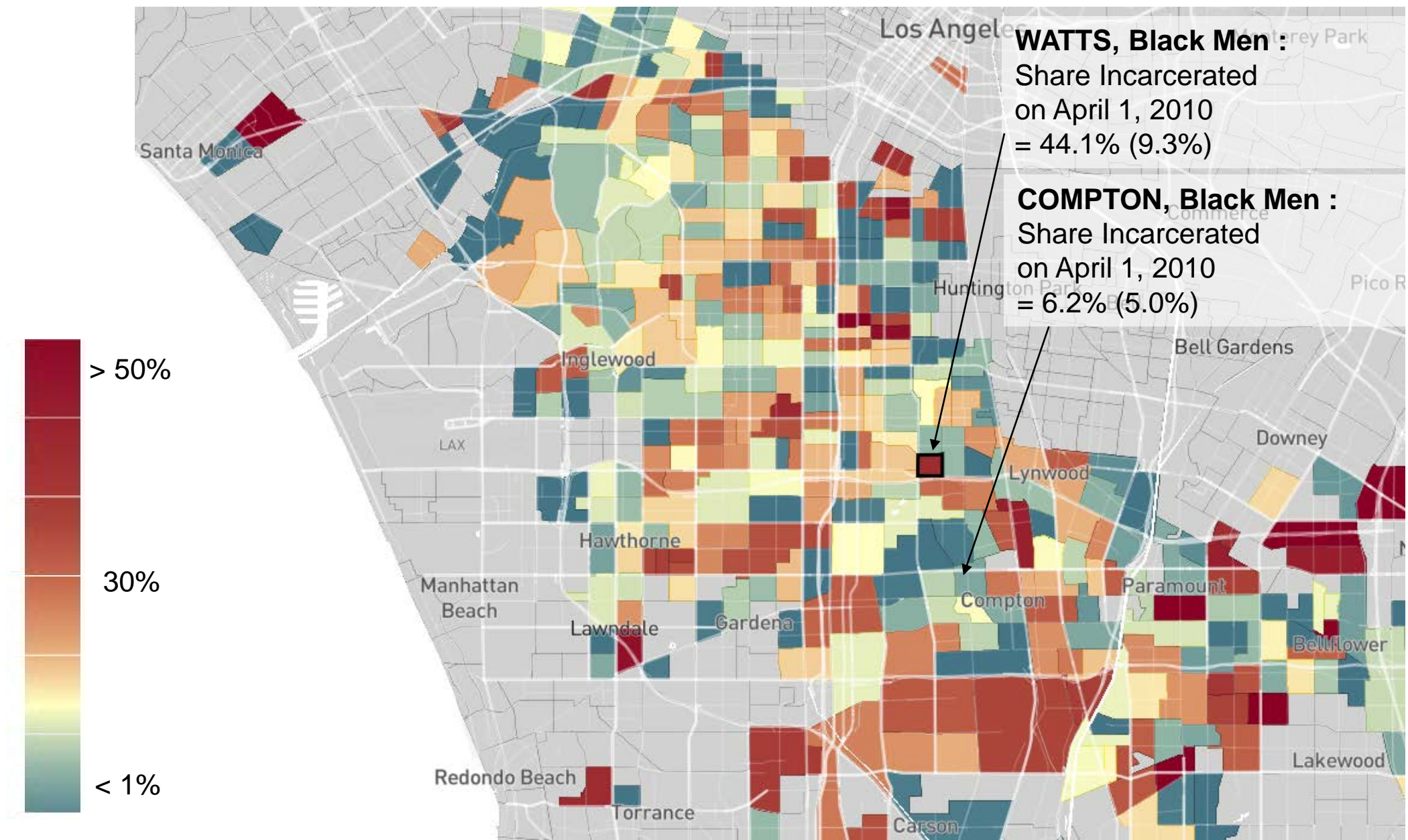
Mean Individual Income for Black Women in Los Angeles with Parents Earning \$27,000 (25th percentile)



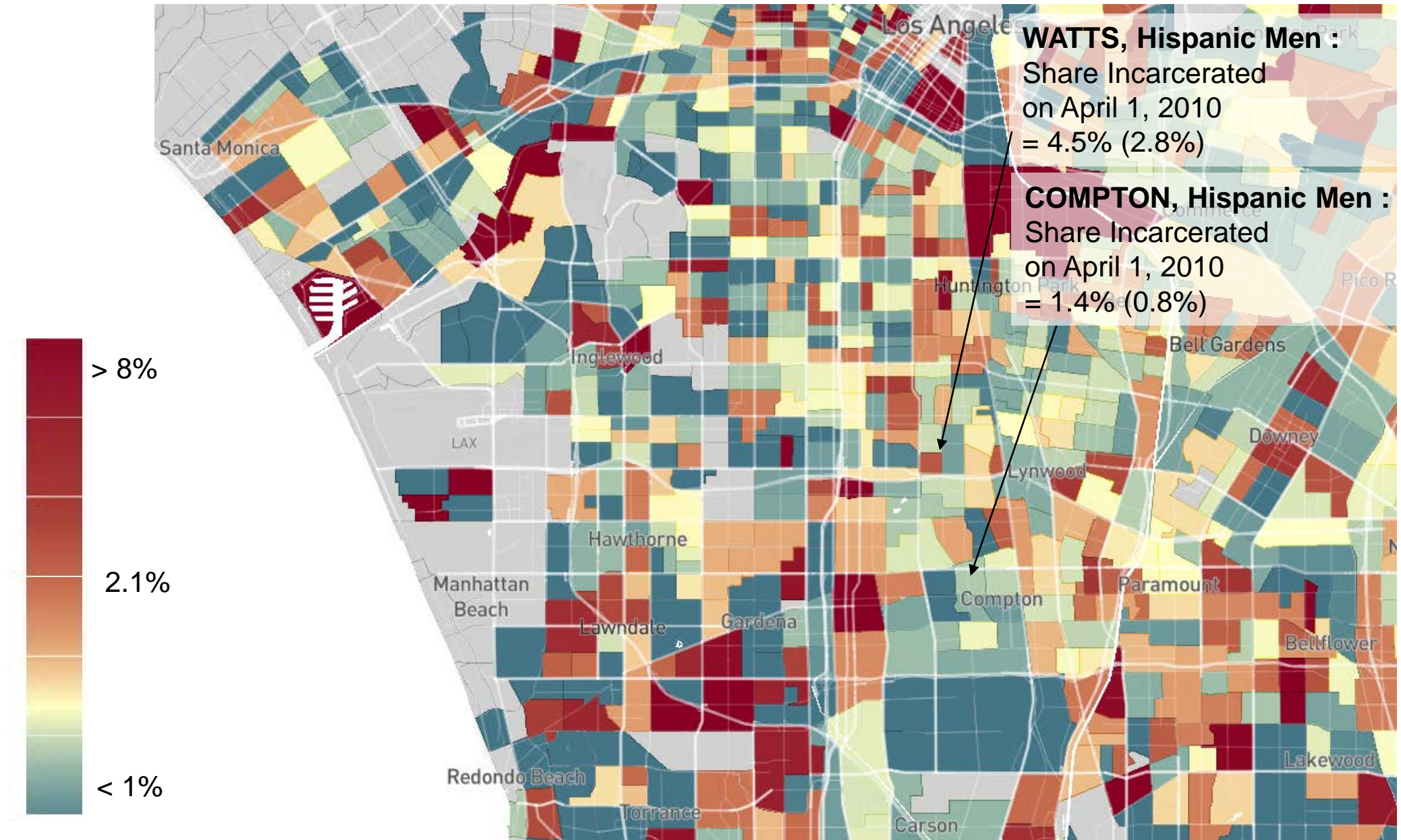
Incarceration Rates for Black Men in Los Angeles with Parents Earning < \$2,200 (1st percentile)



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)

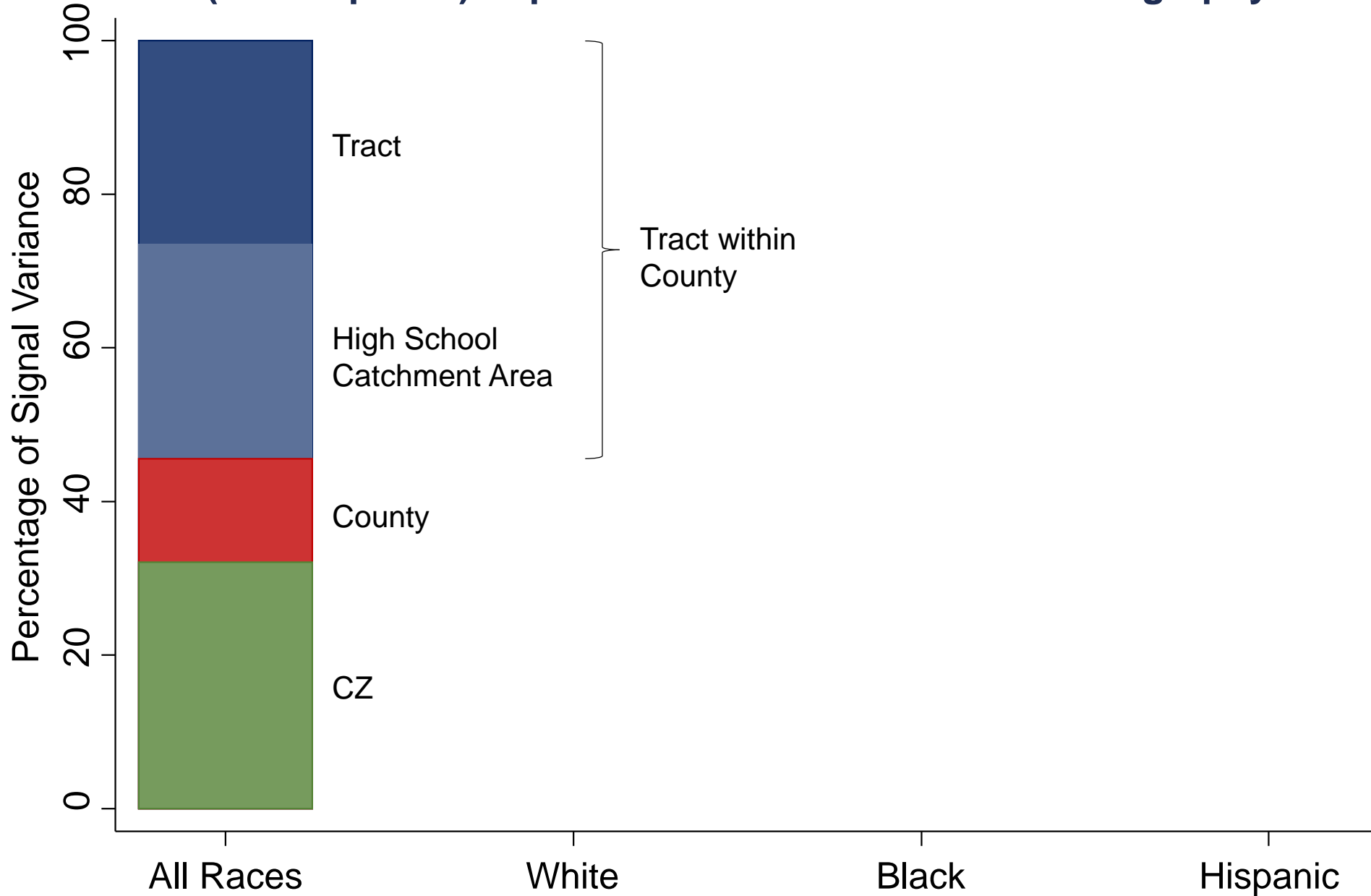


Targeting Place-Based Policies

- Example illustrates three general results on targeting:
 1. Children's outcomes vary widely across nearby tracts → neighborhood where children grow up is a useful tag for policy interventions

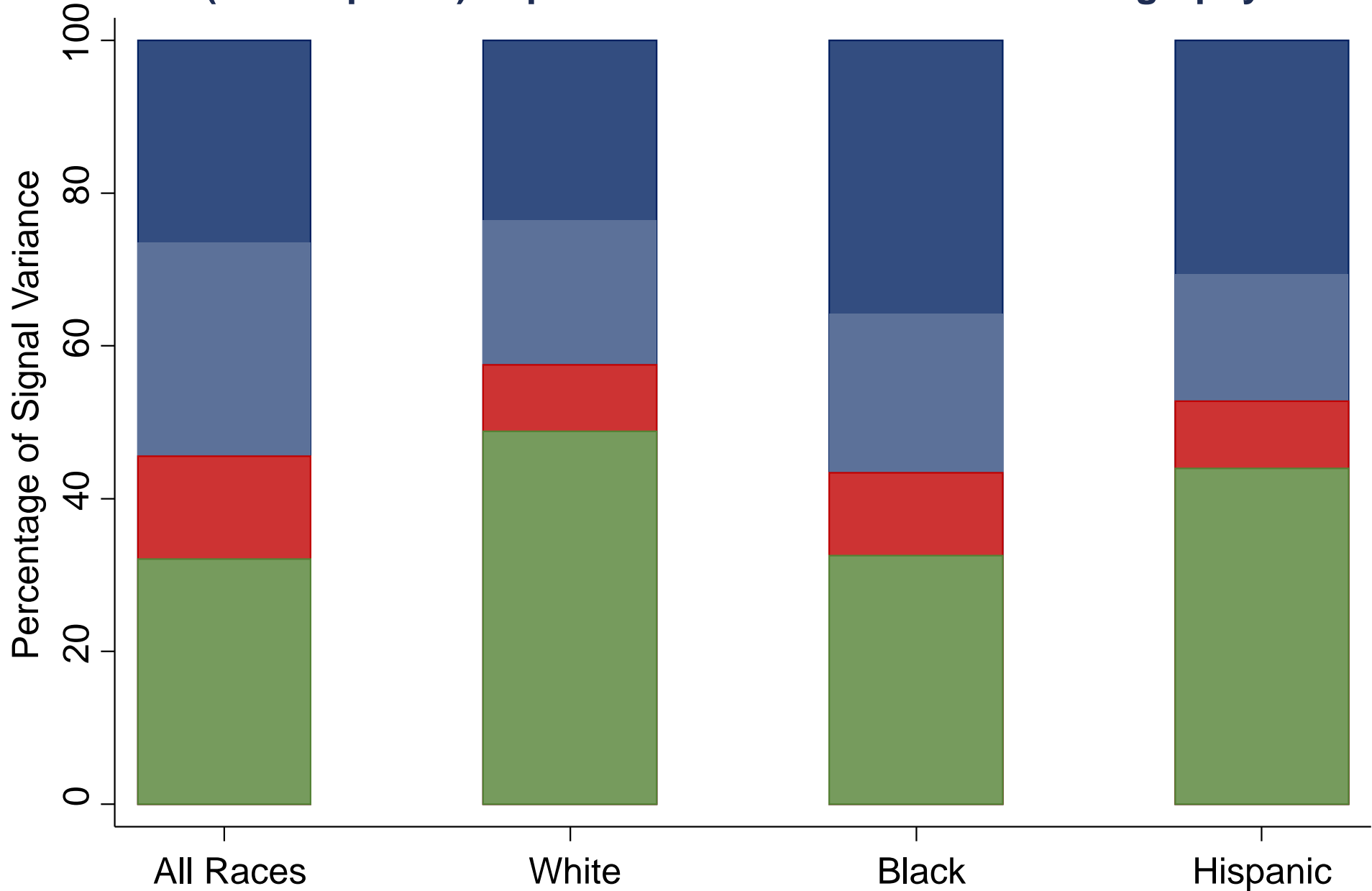


Share of Signal Variance of Tract-Level Mean Child Income Rank (Parent $p = 25$) Explained at Different Levels of Geography





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

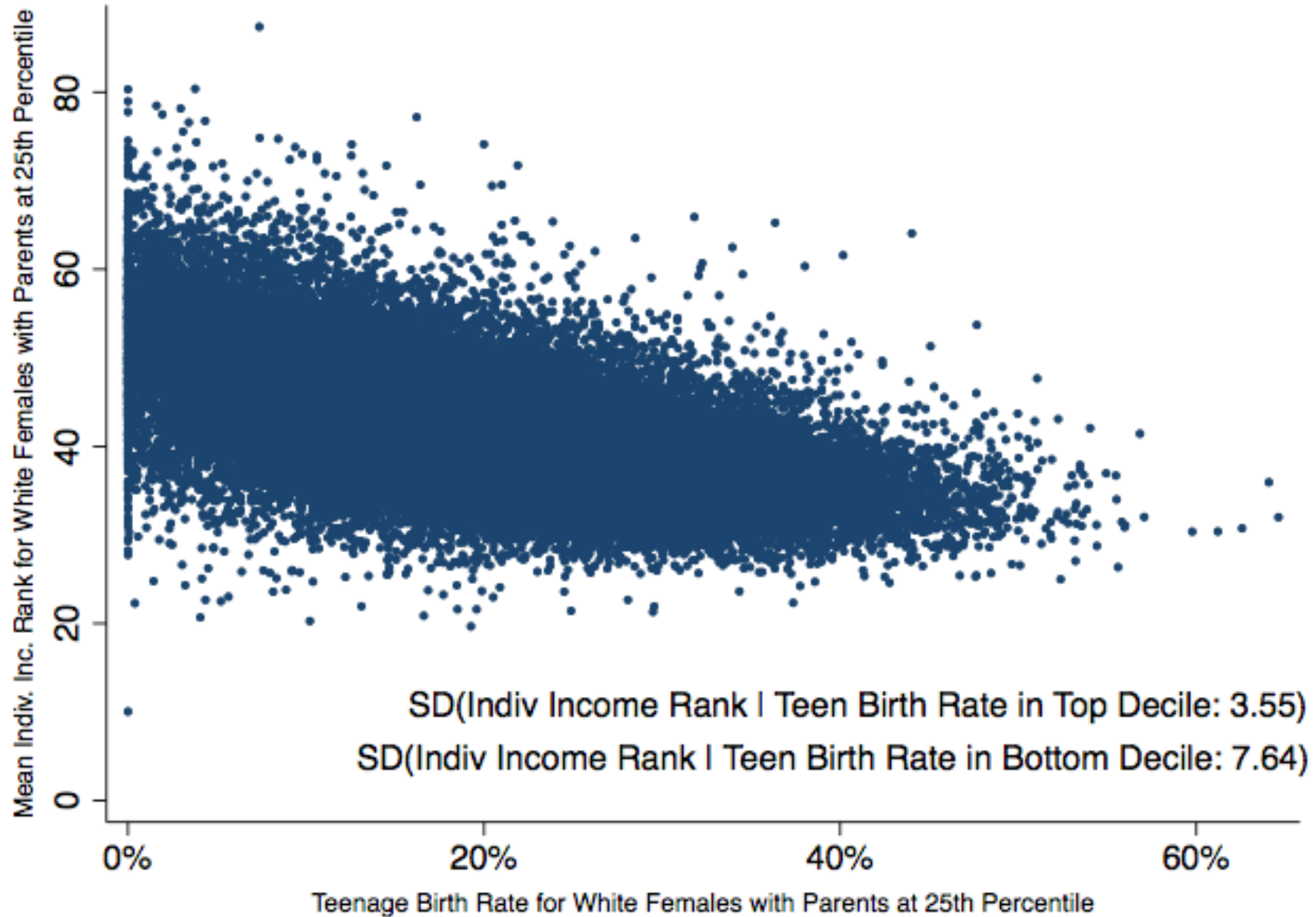




Targeting Place-Based Policies

- 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/outcomes cond. on parent income → neighborhoods not well described by a single-factor model

Relationship between Upward Mobility and Teen Birth Rates White Females



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	Fraction w/ Teen Birth	Fraction Married	Household Income Rank (Parent p = 75)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household Income Rank (Parent p = 25)	1	0.858	0.346	-0.276	-0.480	0.608	0.547
Individual Income Rank		1	0.512	-0.253	-0.418	0.311	0.478
Employment Rate			1	-0.114	-0.071	0.040	0.141
Incarceration Rate				1	0.182	-0.198	-0.154
Fraction with Teen Birth					1	-0.273	-0.350
Fraction Married						1	0.253
Household Income Rank (Parent p = 75)							1

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	0.454
Hispanic			1	0.374	0.602	0.353
Asian				1	0.267	0.465
American Indian & Alaska Natives					1	0.357

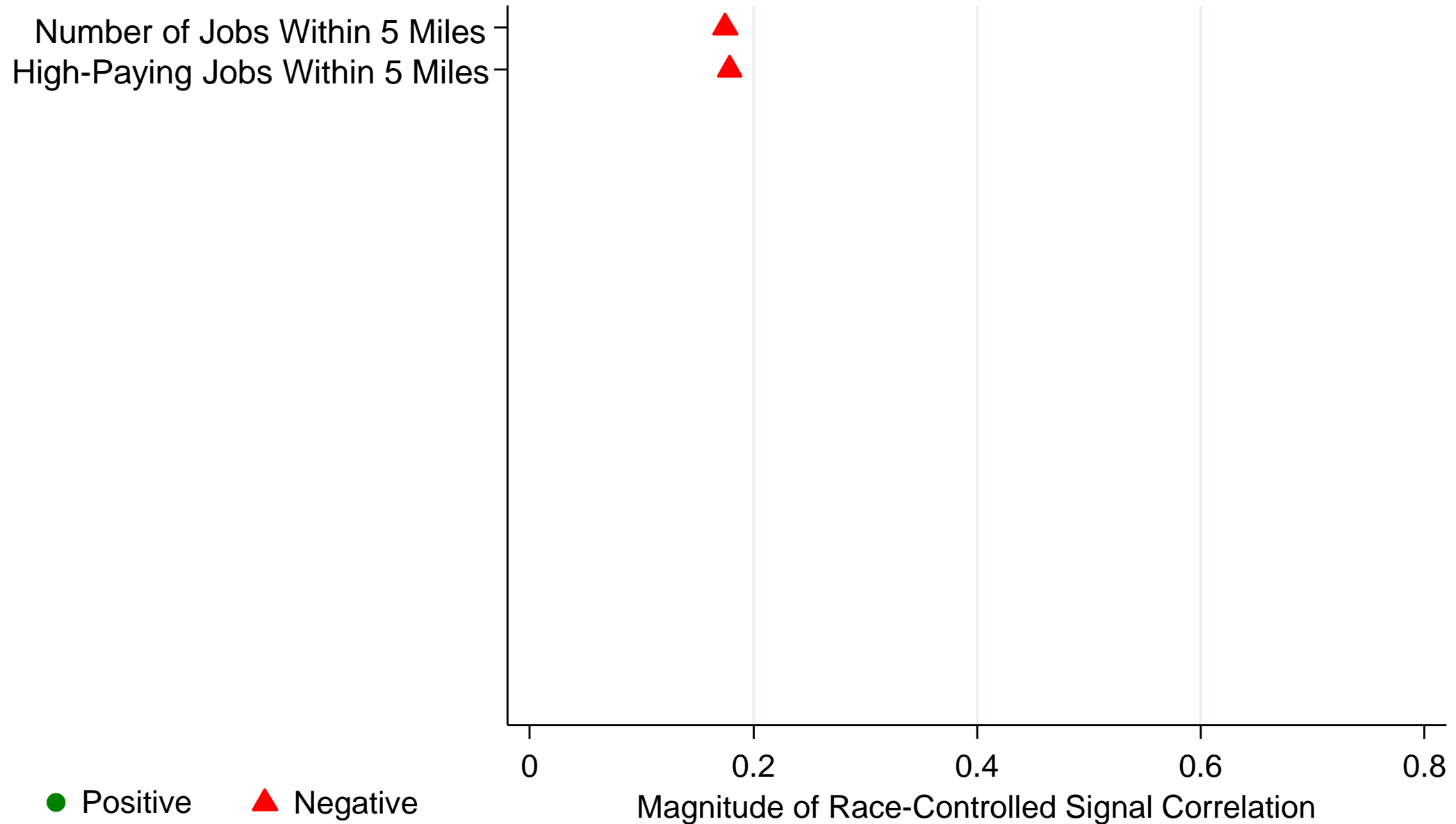
Note: Signal correlations adjusted for sampling error in the outcome variables

Targeting Place-Based Policies

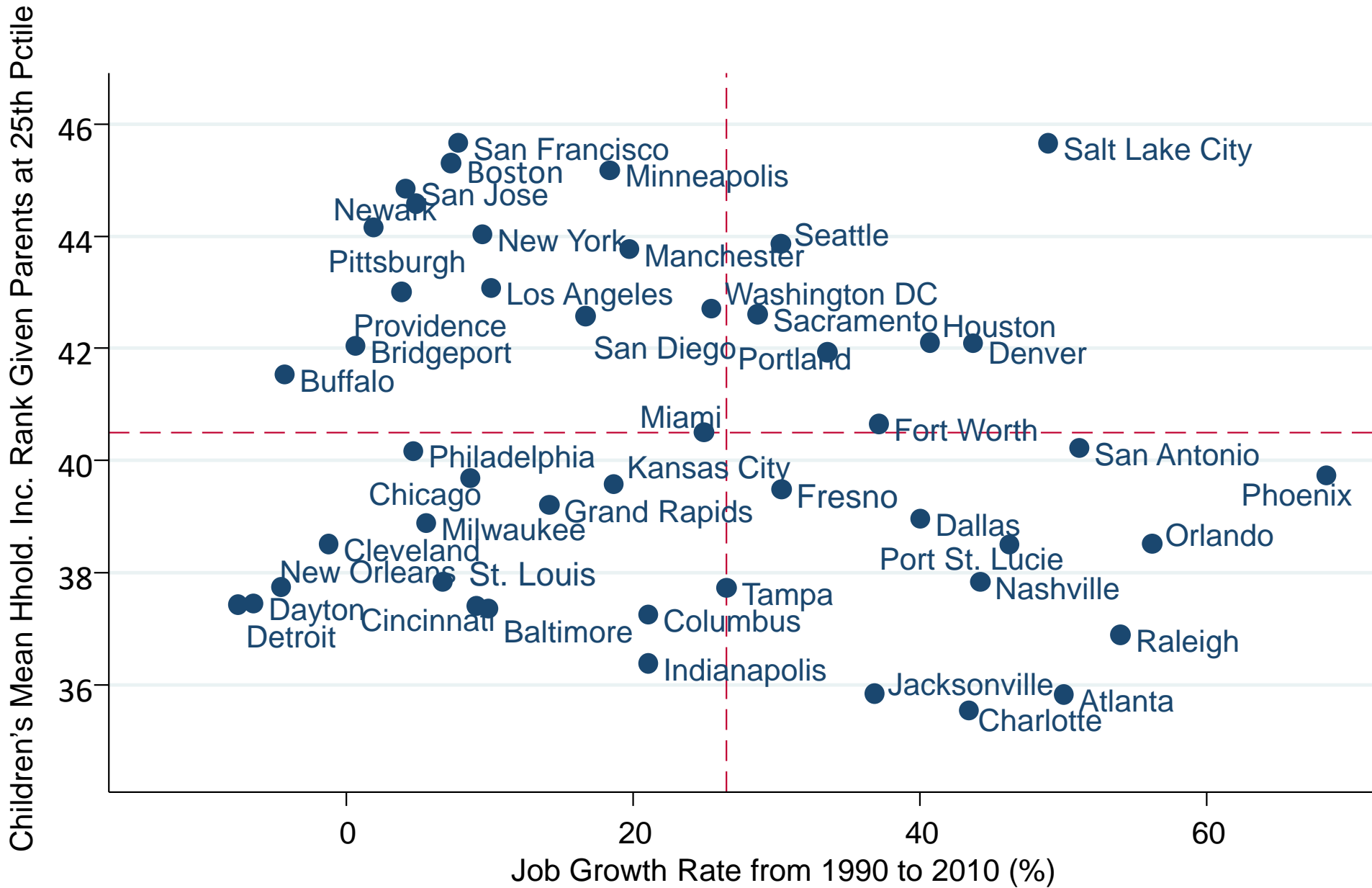
- Example illustrates three general results on targeting:
 1. Children's outcomes vary widely across nearby tracts → location where children grow up is a useful tag for policy interventions
 2. Substantial heterogeneity *within* areas across subgroups and outcomes cond. on parent income → neighborhoods 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

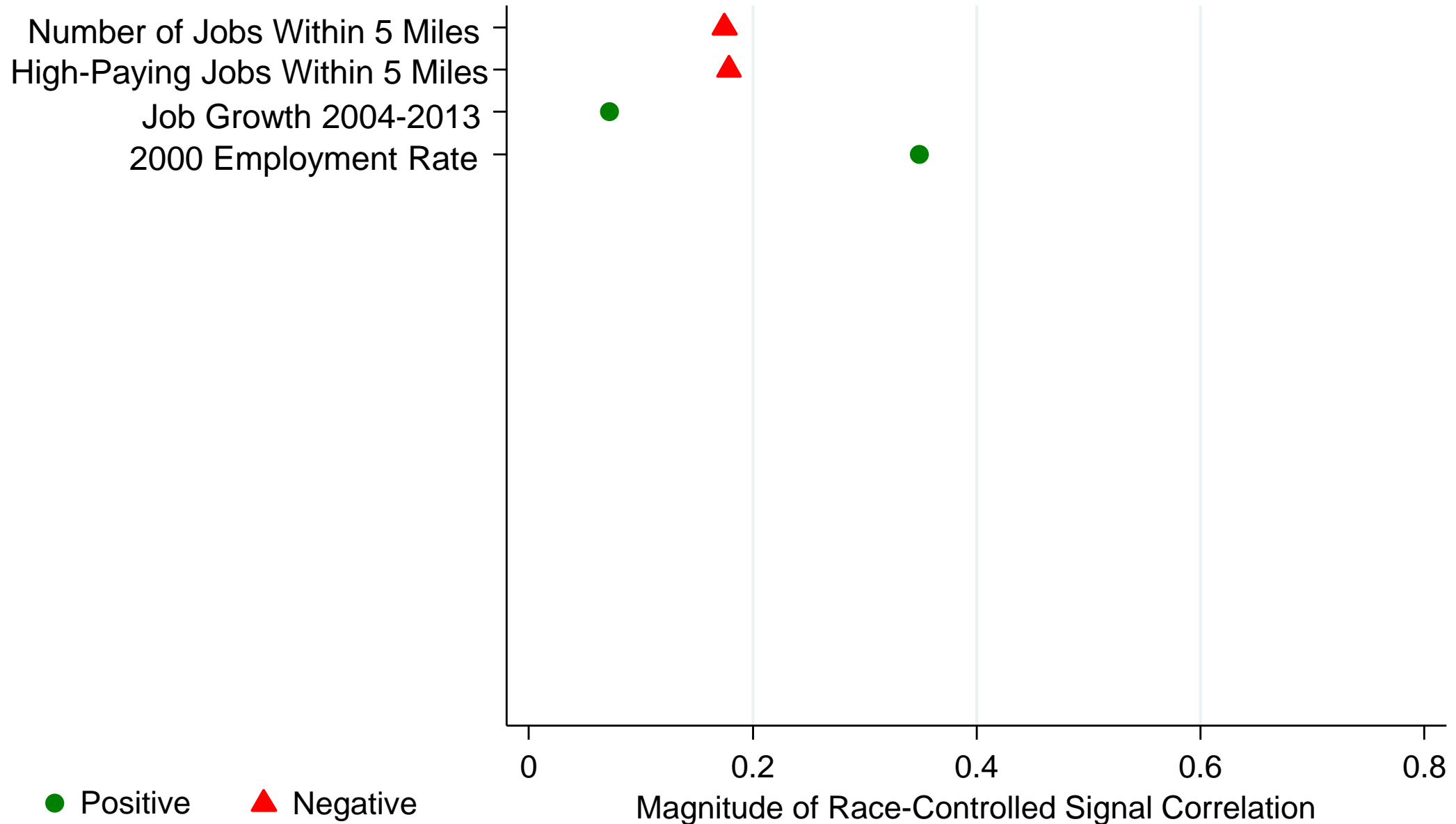


Upward Mobility vs. Job Growth in the 50 Largest Commuting Zones



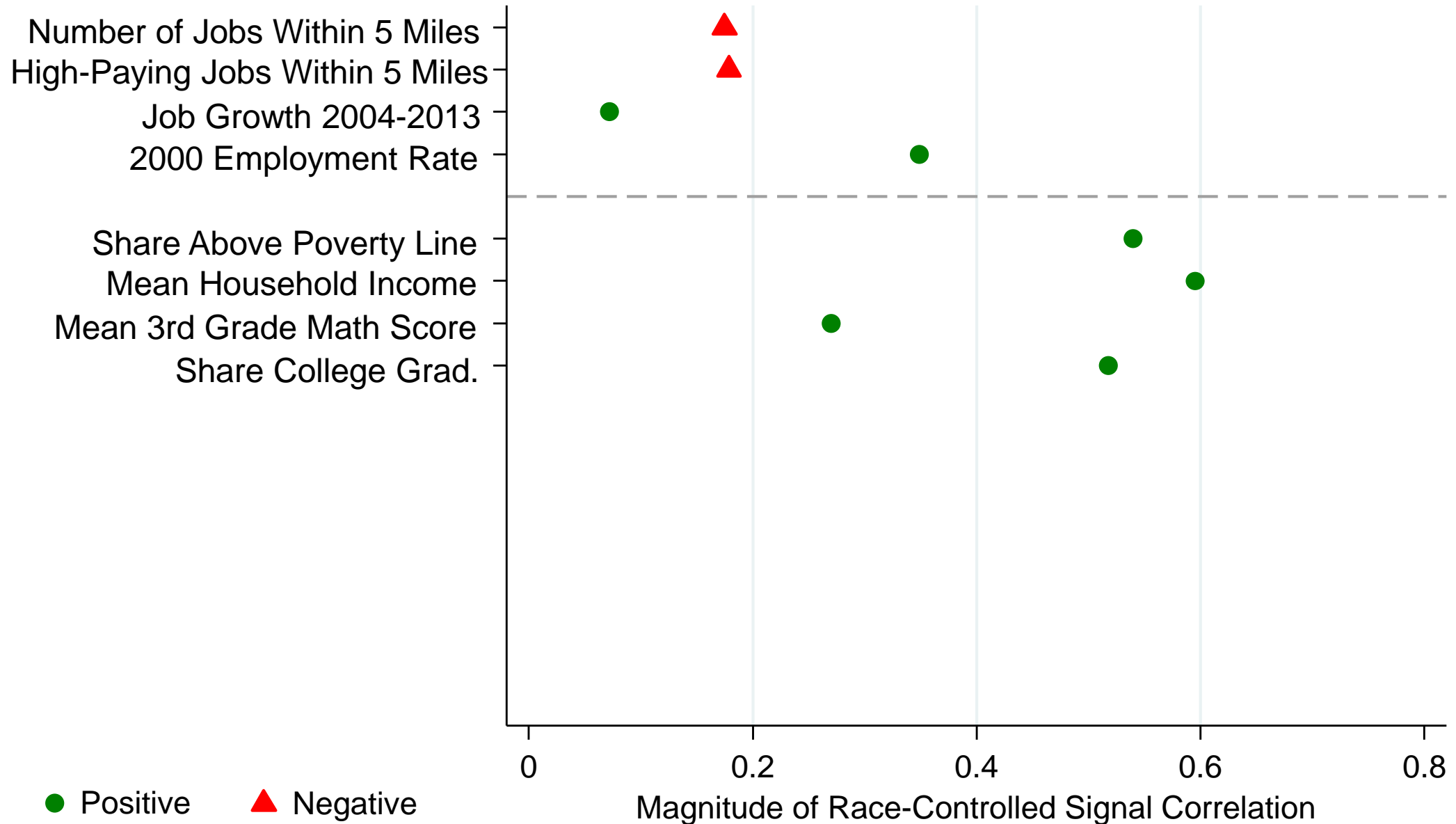
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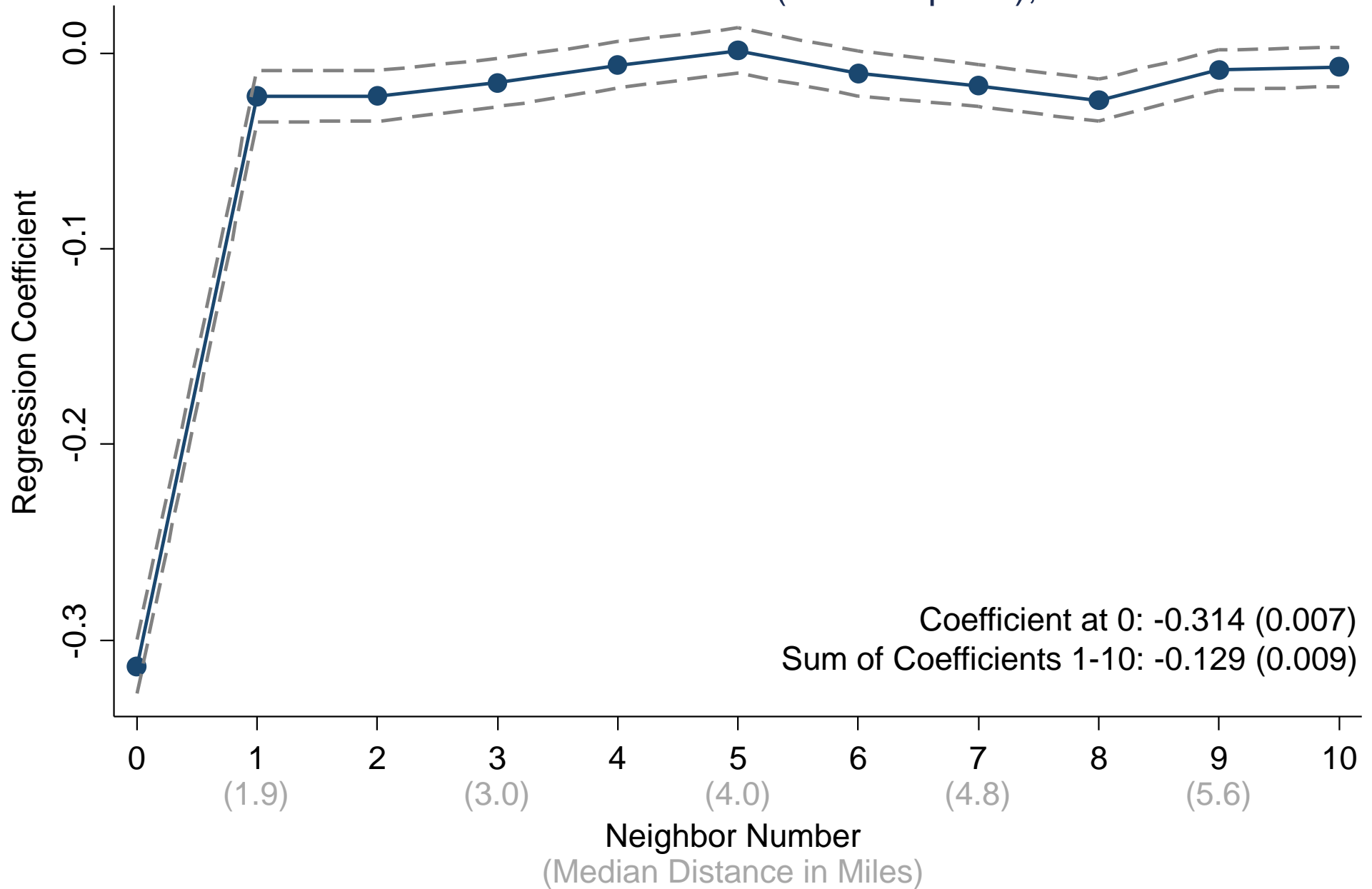
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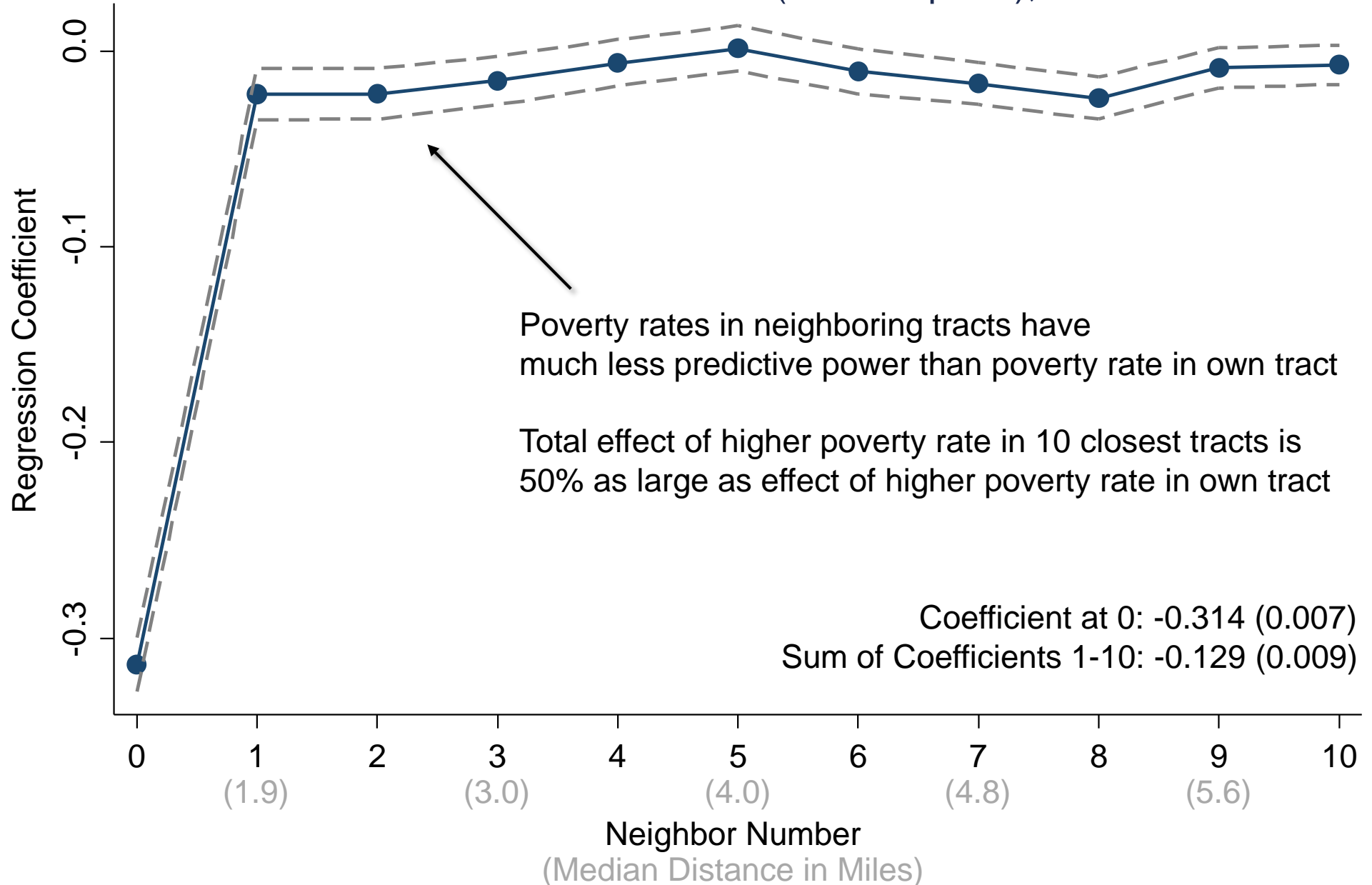
Spatial Decay of Correlation with Tract-Level Poverty Rate

Mean Child Household Income Rank (Parents p=25), White Children



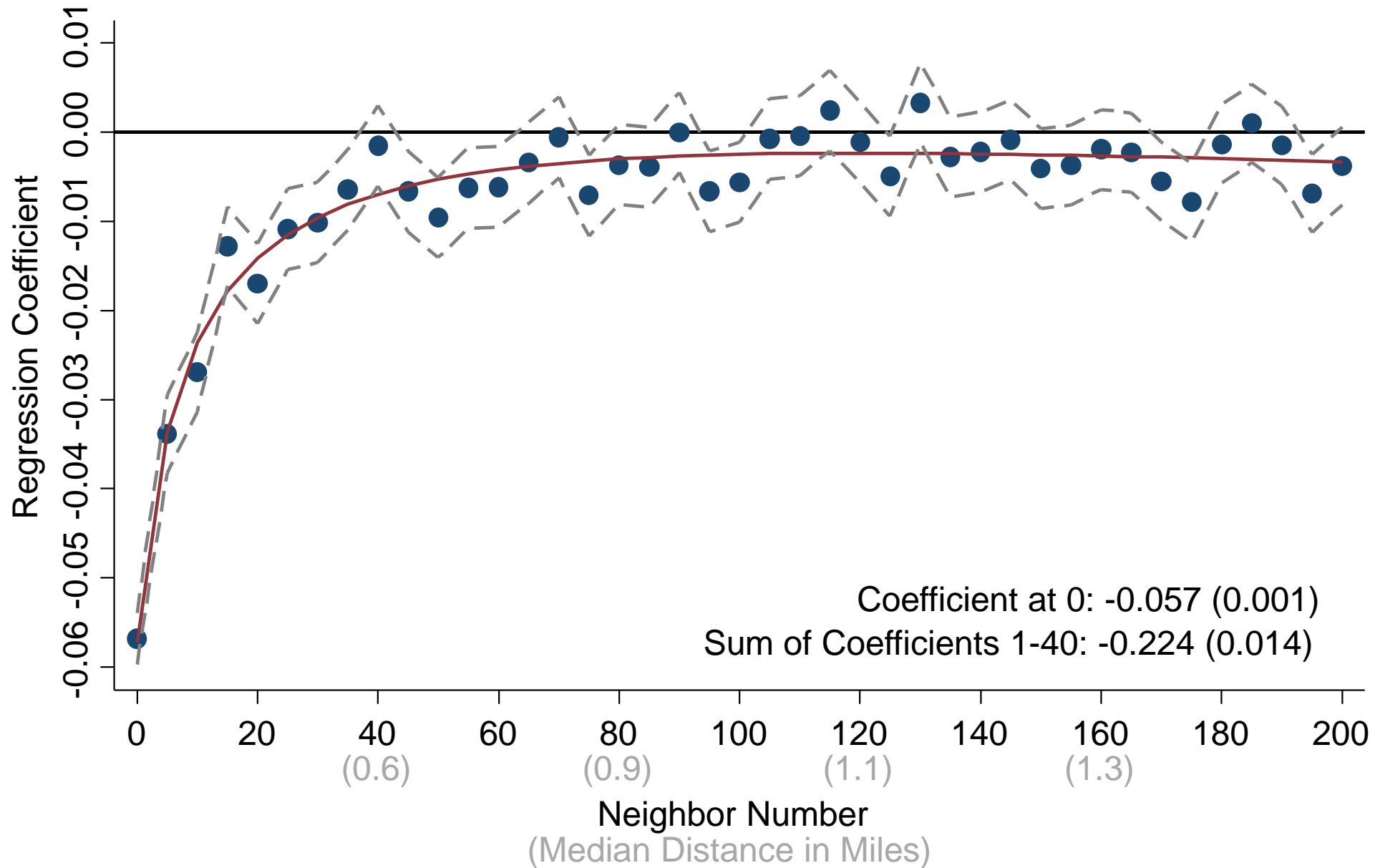
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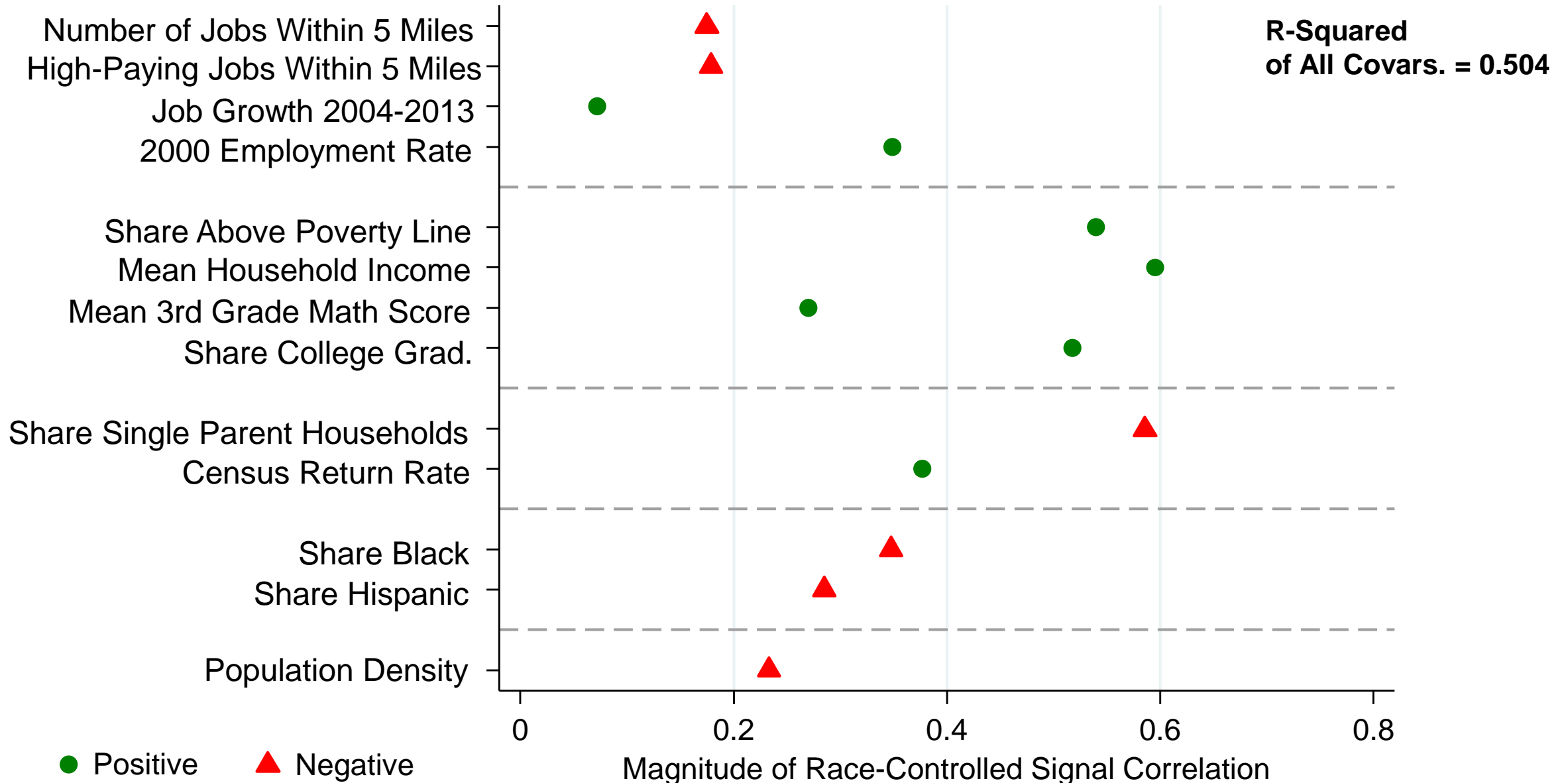
Spatial Decay of Correlation with Block-Level Poverty Rate

Mean Child Household Income Rank (Parents p=25), White Children



Correlations between Tract-Level Covariates and Household Income Rank

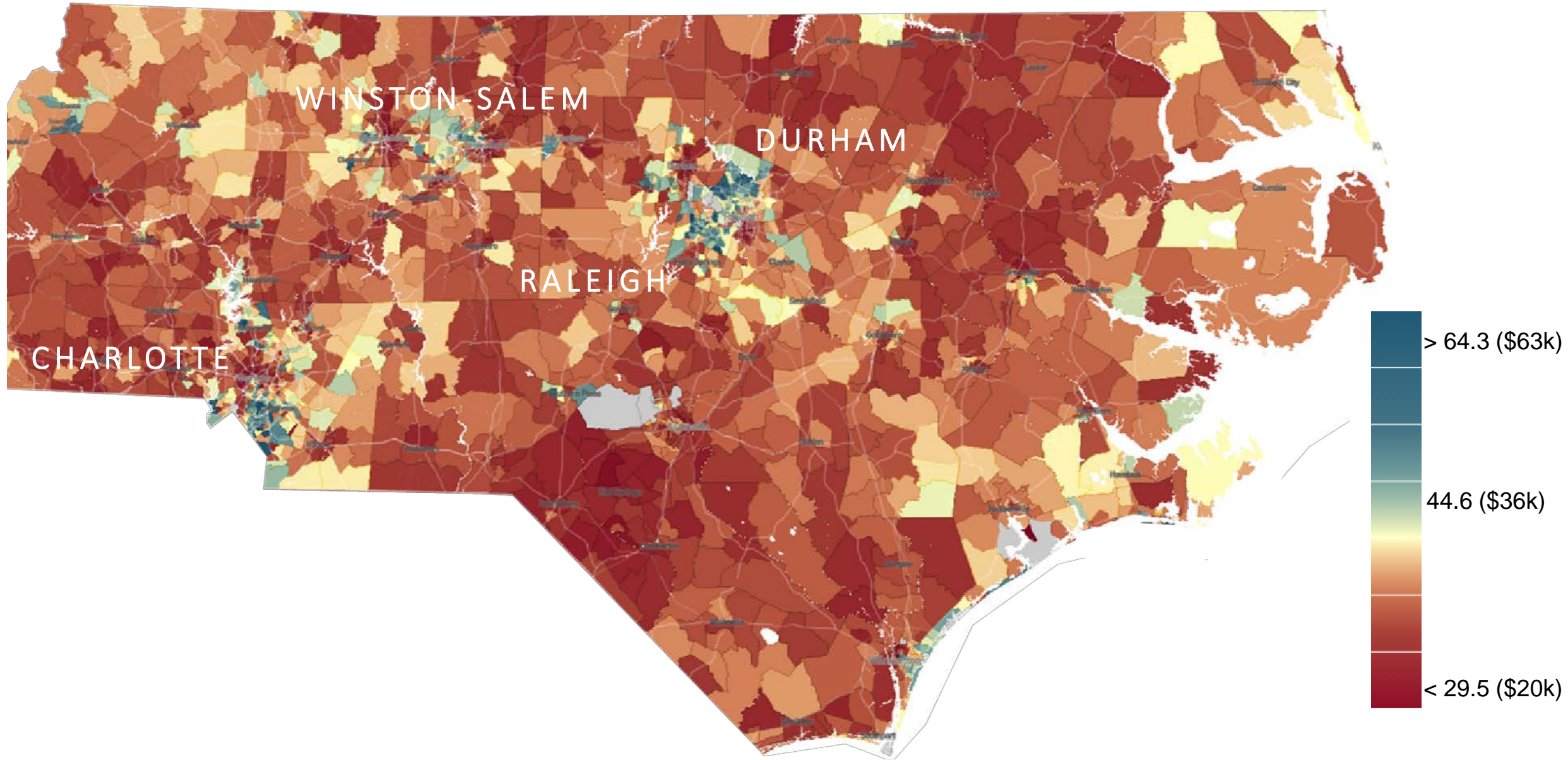
Race-Adjusted, Parent Income at 25th Percentile





Do Cities Offer Greater Opportunities for Upward Mobility?

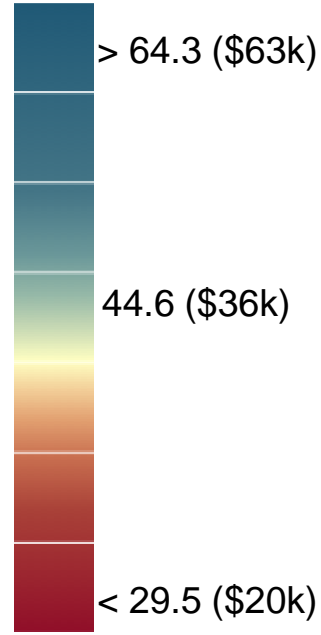
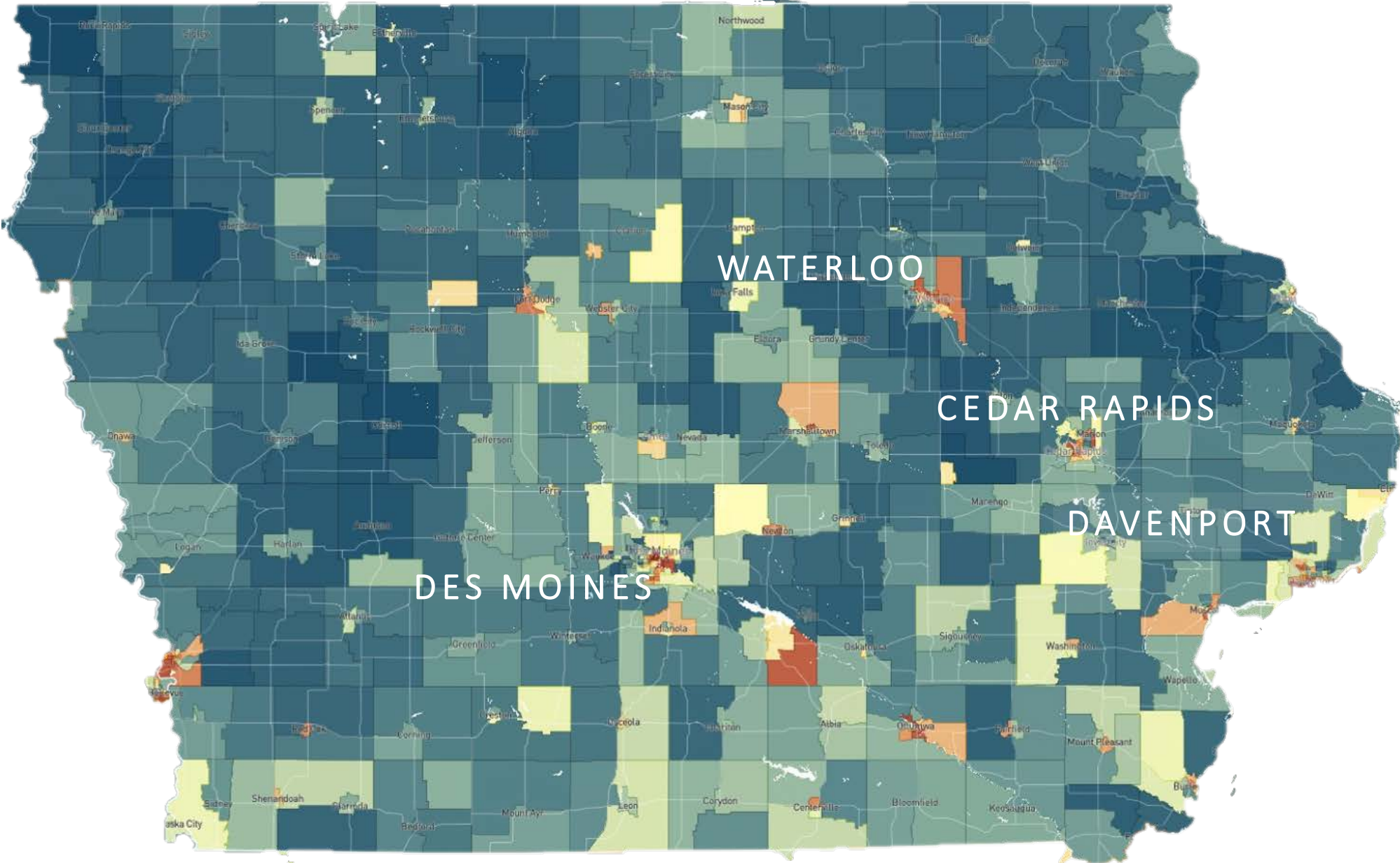
Average Income for White Children with Parents Earning \$25,000 in North Carolina





Do Cities Offer Greater Opportunities for Upward Mobility?

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



Using Location as a Tag for Policy

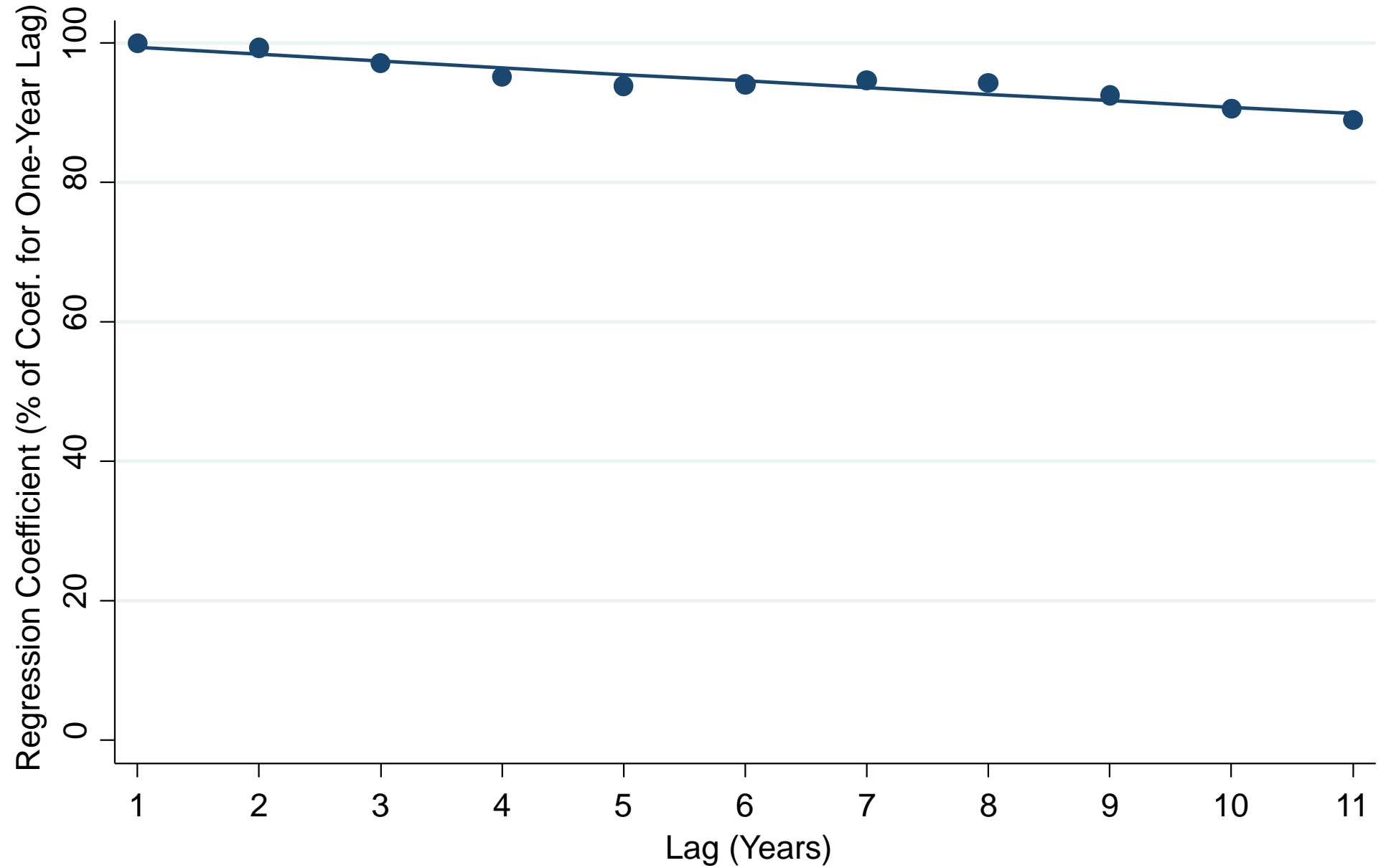
- Tract-level estimates of children's appear to provide new information that could be helpful in identifying areas where opportunity is most lacking
- Practical challenge in using these estimates to inform policy: they come with a lag, since one must wait until children grow up to observe their earnings
- 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?

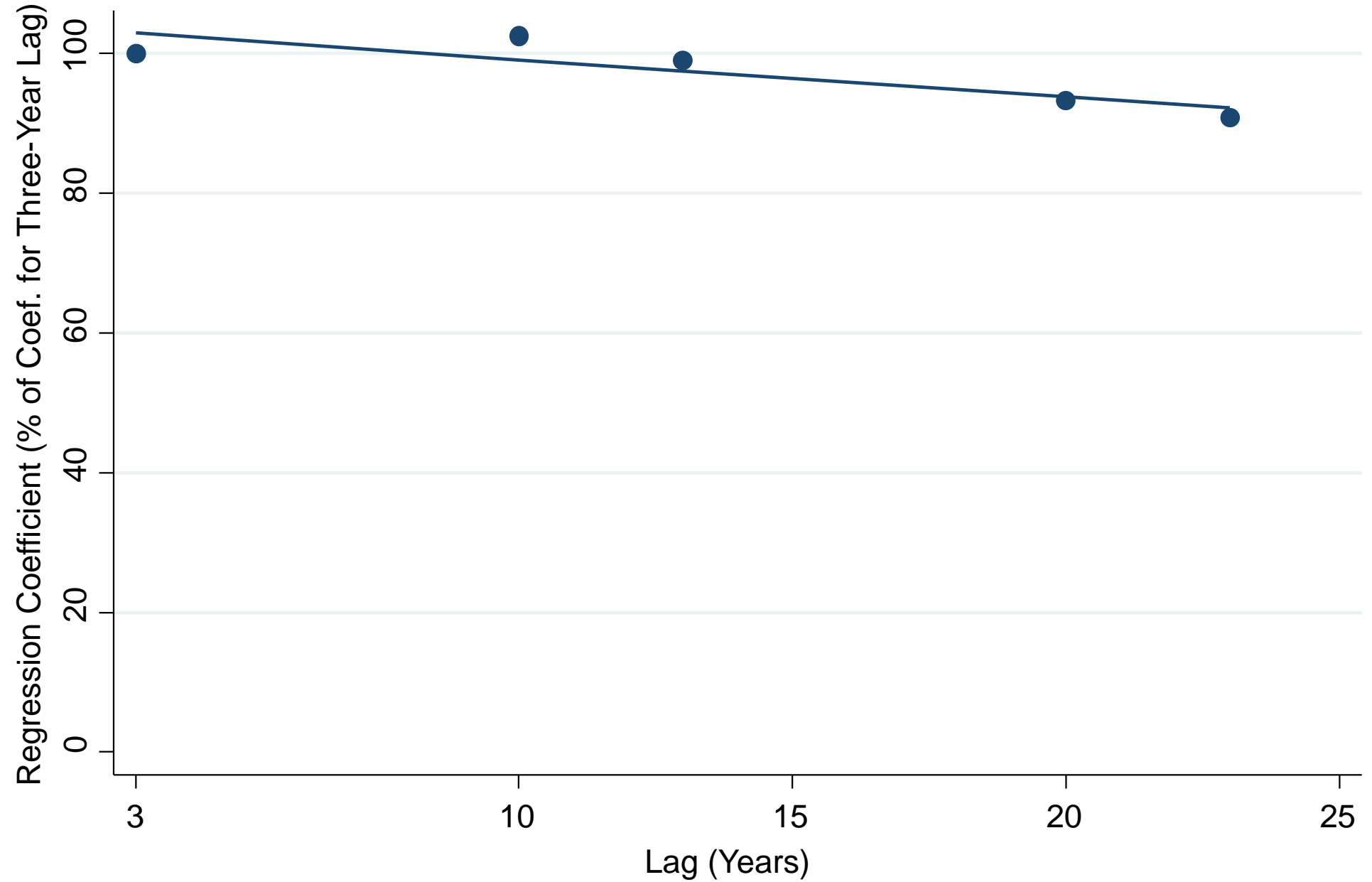
- Assess predictive value of historical estimates in two steps:
 1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power

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



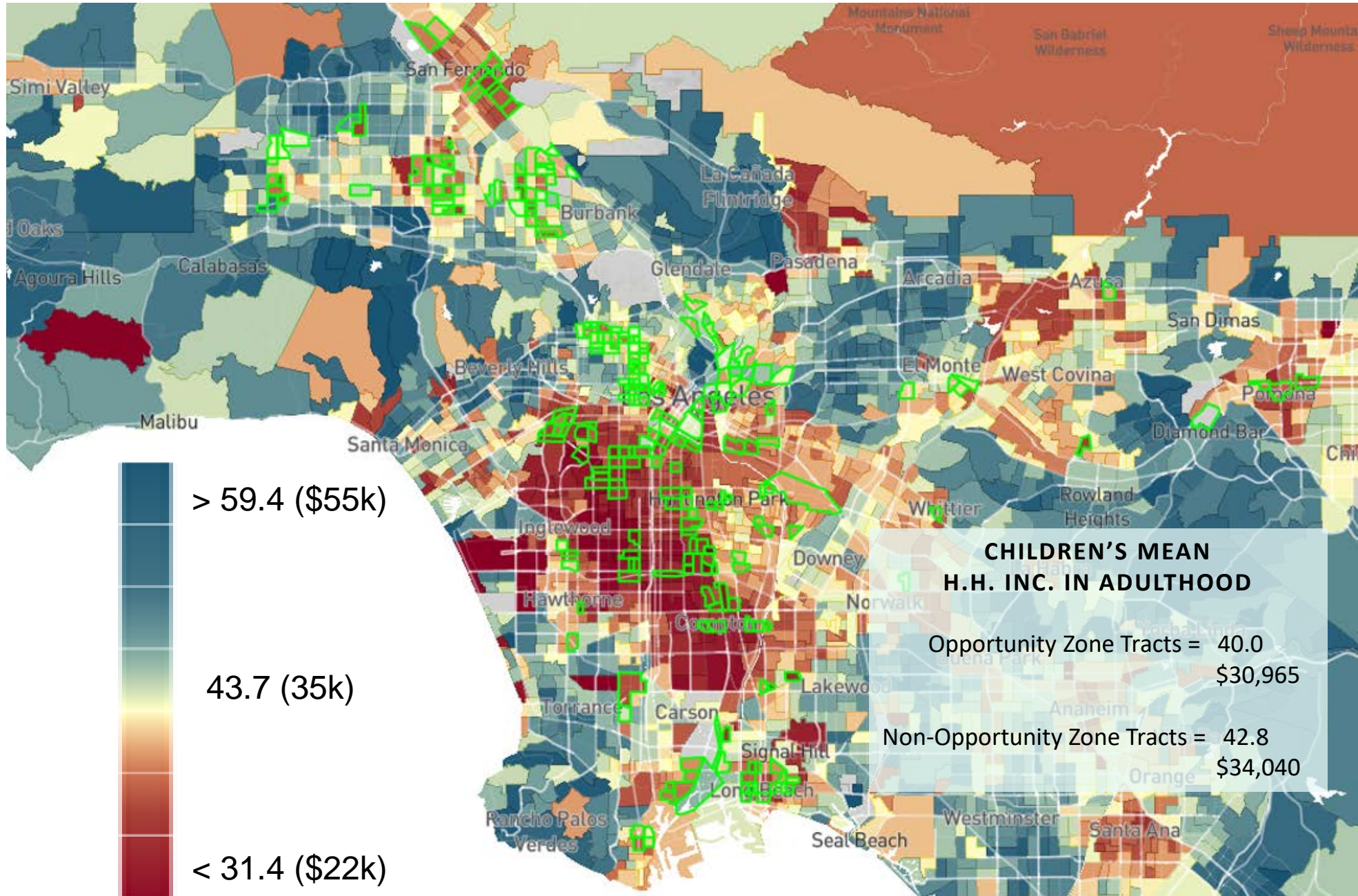
Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

- 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

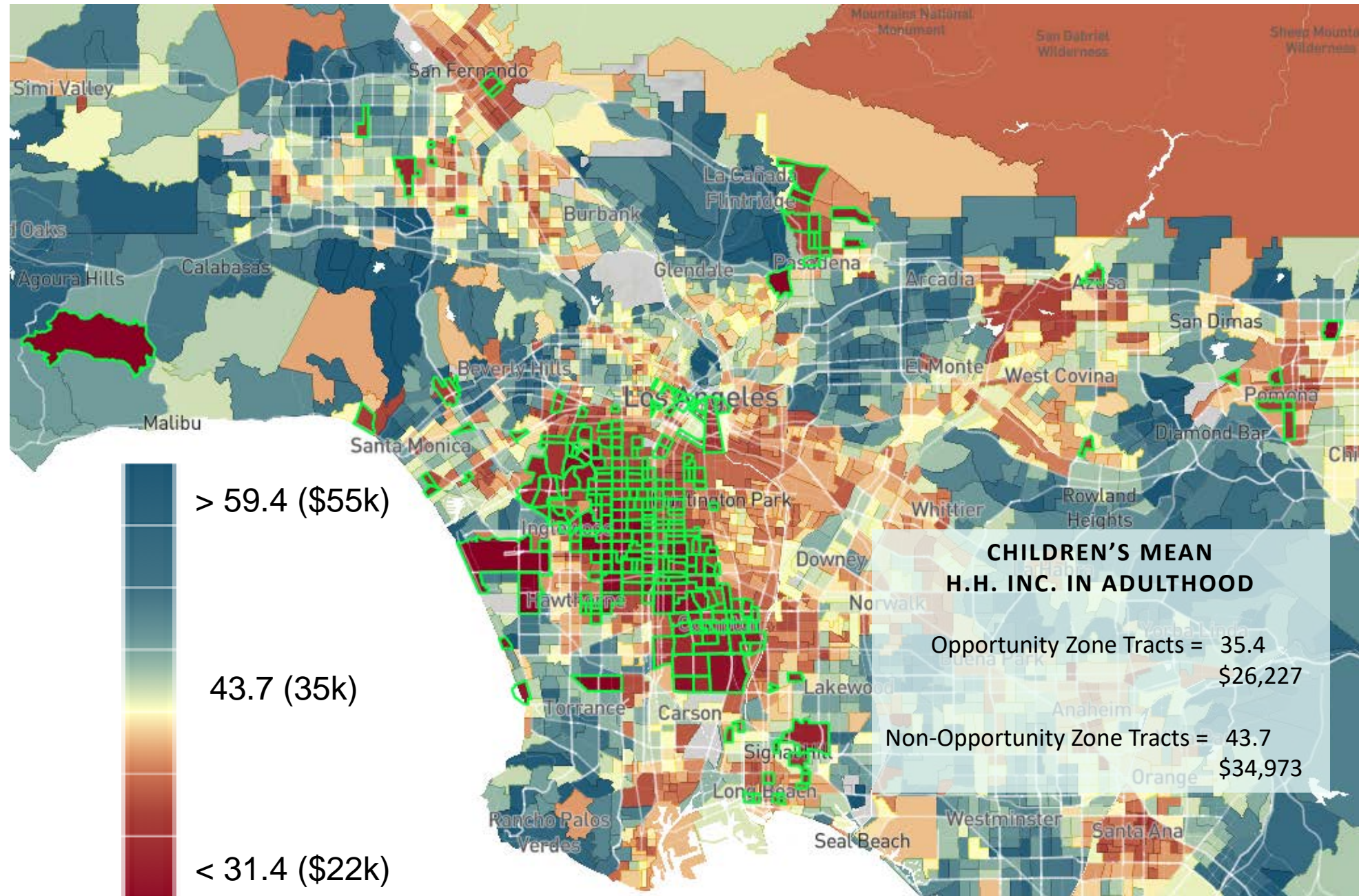
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 - When predicting upward mobility for 1989 cohort, incremental R-squared of covariates is 20% of the R-squared of upward mobility for 1979 cohort
 - Correlation of predicted values using models with vs. without neighborhood characteristics exceeds 0.85
- Tract-level estimates of outcomes provide informative (but imperfect) predictors of economic opportunity for children today

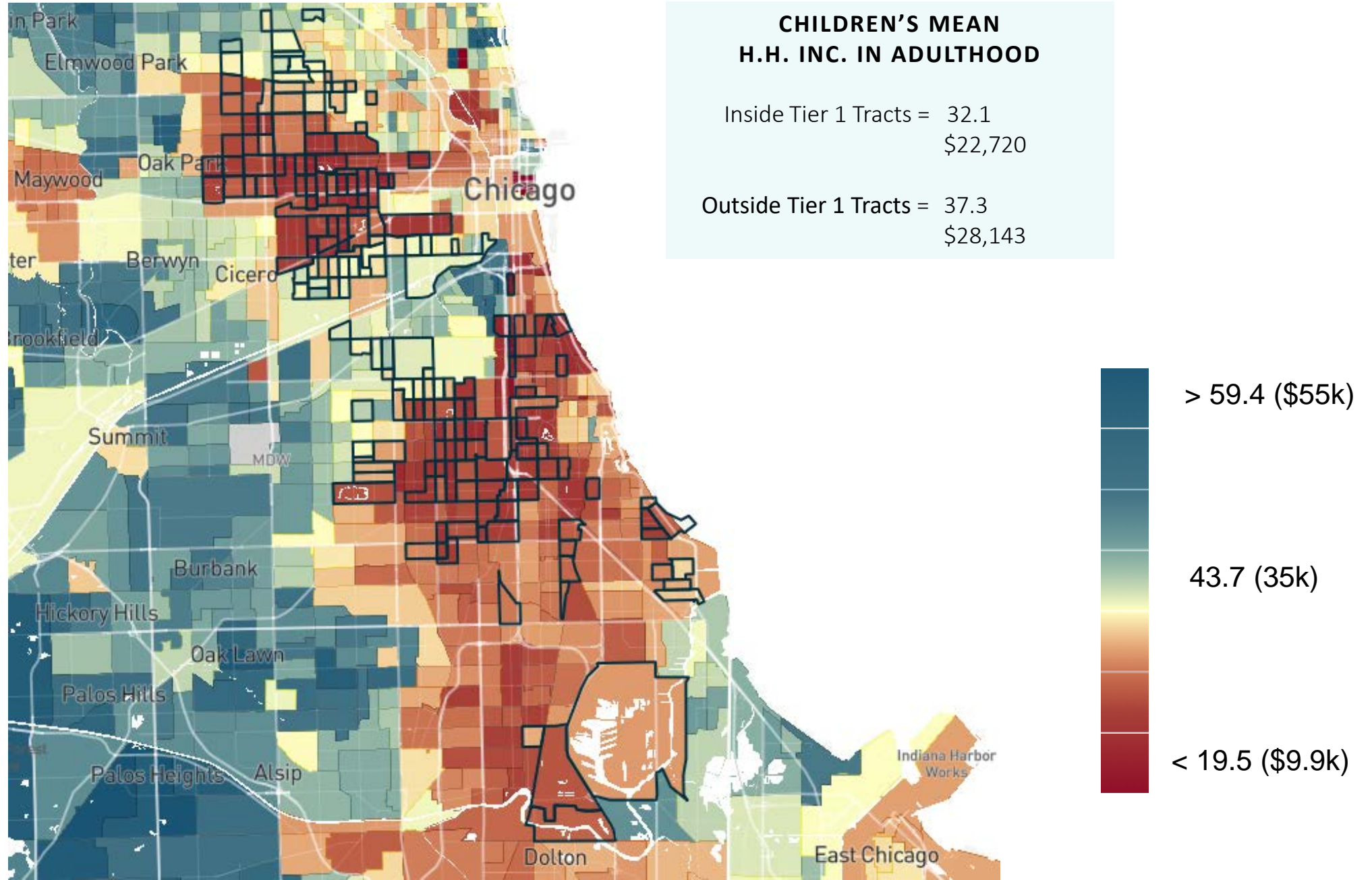
Designated Opportunity Zones in Los Angeles County



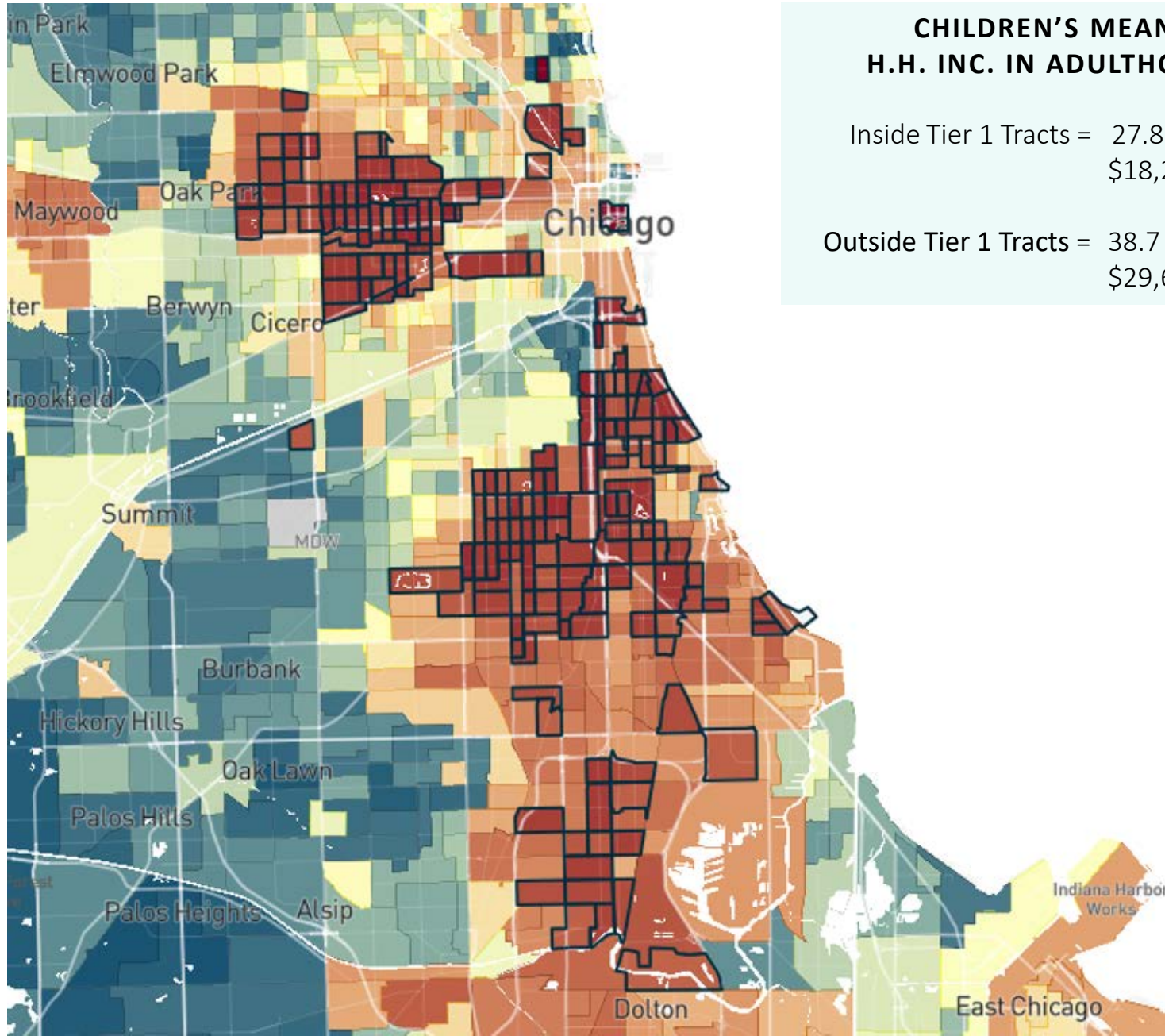
Hypothetical Opportunity Zones using Upward Mobility Estimates



Preferential Admission Tracts to Selective Chicago Public Schools



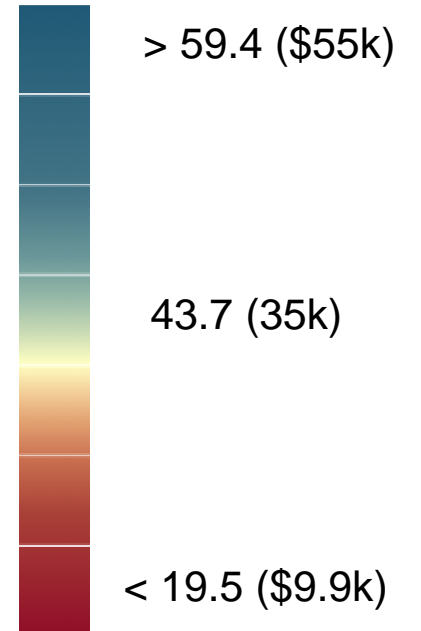
Hypothetical Admission Tracts using Upward Mobility Estimates



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

Inside Tier 1 Tracts = 27.8
\$18,286

Outside Tier 1 Tracts = 38.7
\$29,624



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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

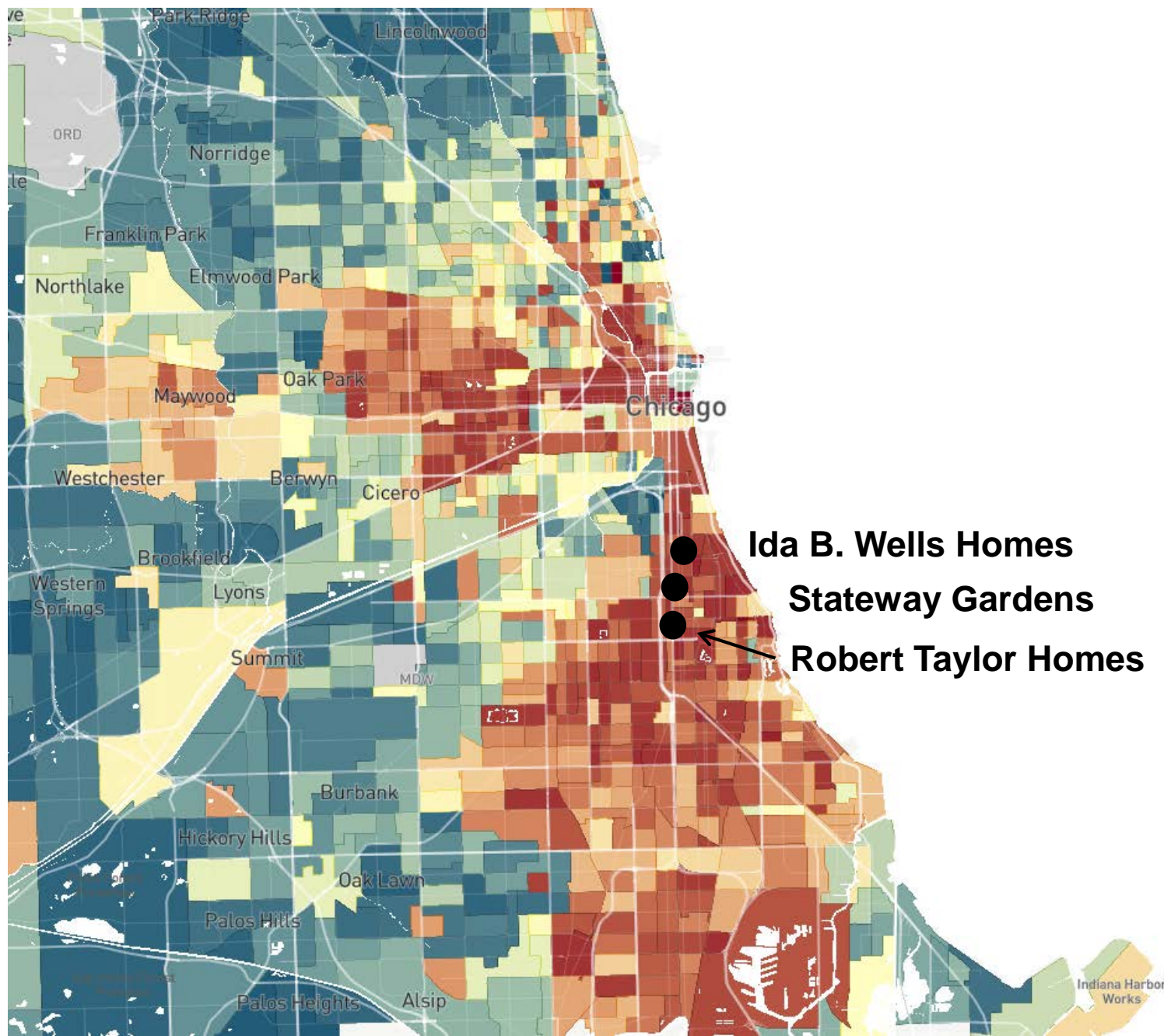
Identifying Causal Effects of Place

- 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

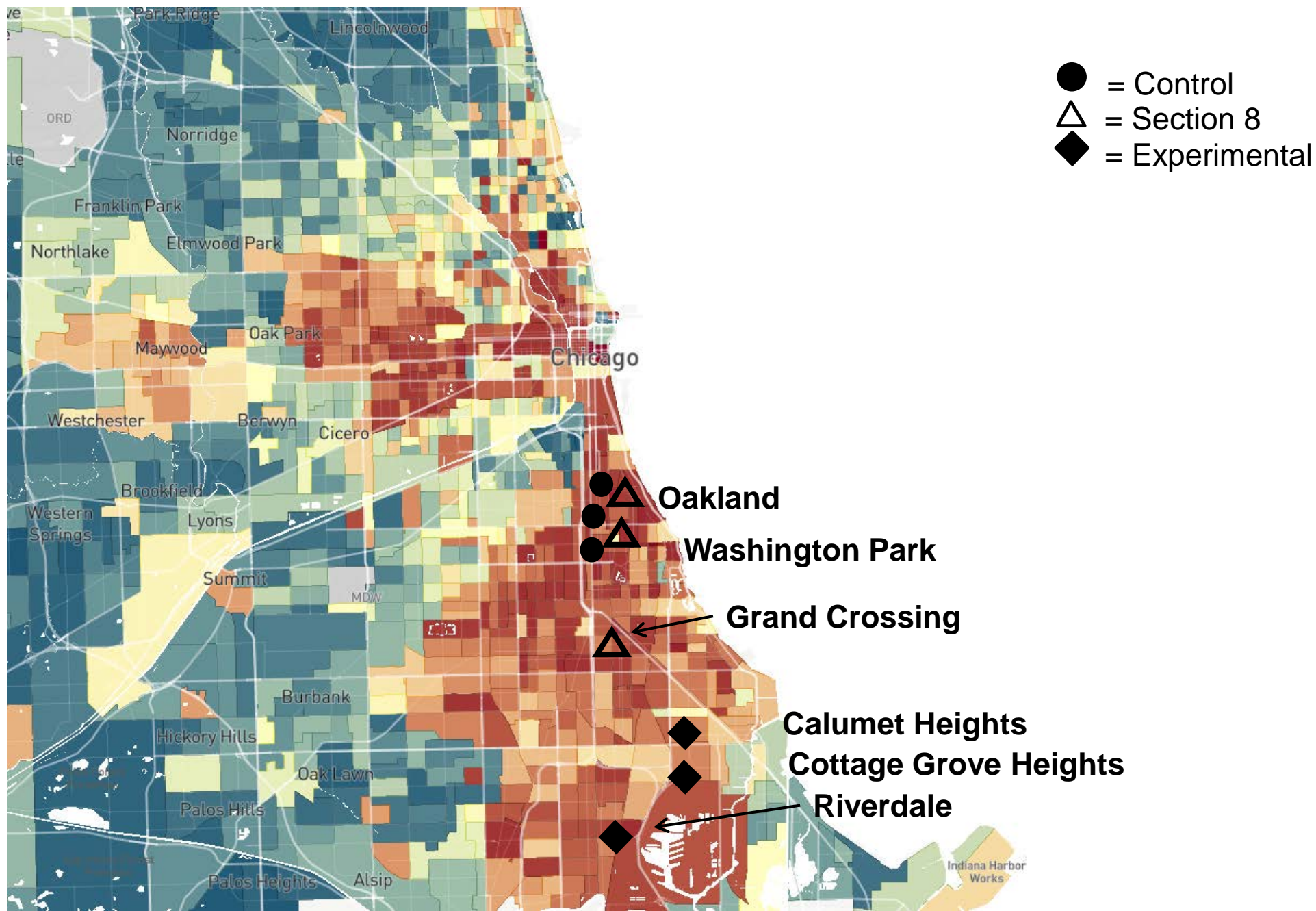
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago



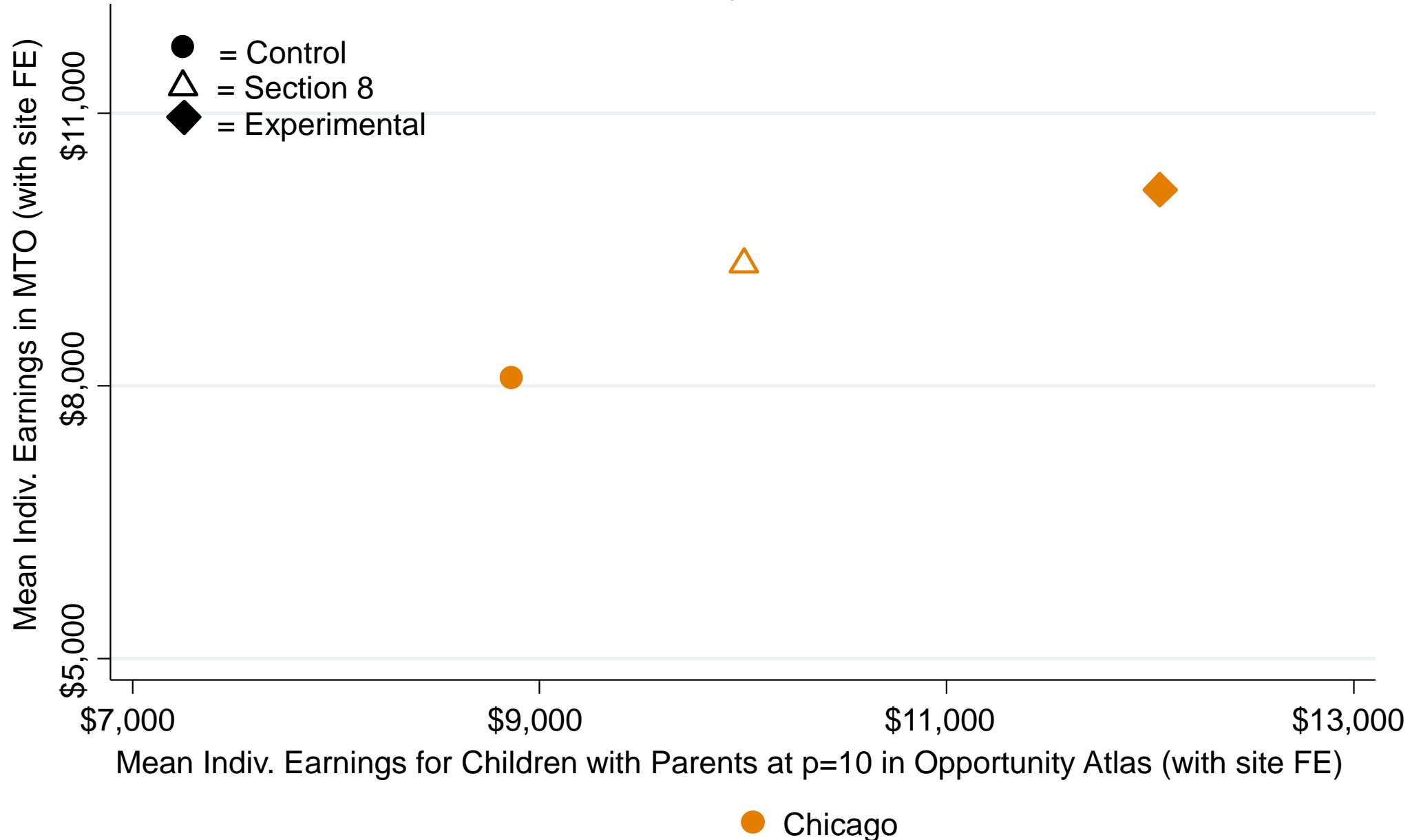
- = Control
- △ = Section 8
- ◆ = Experimental

Ida B. Wells Homes
Stateway Gardens
Robert Taylor Homes

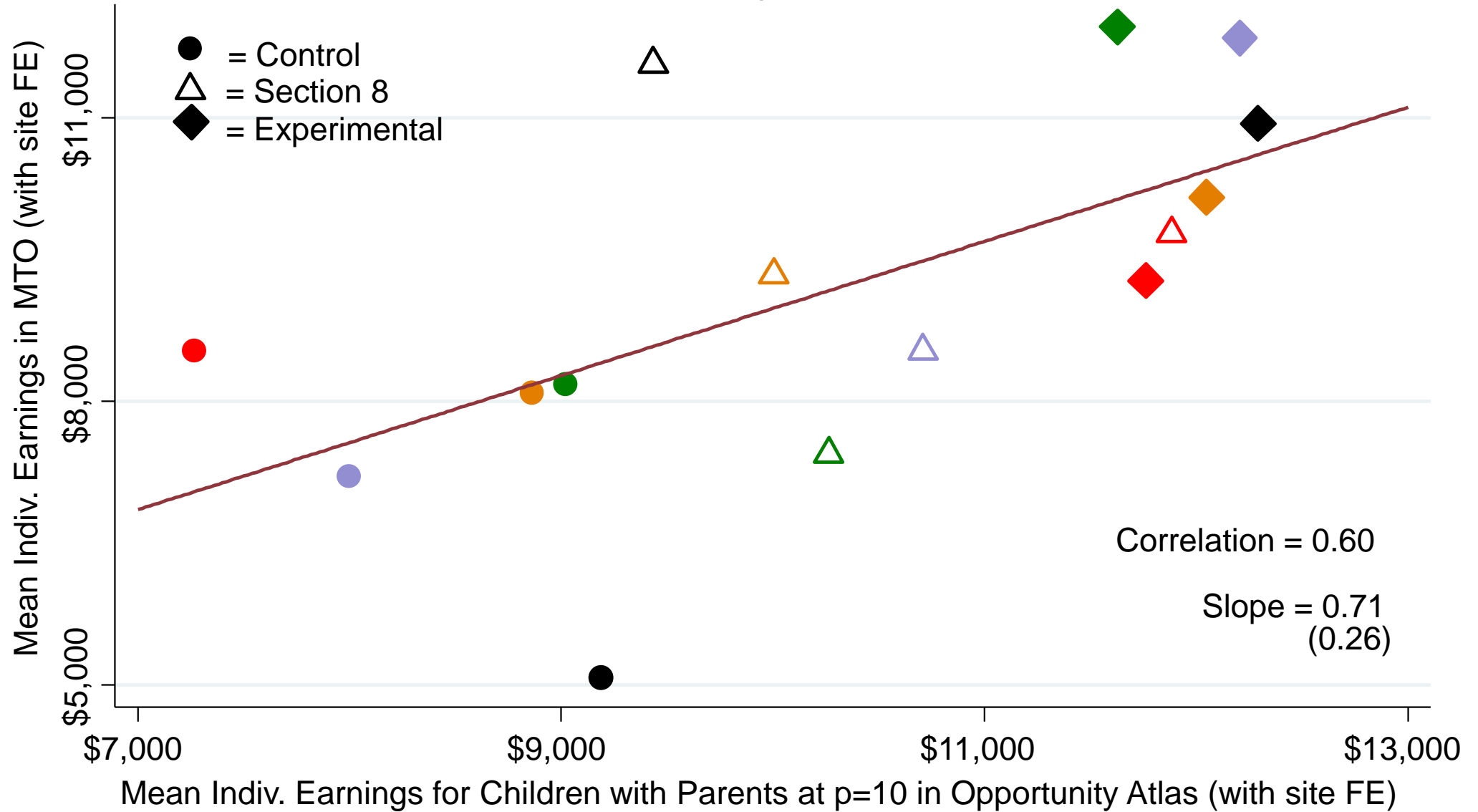
Moving To Opportunity Experiment: Origin and Destination Locations in Chicago



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



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



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 (2018)
 - 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

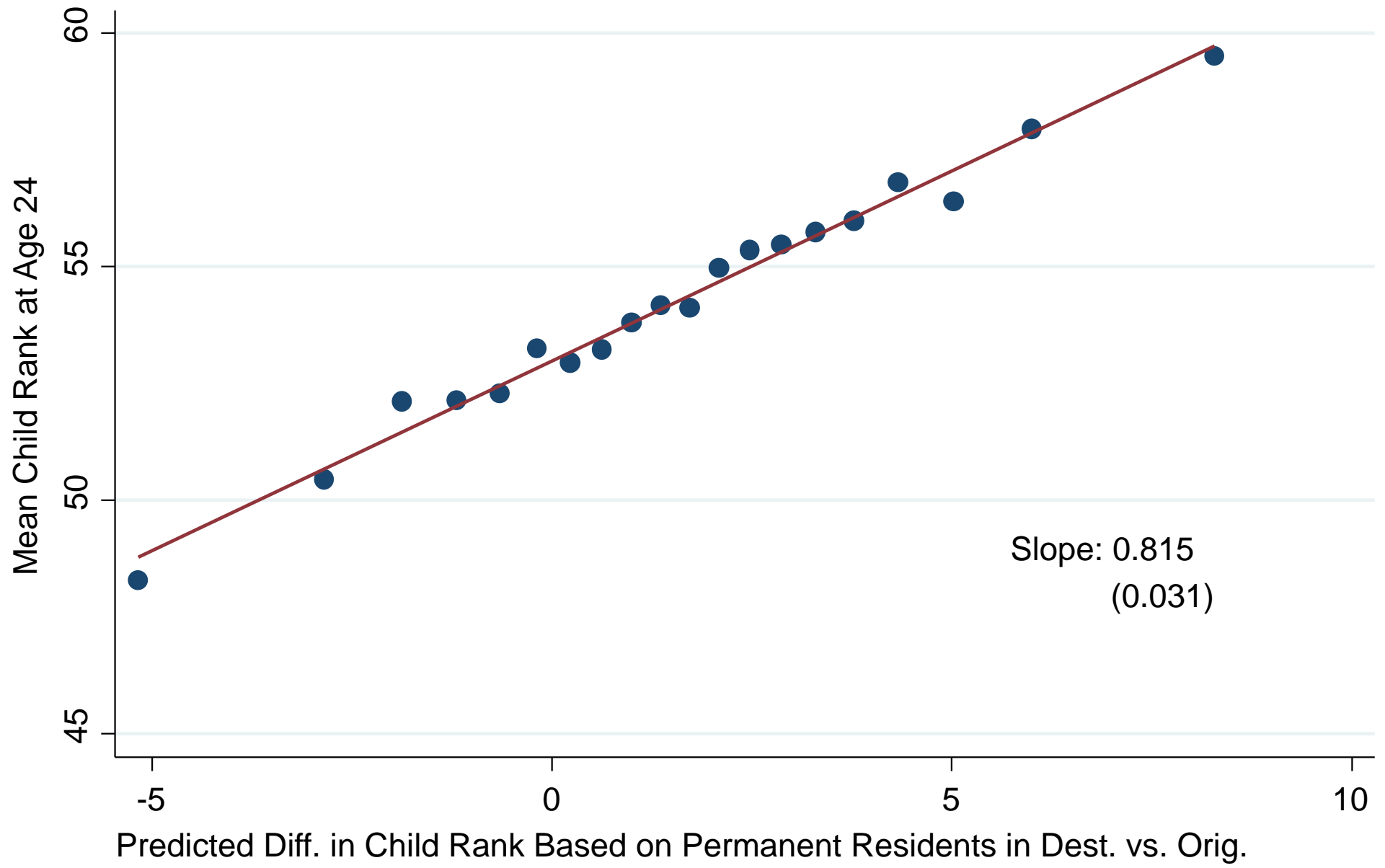
- To begin, consider families who move when child is exactly 5 years old
- Regress child's income rank in adulthood y_i on mean rank of children with same parental income level in destination:

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

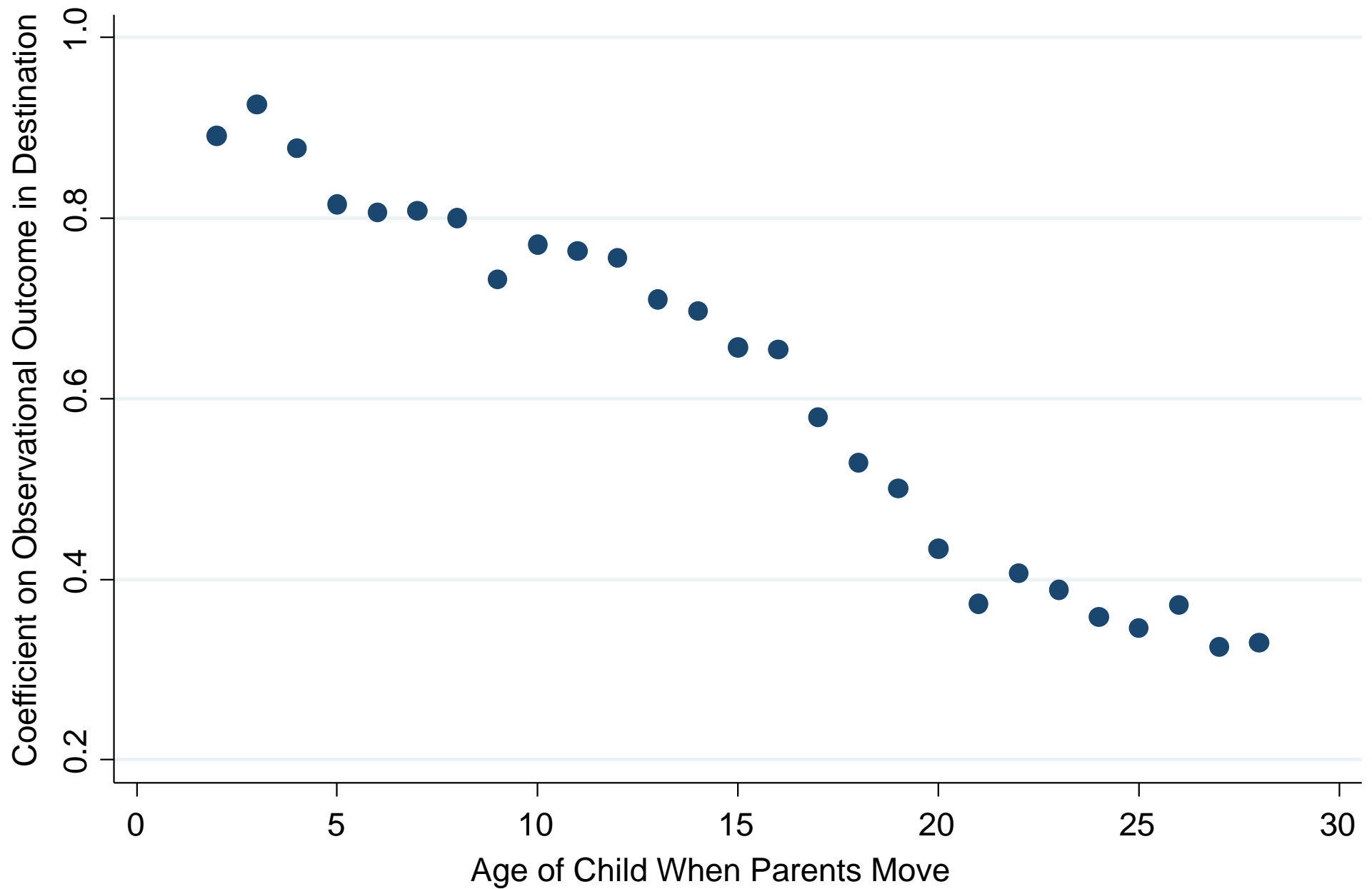
- Include parent decile (q) by origin (o) fixed effects to identify b_m purely from differences in destinations

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

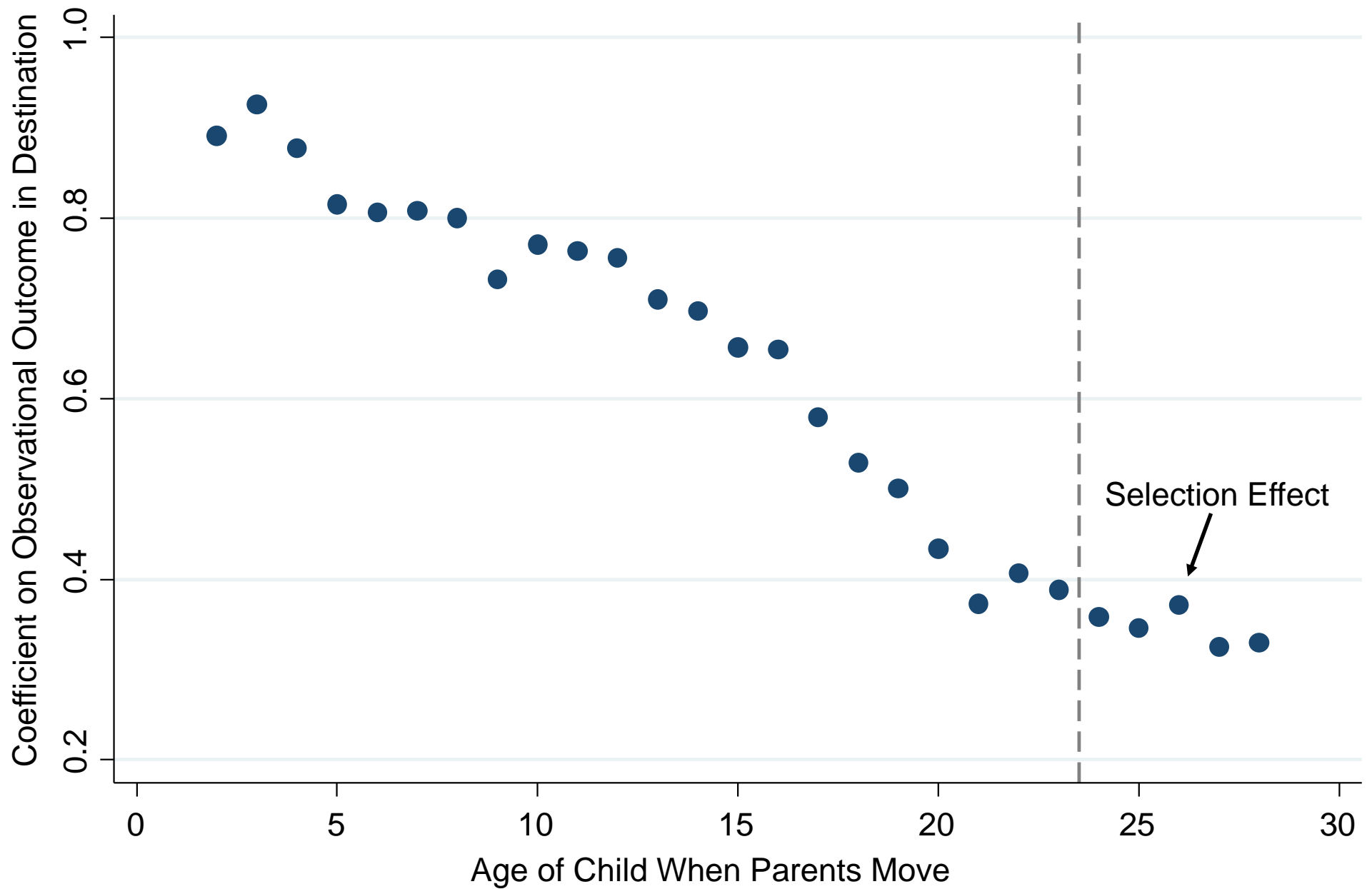
For Children Who Move at Age 5



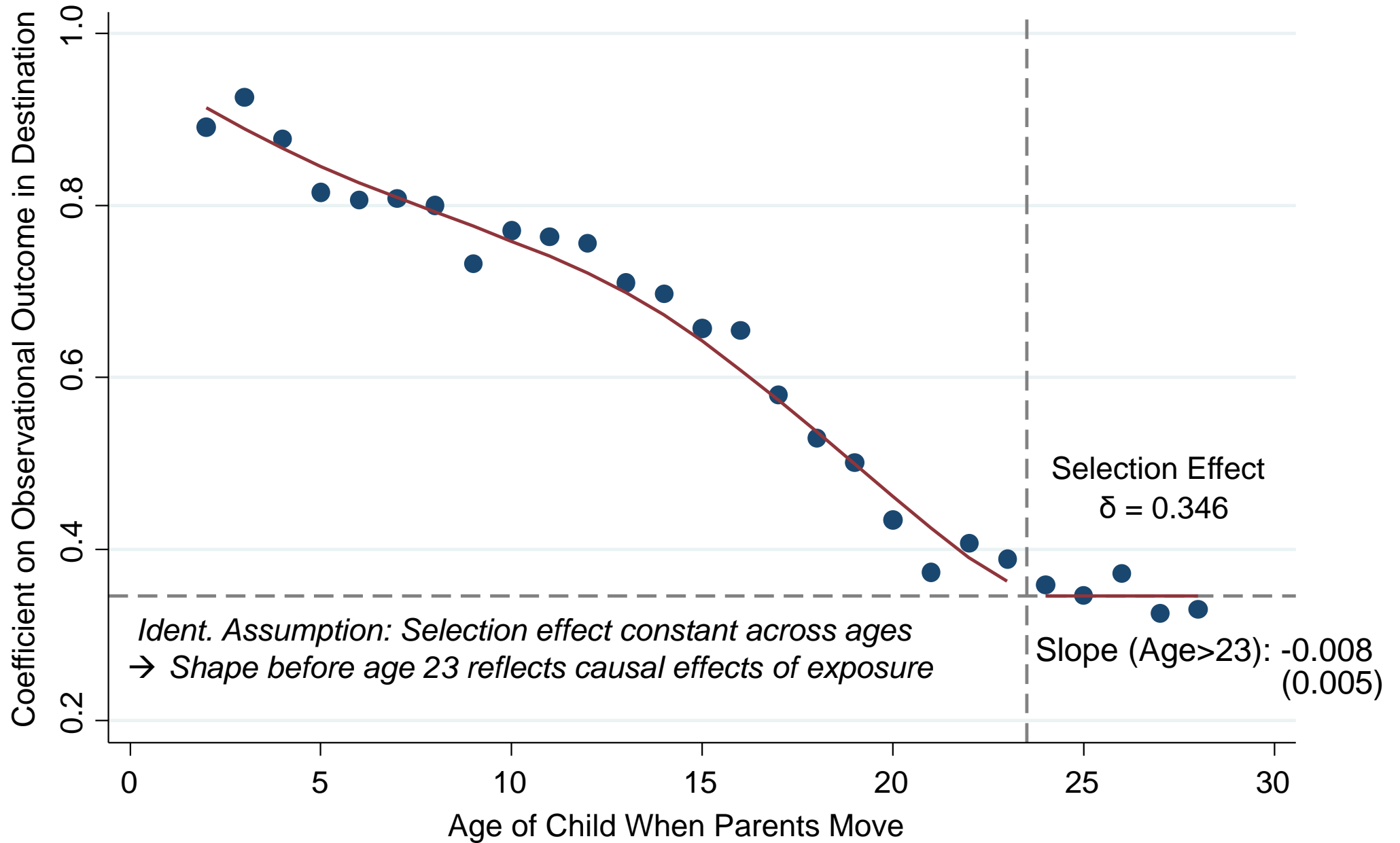
Childhood Exposure Effects on Household Income Rank at Age 24



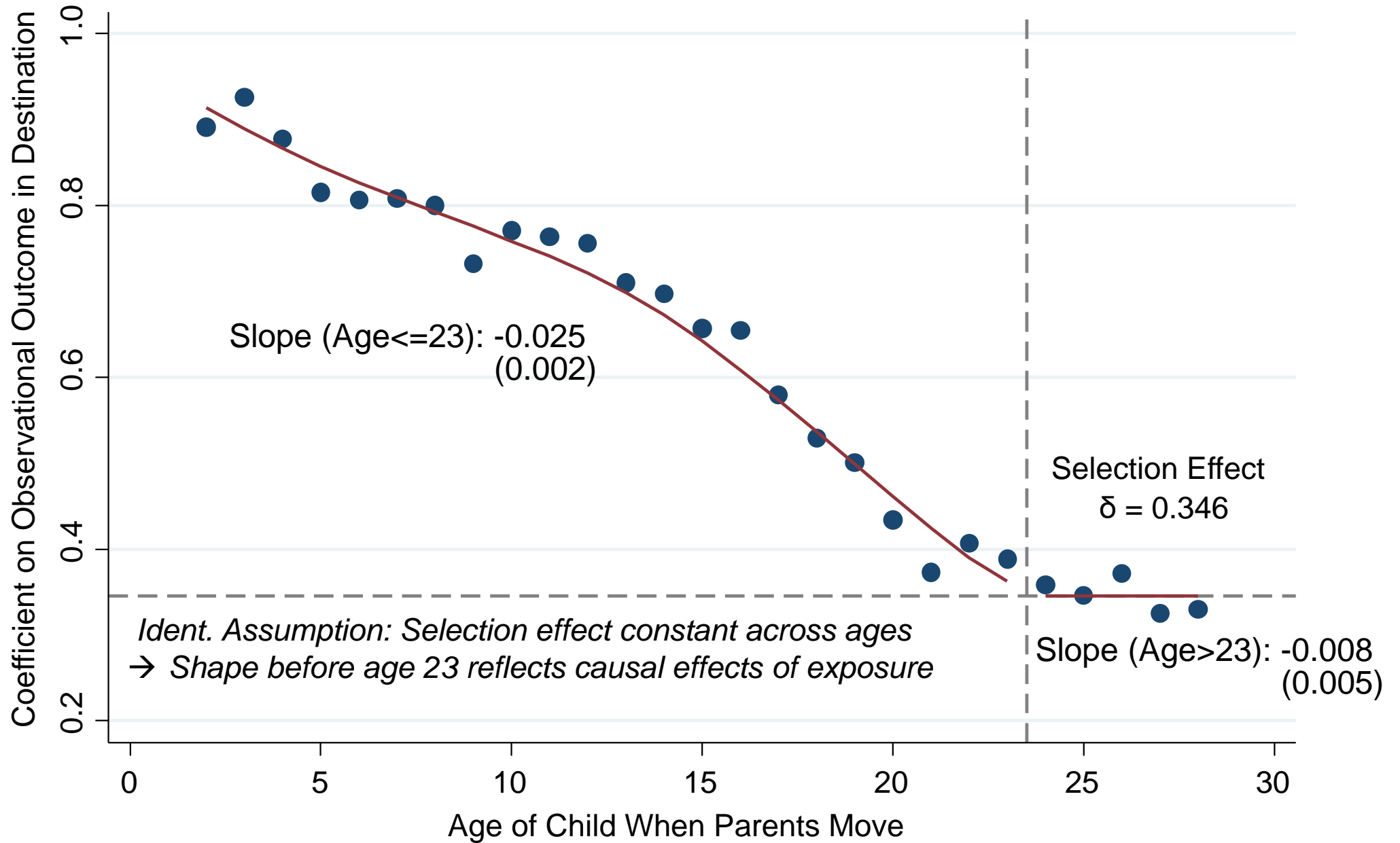
Childhood Exposure Effects on Household Income Rank at Age 24



Childhood Exposure Effects on Household Income Rank at Age 24



Childhood Exposure Effects on Household Income Rank at Age 24



Identifying Causal Exposure Effects

- Use two approaches to evaluate validity of key assumption, following Chetty and Hendren (2018):
 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	Controls for Cohort Diffs.	Family FEs
	(1)	(2)	(3)
Age <= 23	-0.027 (0.001)	-0.028 (0.001)	-0.021 (0.002)
Age > 23	-0.008 (0.009)	-0.007 (0.008)	-0.004 (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 (2018):
 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	-0.025 (0.002)	-0.003 (0.002)
Prediction for Females	-0.001 (0.003)	-0.026 (0.003)
Num. of Obs.	1,146,000	1,082,000

Note: Standard errors in parentheses

Childhood Exposure Effects on Other Outcomes

Outcome:	Income Rank at 24	Married at 30	Incarceration
	(1)	(2)	(3)
Mean Income Rank at 24	-0.026 (0.002)	0.003 (0.004)	-0.001 (0.001)
Frac. Married at 30	-0.002 (0.001)	-0.025 (0.002)	0.000 (0.000)
Incarceration Rate	-0.017 (0.009)	-0.019 (0.023)	-0.036 (0.005)
Num. of Obs.	2,222,000	1,614,000	1,481,000

Note: Each column shows the coefficients from a single regression. Standard errors in parentheses.

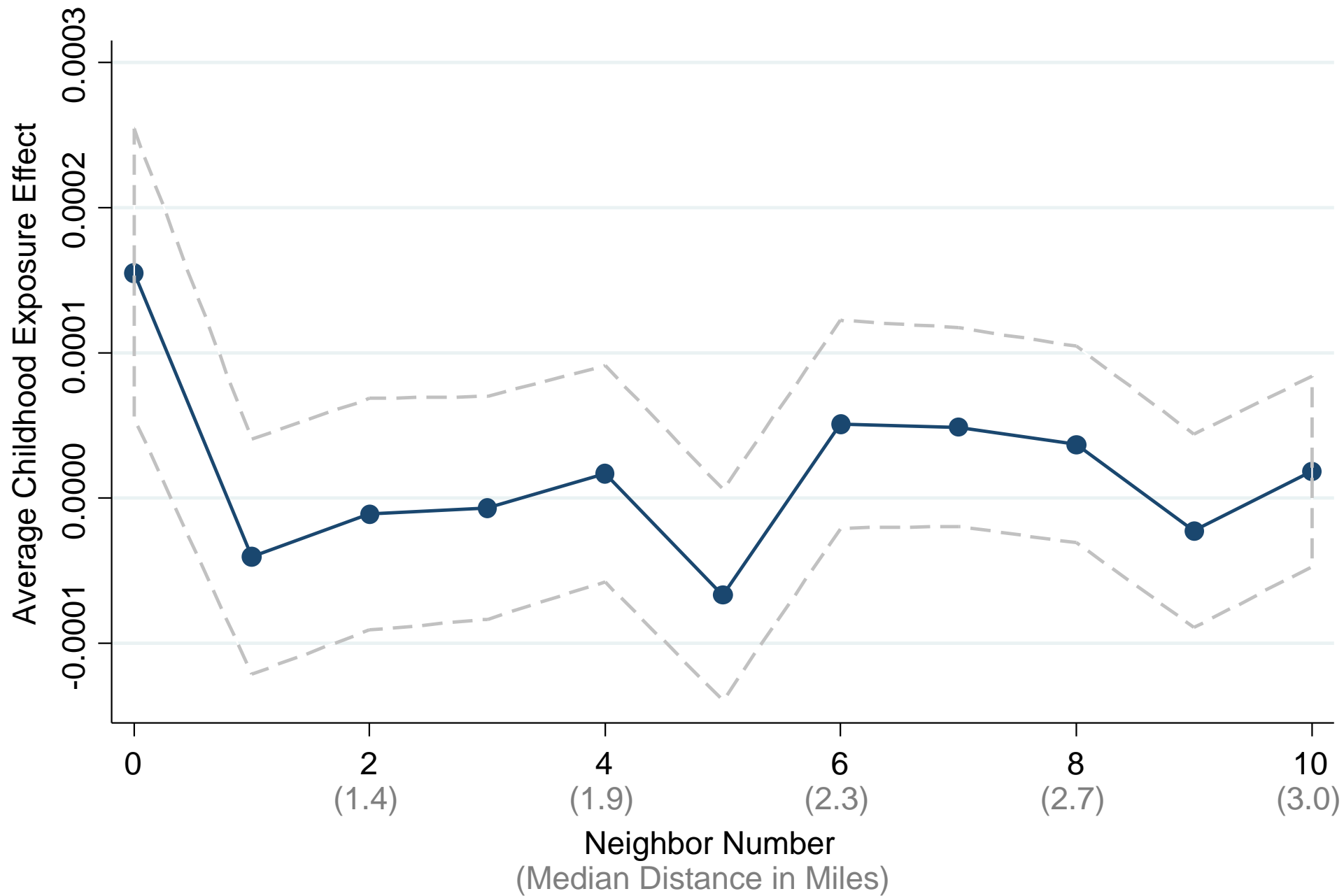
Childhood Exposure Effects on Household Income Rank at Age 24

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

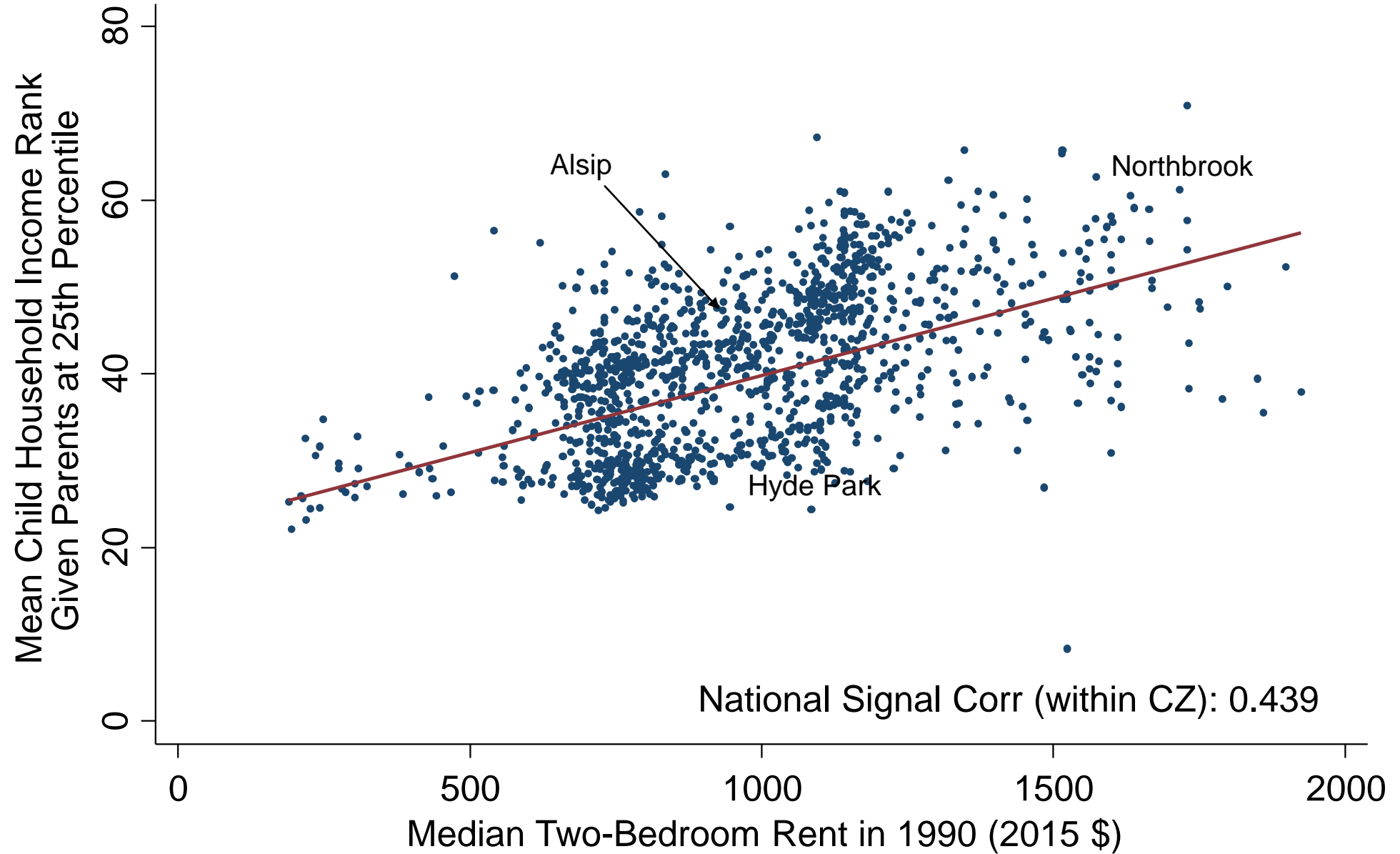


The Price of Opportunity

- Moving at birth from tract at 25th percentile of distribution of upward mobility to a tract at 75th percentile within county → \$206,000 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

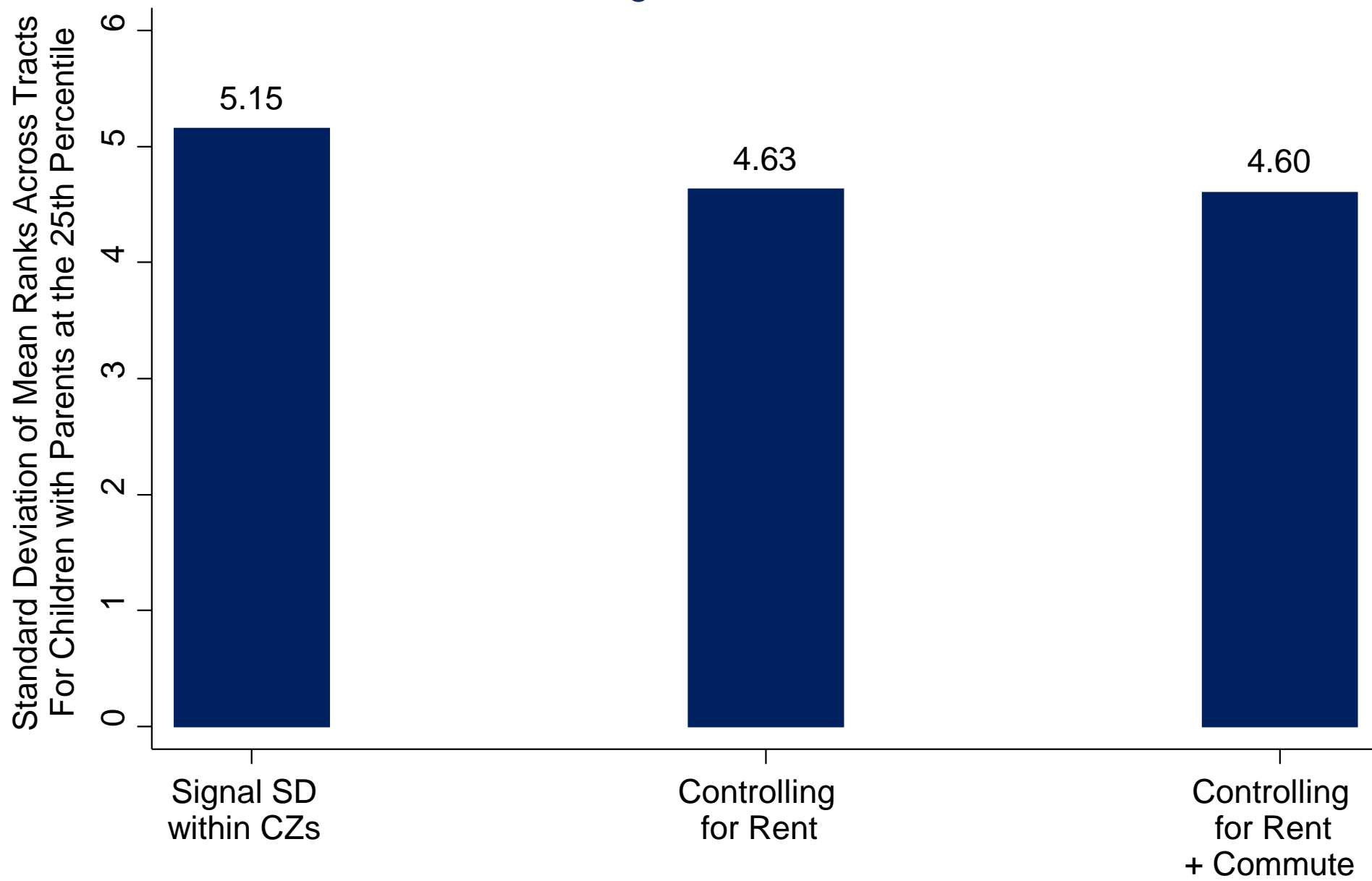
Children with Parents at 25th Percentile





Residual Standard Deviation of Mean Ranks Across Tracts Within CZs

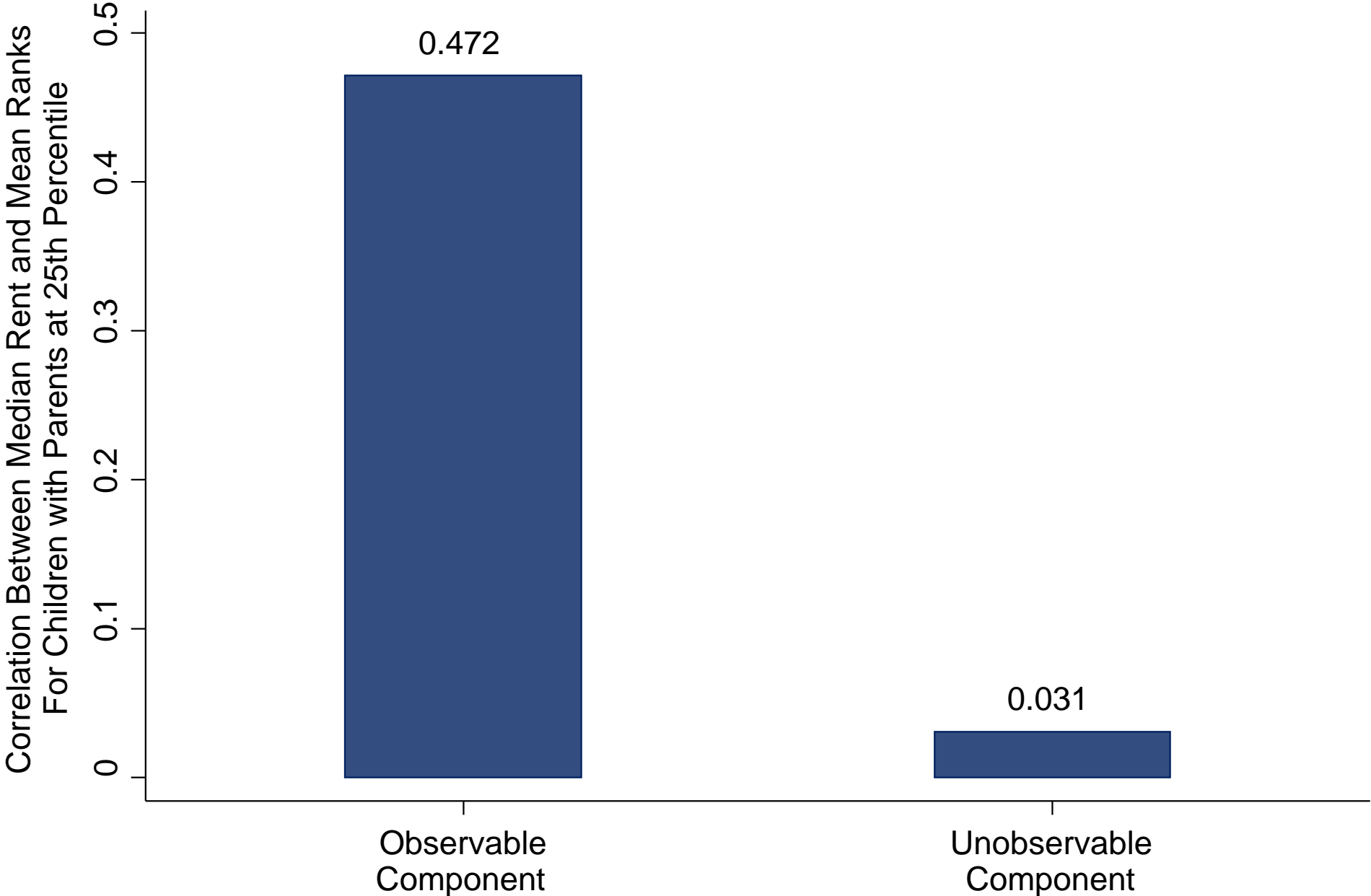
Controlling for Rent and Commute Time



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 2016, Christensen and Timmins 2018]

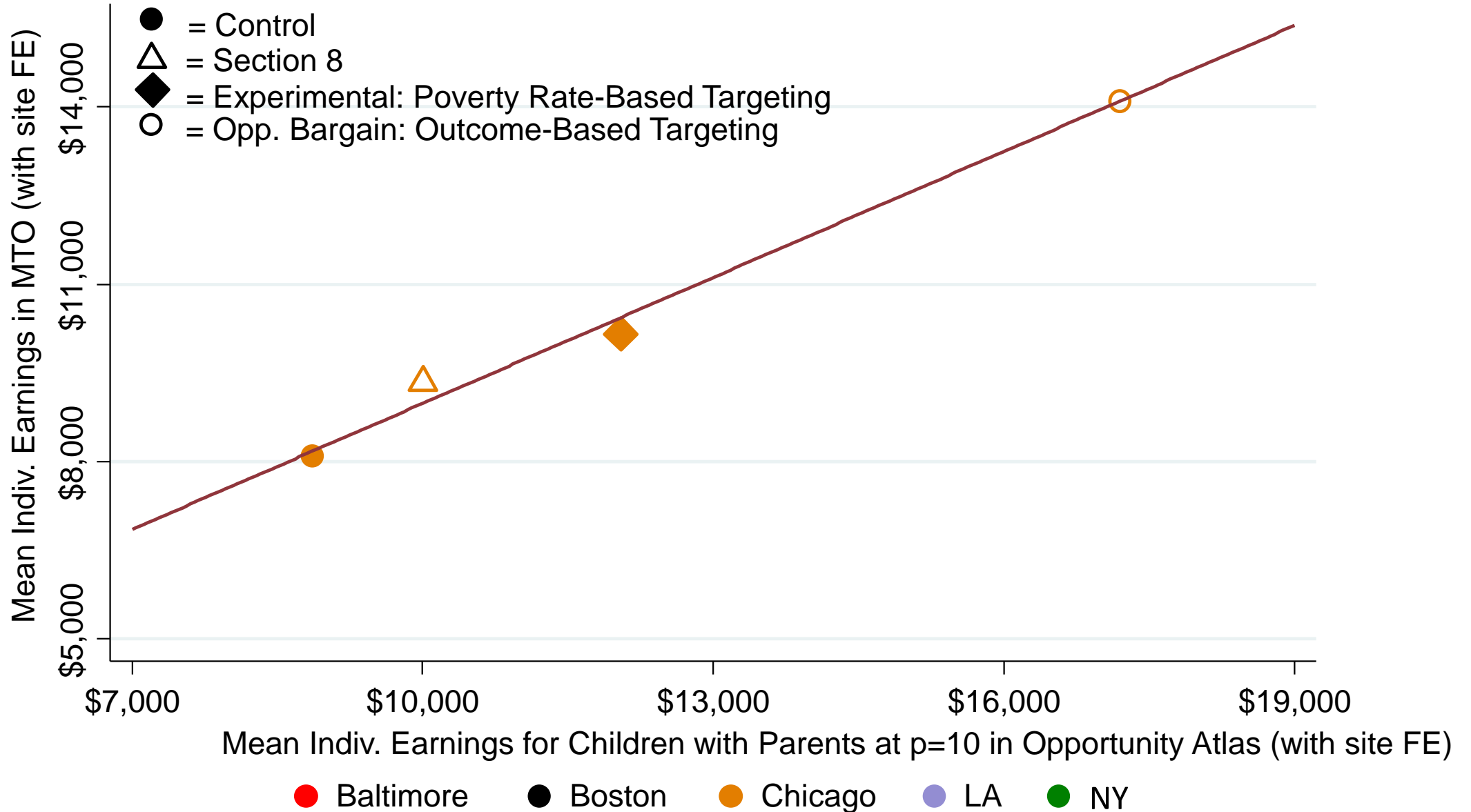
Correlation Between Rents and Observable vs. Unobservable Component of Outcomes



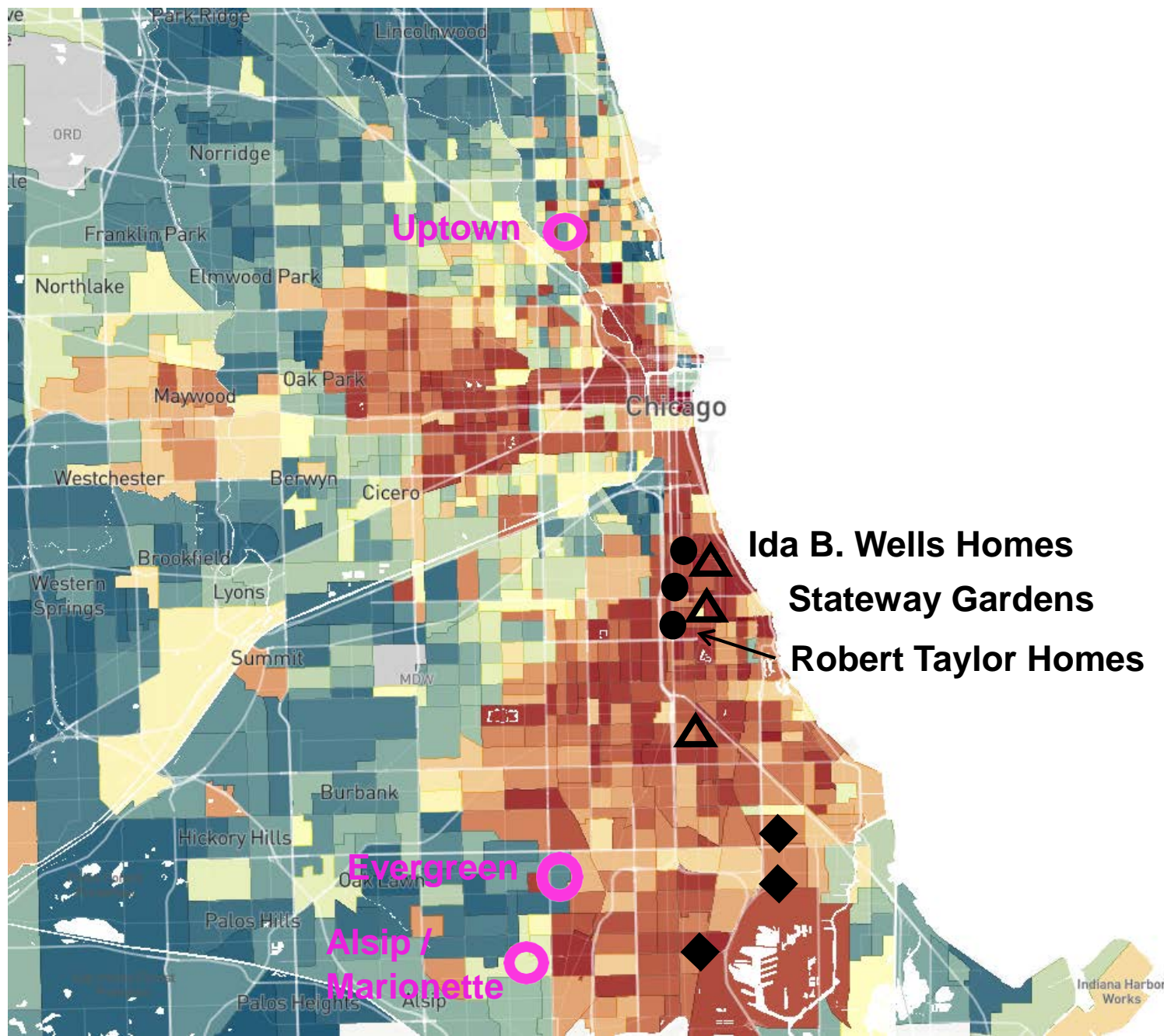
Opportunity Bargains

- 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 \$41,000
- 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



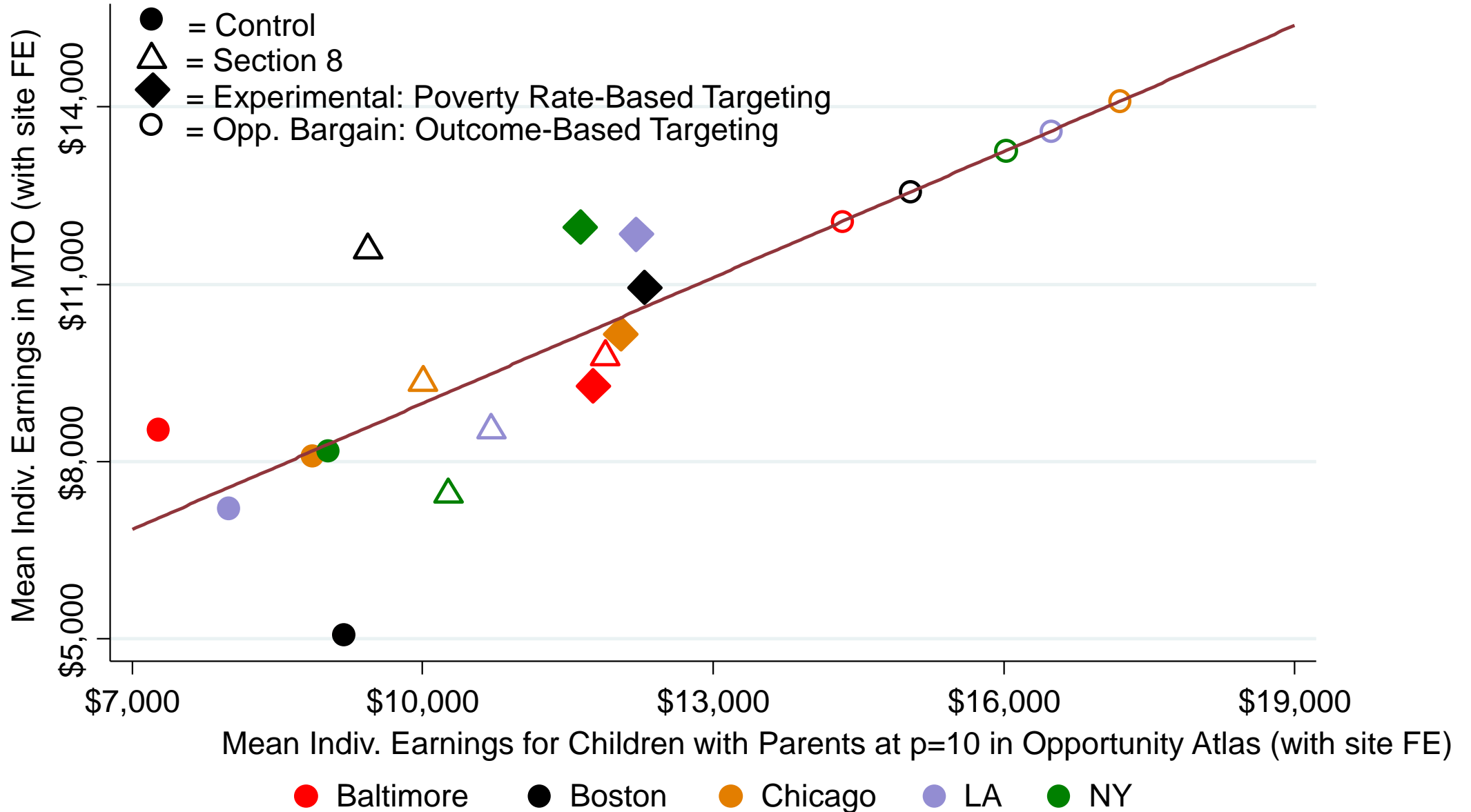
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago



- = Control
- △ = Section 8
- ◆ = Experimental
- = Opp. Bargains

Ida B. Wells Homes
Stateway Gardens
Robert Taylor Homes

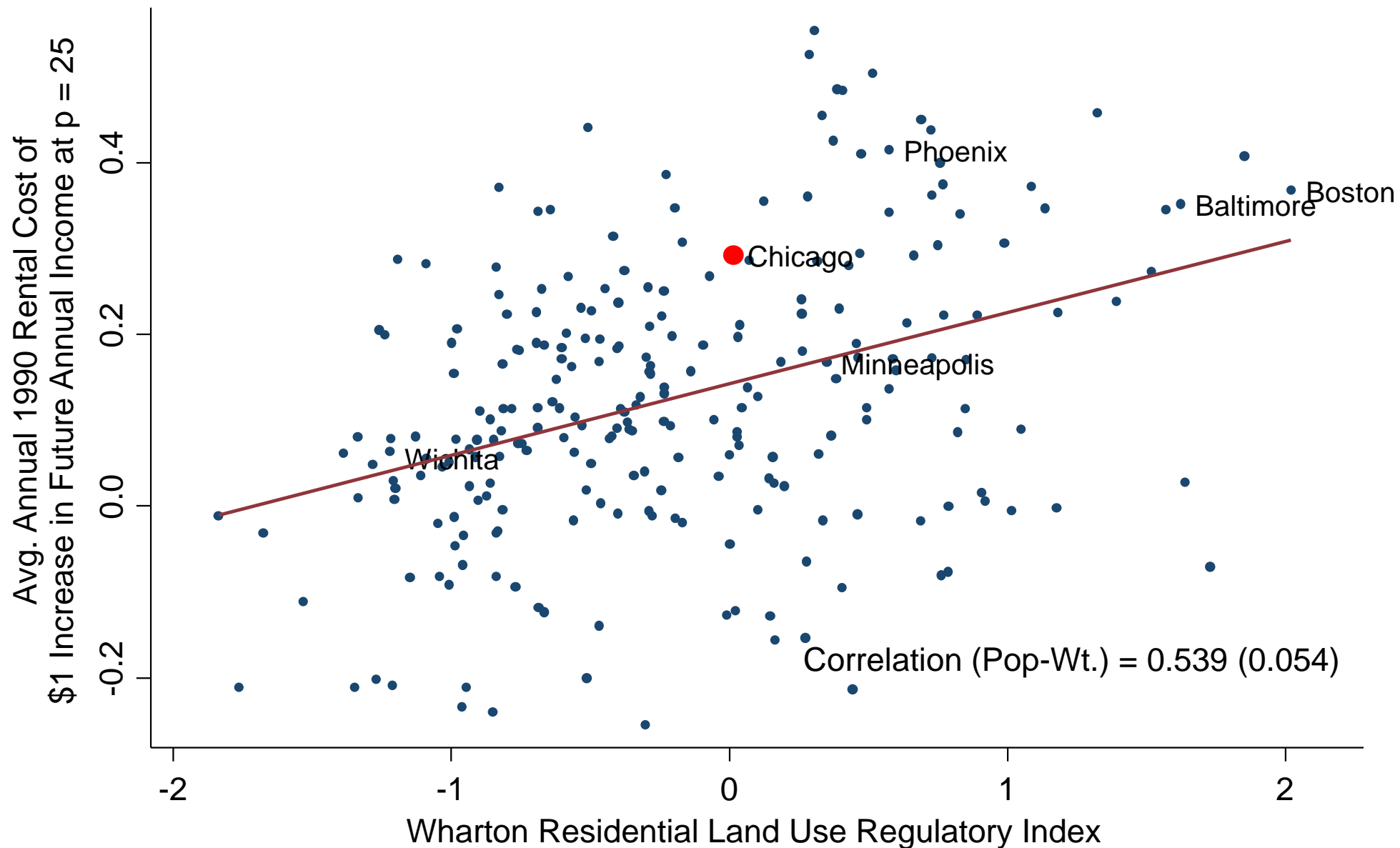
Predicted Impacts of Moving to “Opportunity Bargain” Areas in MTO Cities



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 Honolulu 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

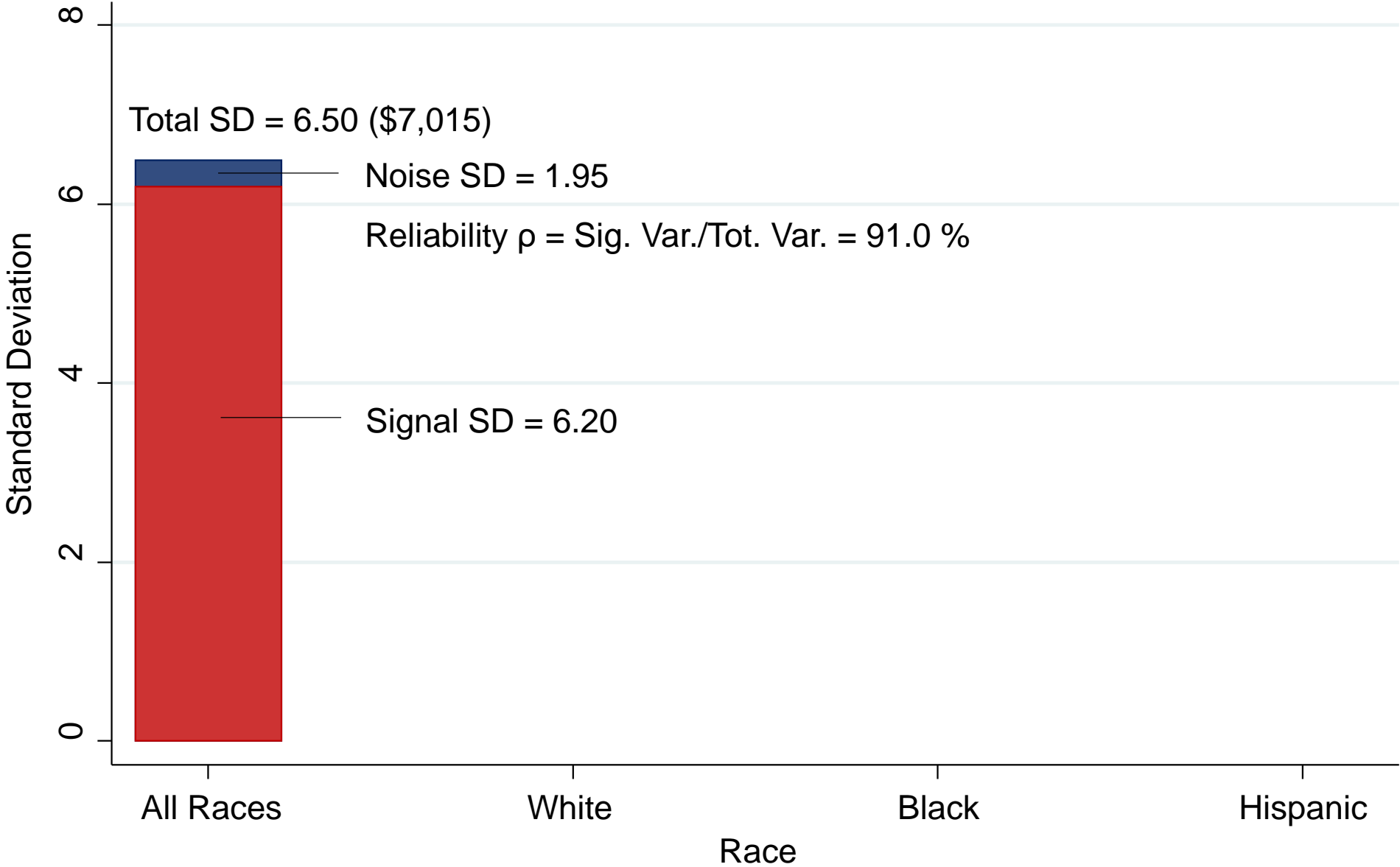
 2. Supporting policy interventions to improve economic opportunity at a local level

Supplementary Results

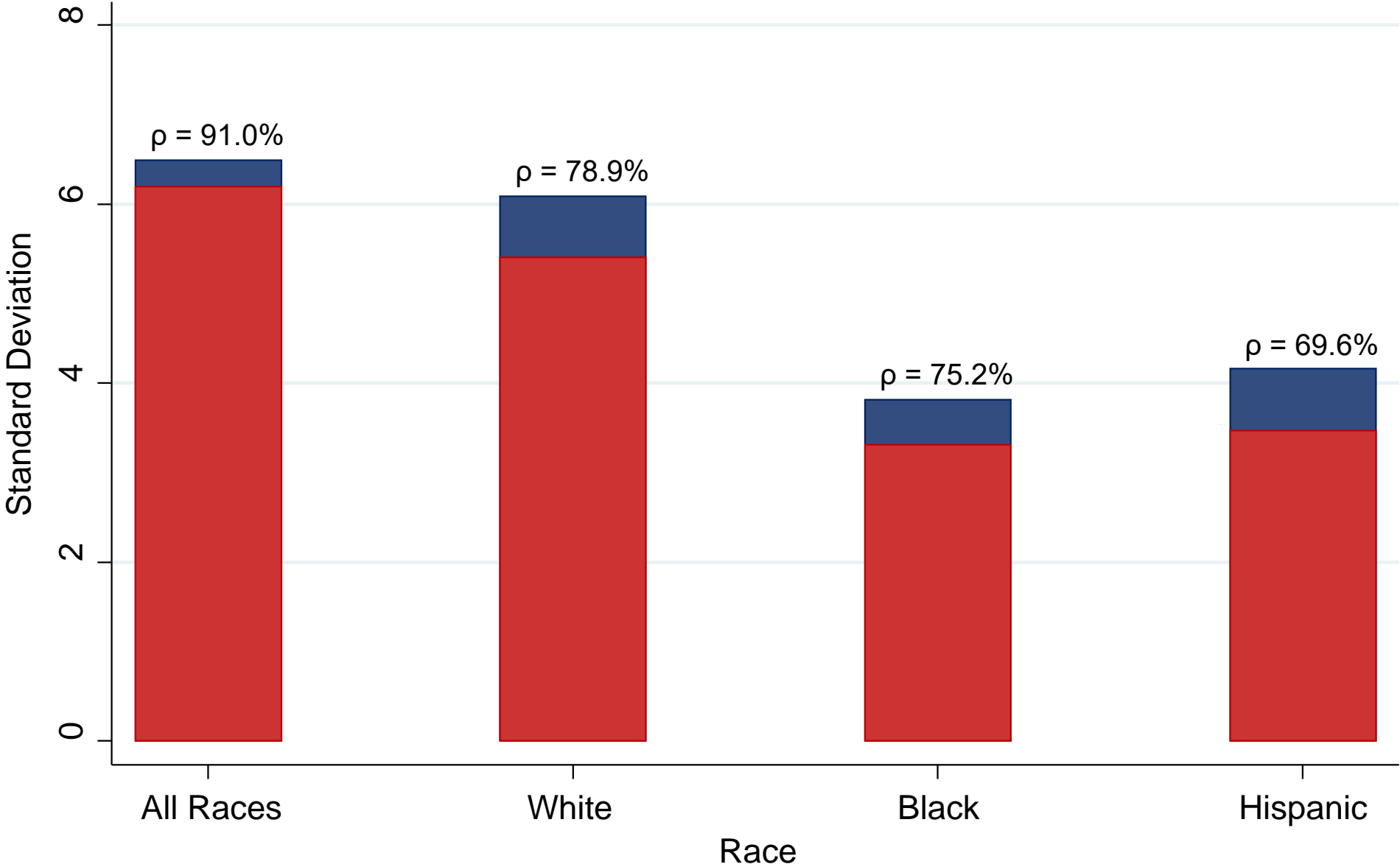
Reliability of Tract-Level Estimates

- 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

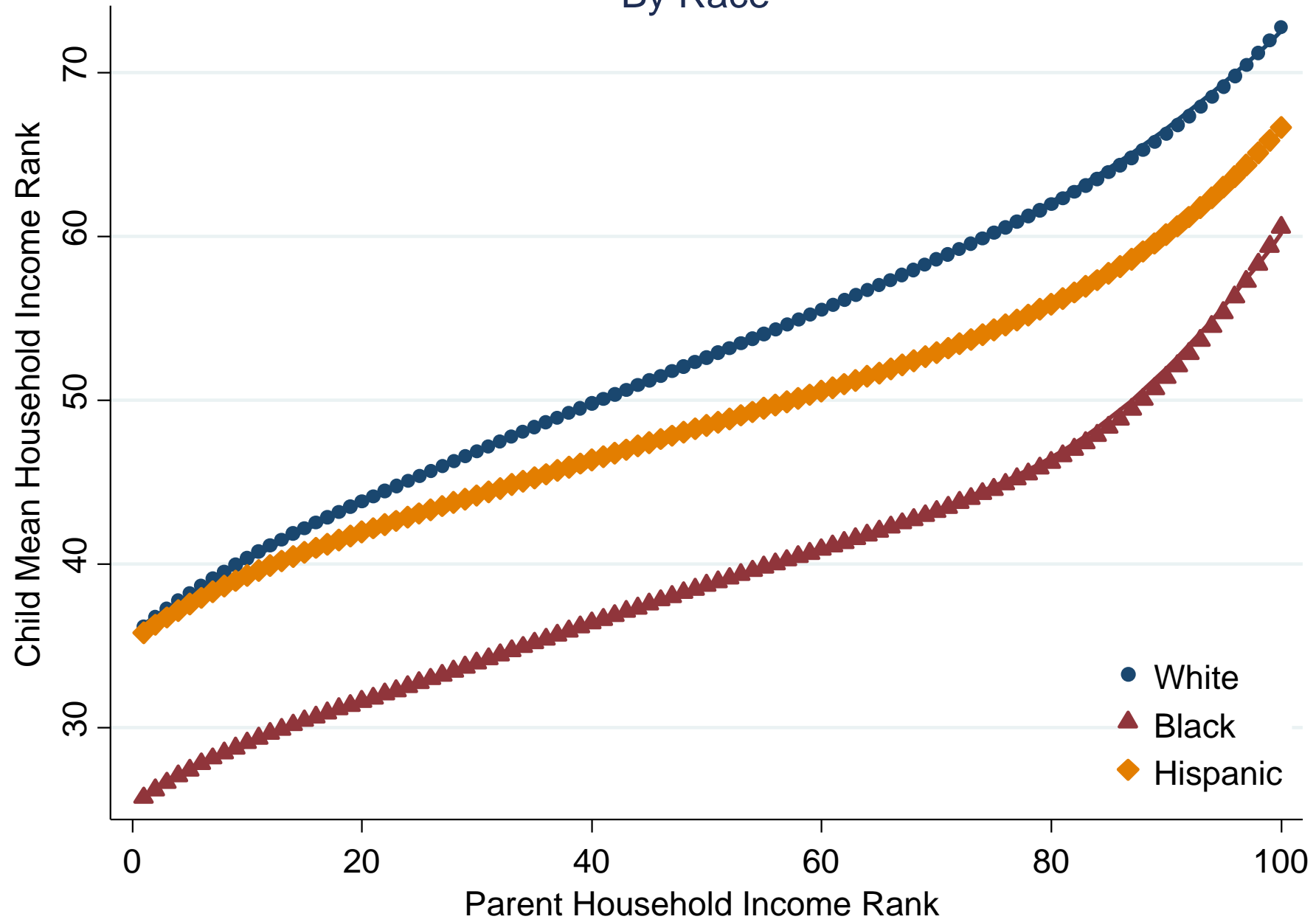
Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates For Children With Parents at 25th Percentile



Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates For Children With Parents at 25th Percentile



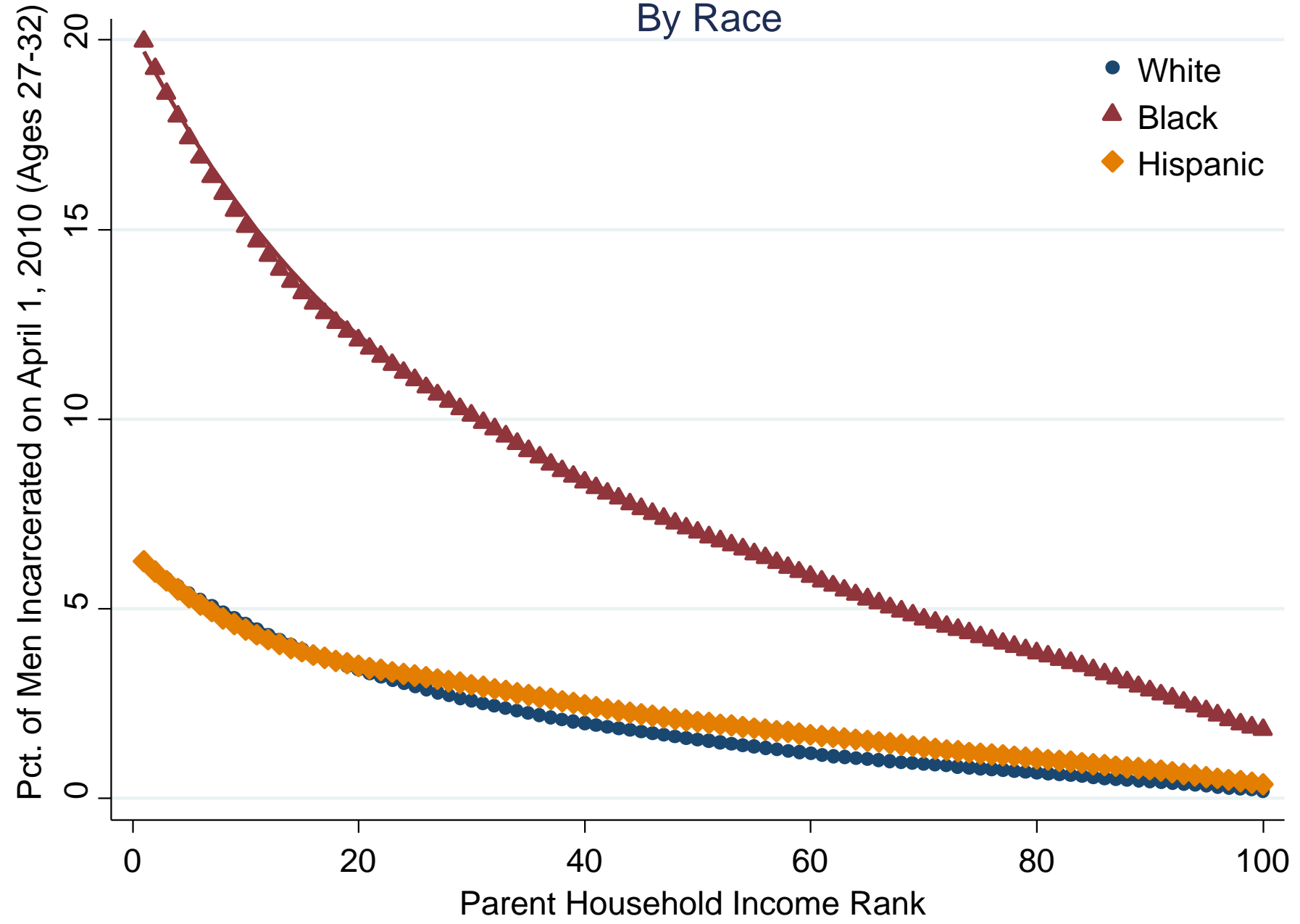
Mean Child Household Income Rank vs. Parent Household Income Rank By Race



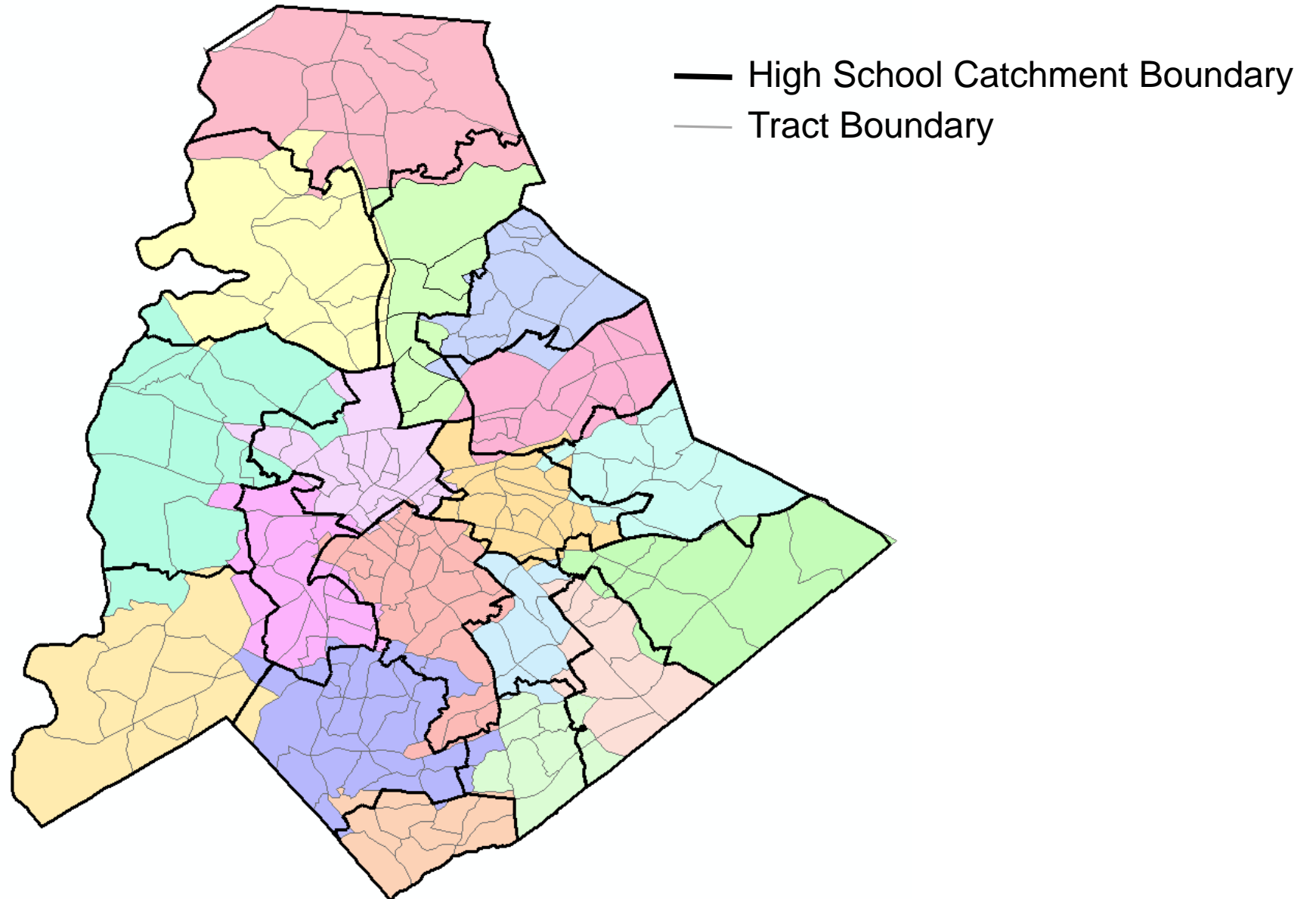


Incarceration Rates vs. Parent Household Income Rank

By Race

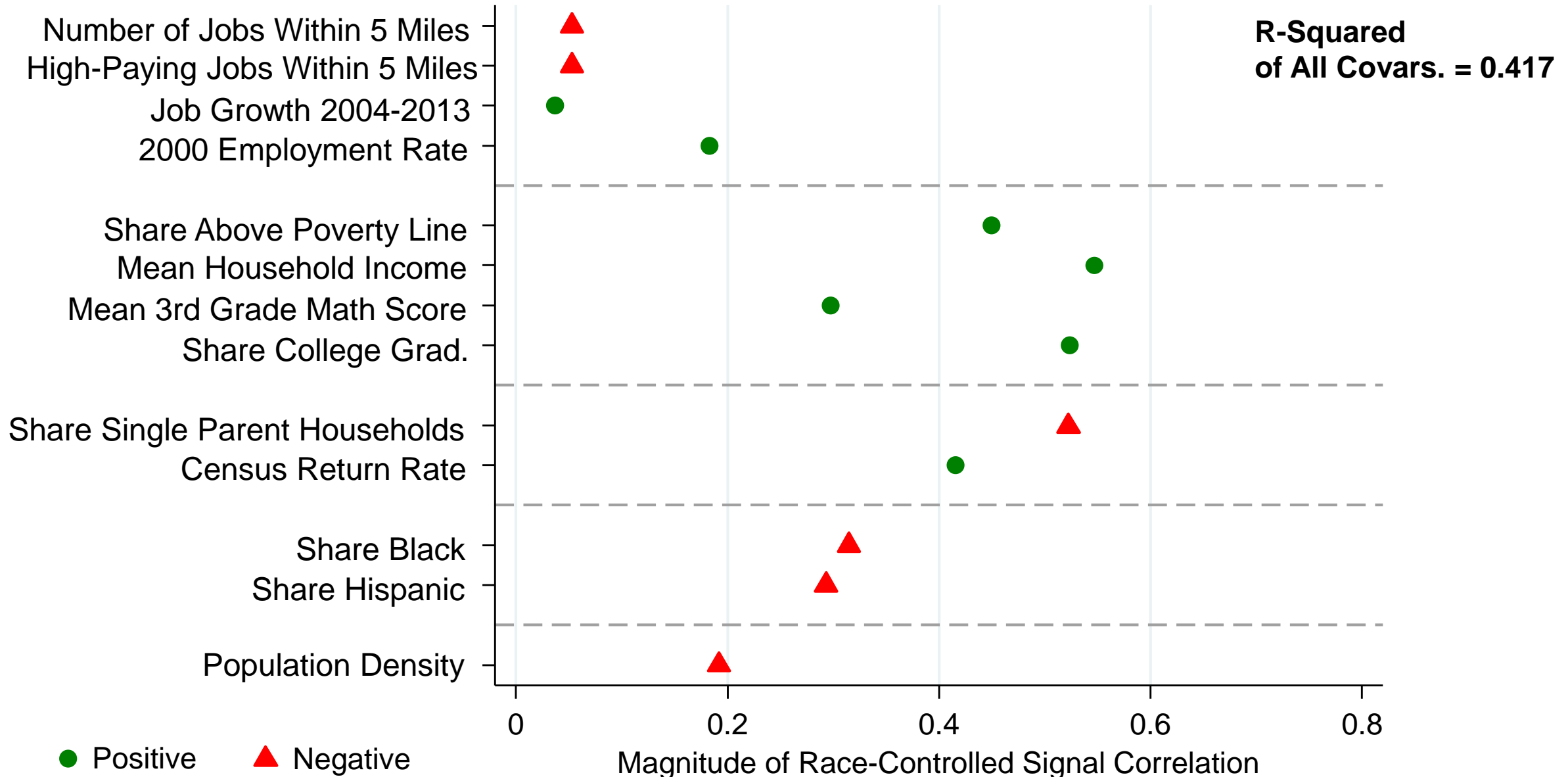


School Catchment Zones in Mecklenburg County: Boundaries vs. Assignment of Tracts to Catchment Zones

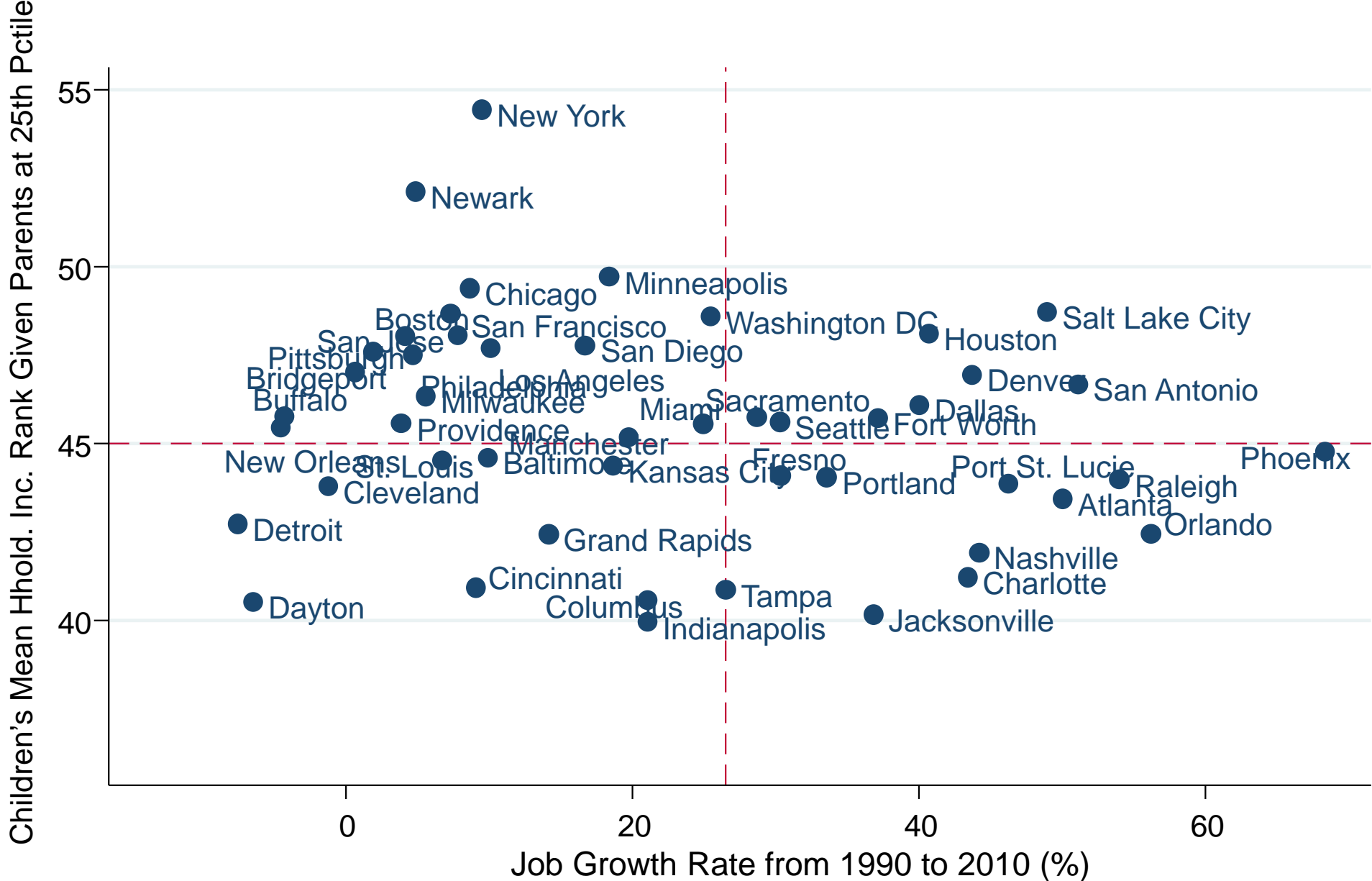


Correlations between Tract-Level Covariates and Household Income Rank

Race-Adjusted, Parent Income at 75th Percentile

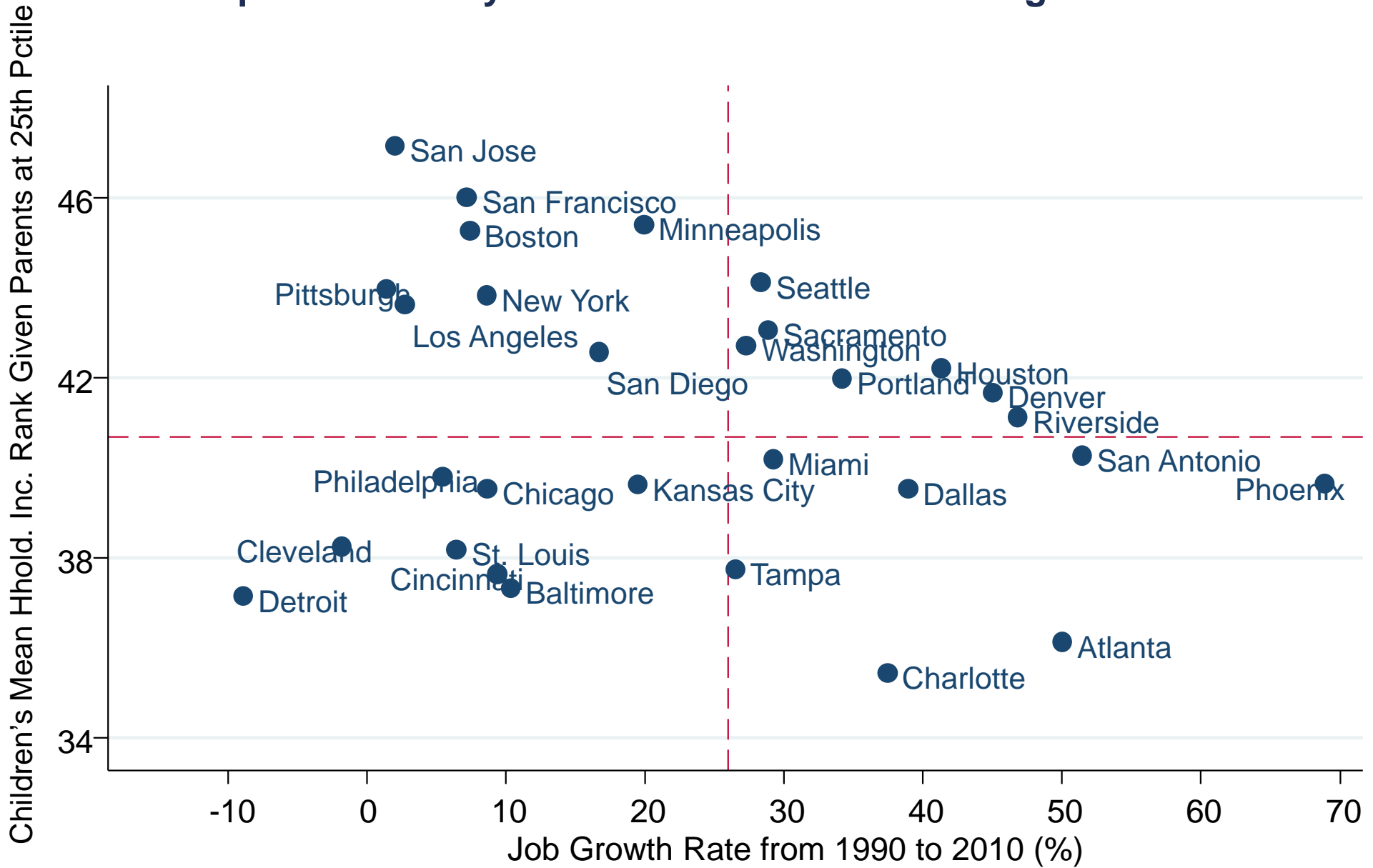


Upward Mobility for Whites vs. Job Growth in the 50 Largest Commuting Zones



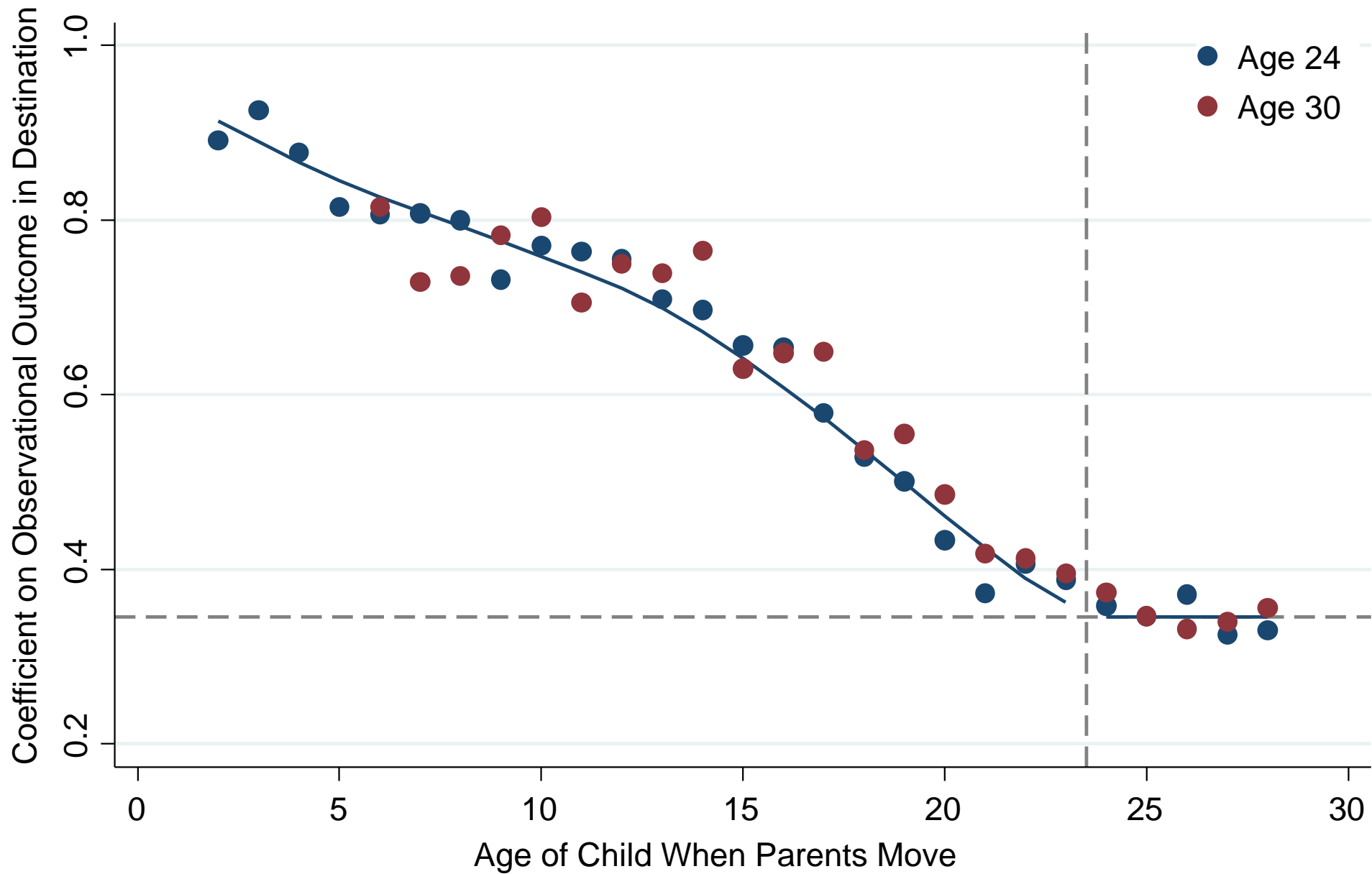


Upward Mobility vs. Job Growth in the 30 Largest MSAs

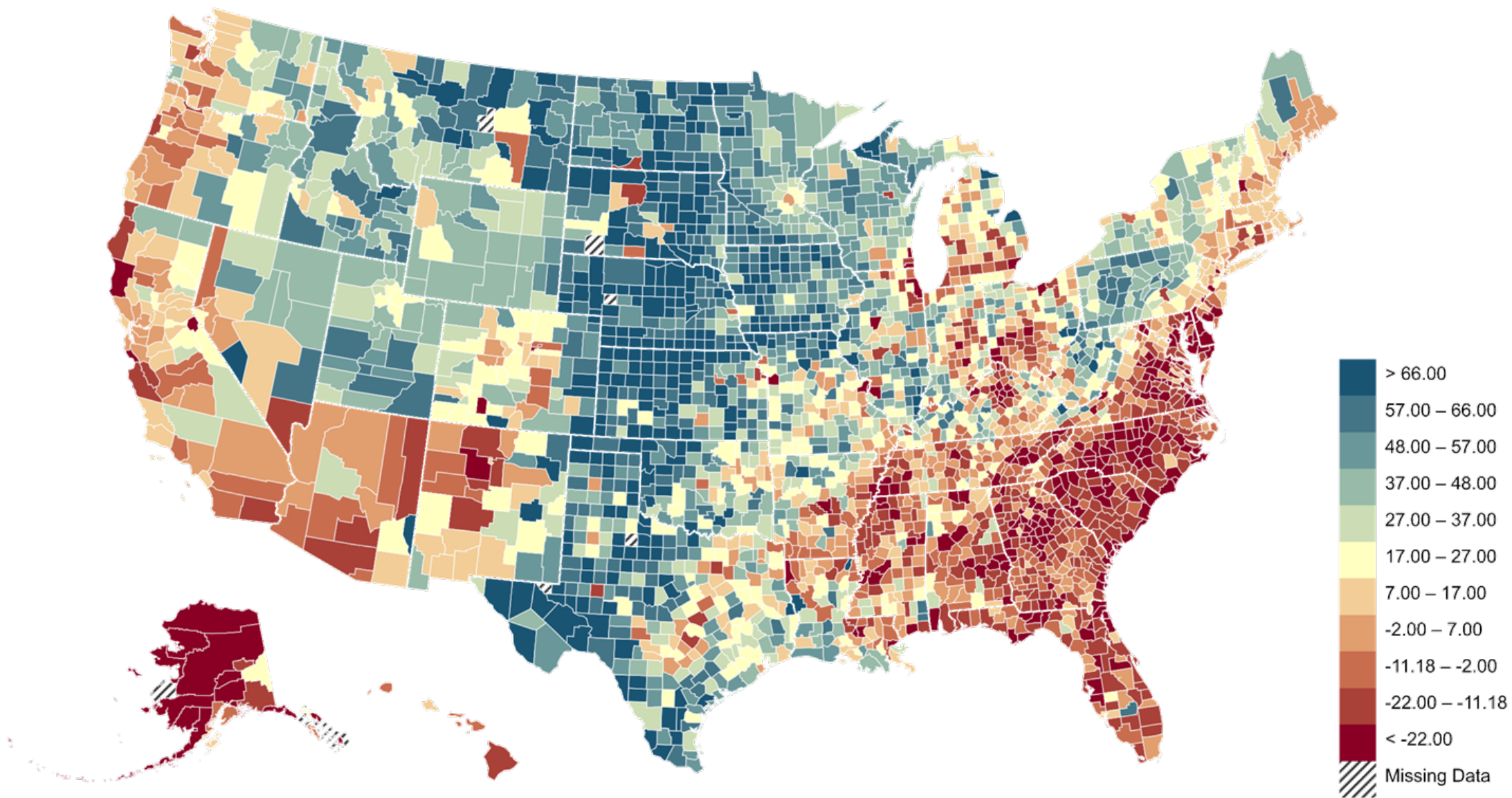


Correlation (across all MSAs): -0.07

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



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