

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 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

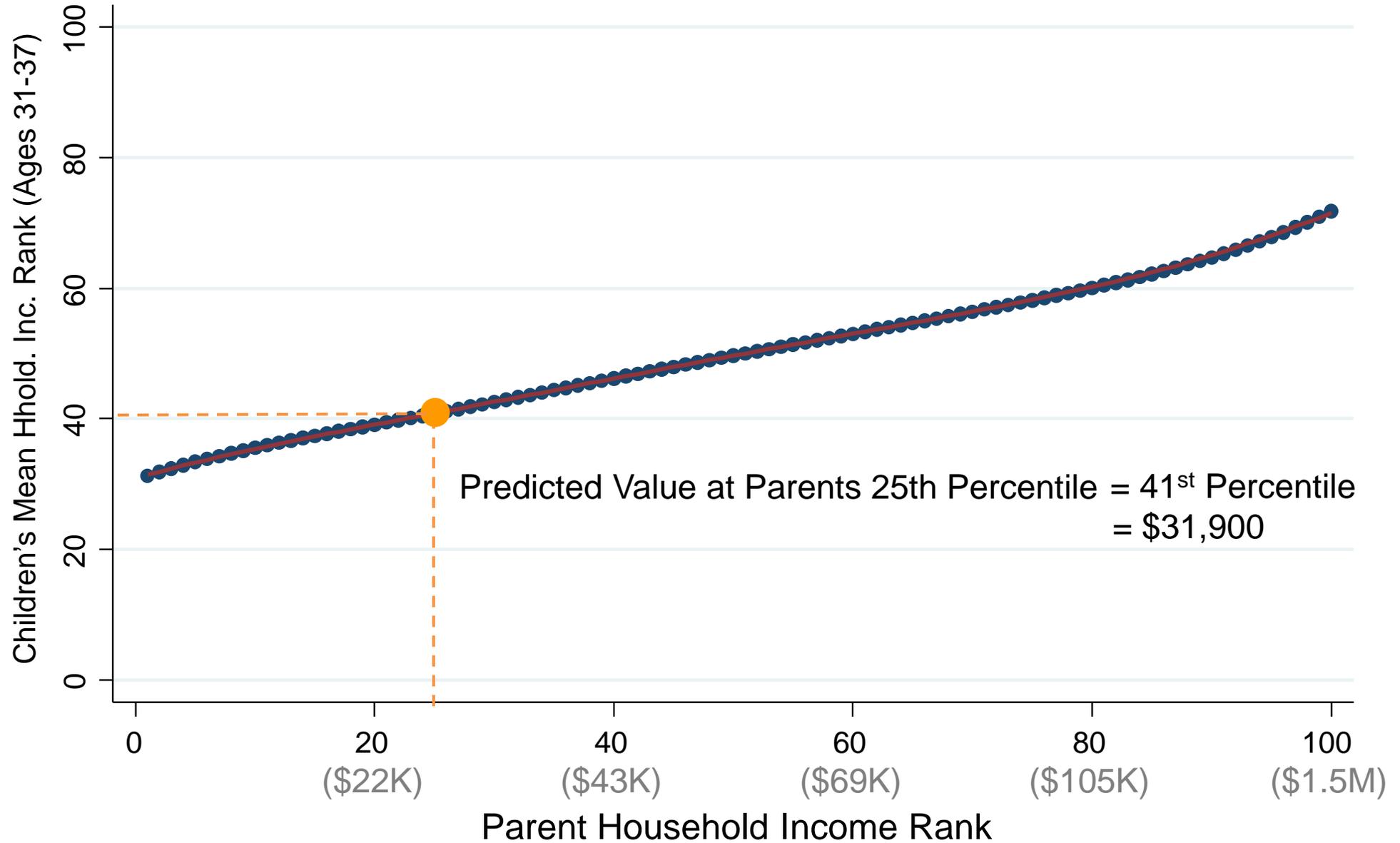
Data Sources and Sample Definitions

- 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

Income Definitions

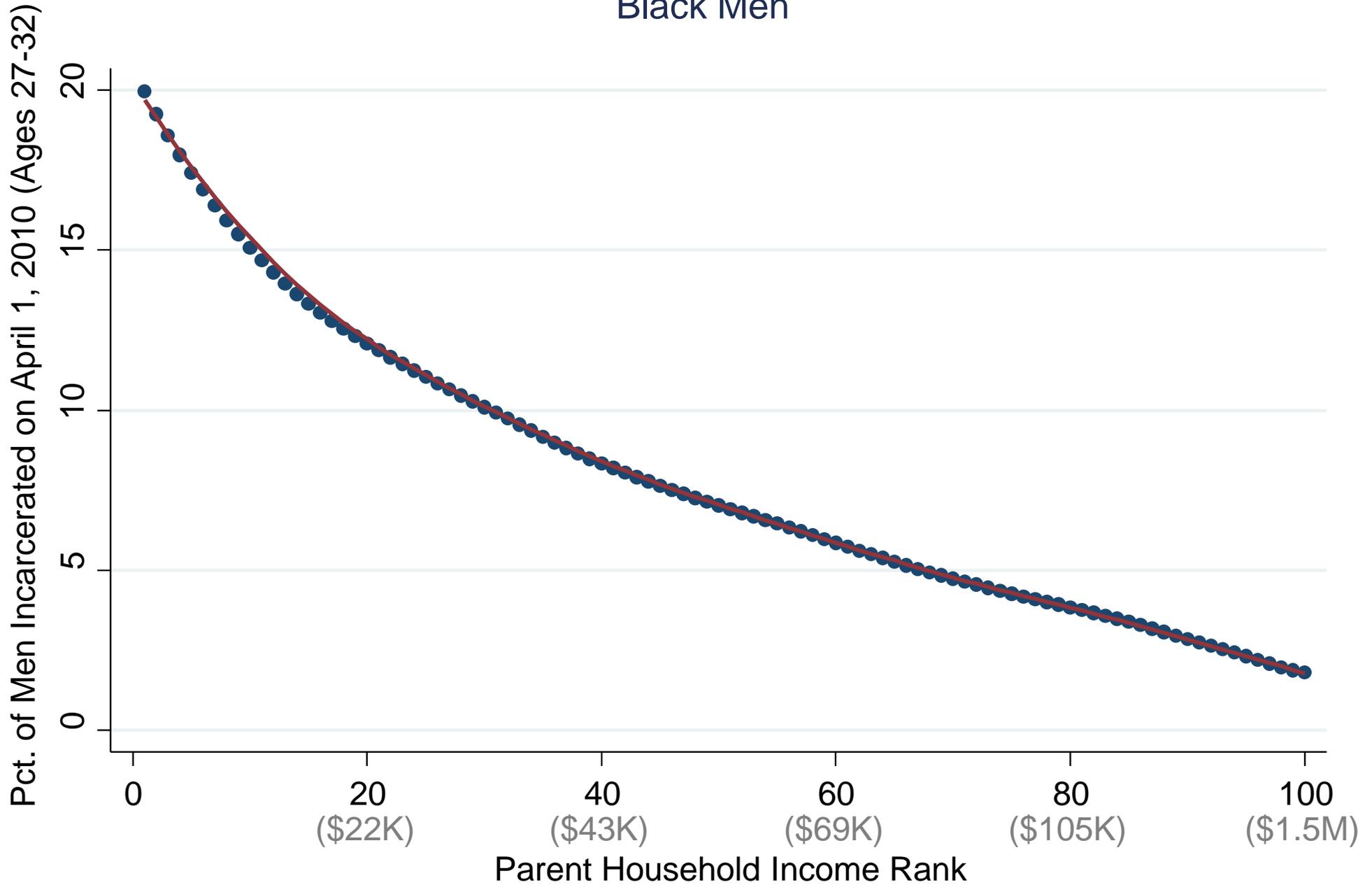
- Parents' pre-tax household incomes: mean Adjusted Gross Income from 1994-2000, assigning non-filers zeros
- Children's pre-tax incomes measured in 2014-15 (ages 31-37)
 - Non-filers assigned incomes based on W-2's (available since 2005)
- To mitigate lifecycle bias, focus on **national** percentile ranks: rank children relative to others in their birth cohort and parents relative to other parents

Mean Child Household Income Rank vs. Parent Household Income Rank



Incarceration Rates vs. Parent Household Income Rank

Black Men



The Opportunity Atlas via Two Applications

1 **Observational Variation and Targeting**

2 **Causal Effects and Neighborhood Choice**

The Opportunity Atlas via Two Applications

1 Observational Variation and Targeting

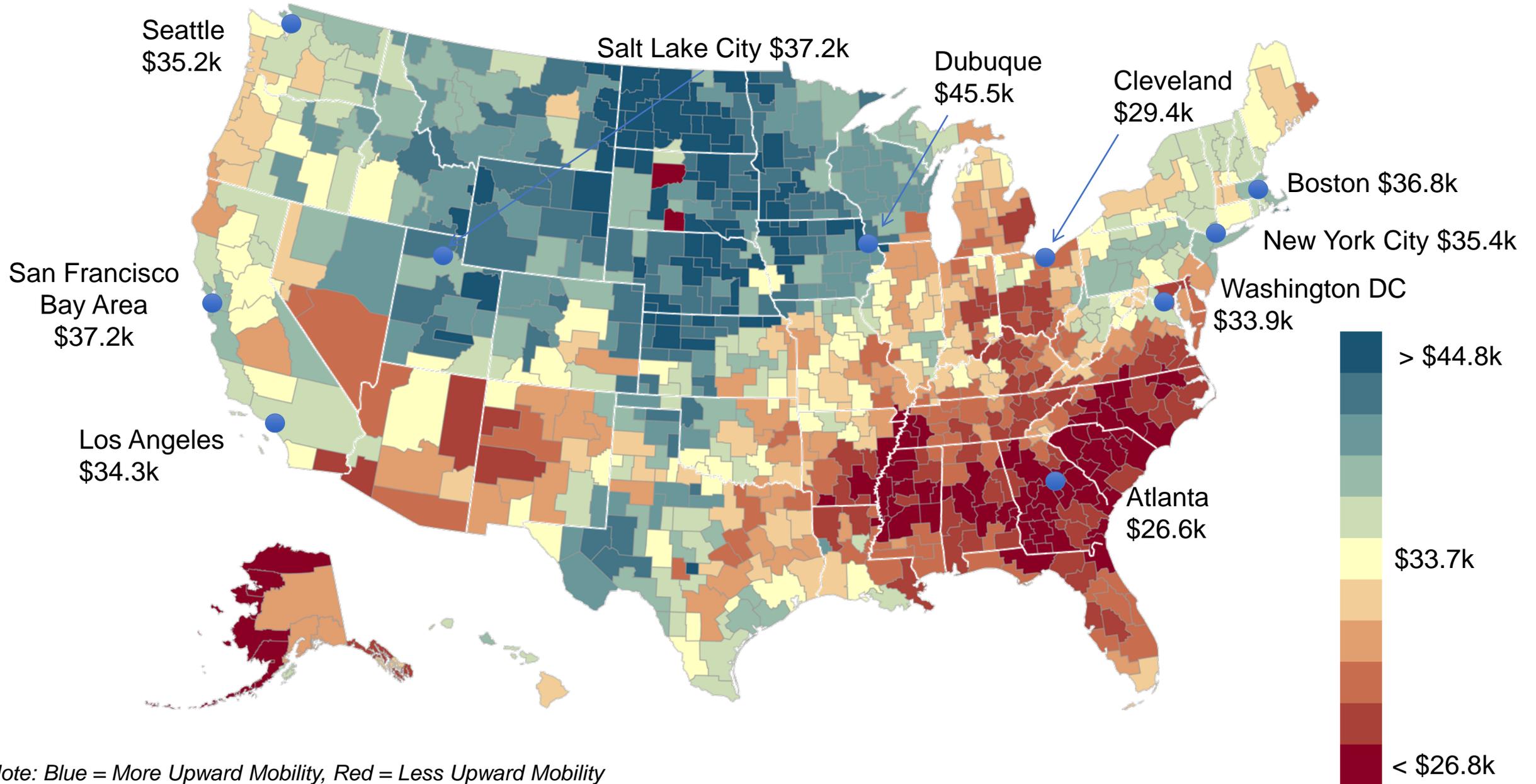
2 Causal Effects and Neighborhood Choice

Observational Variation and Targeting

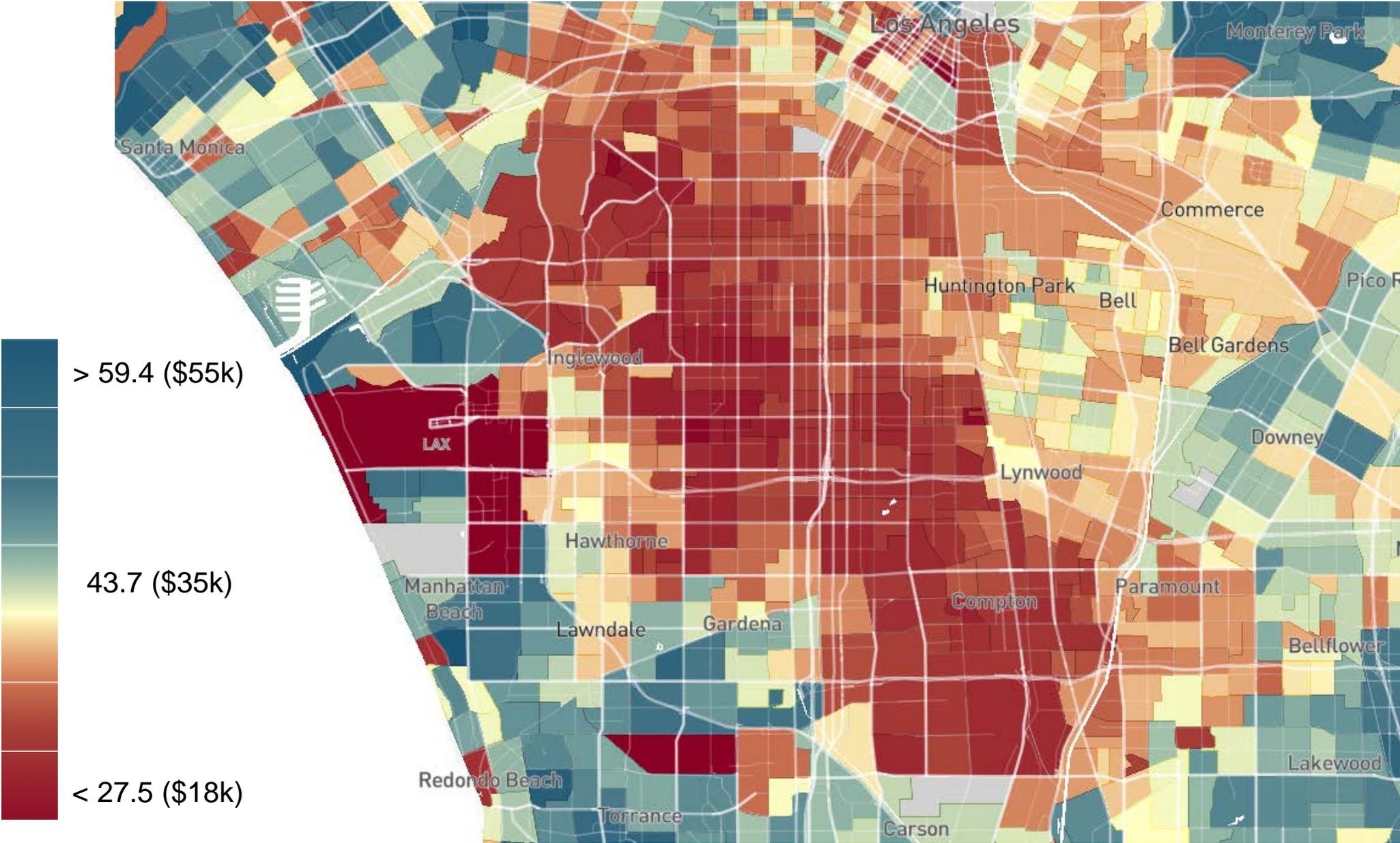
- Many policies target areas based on characteristics such as the poverty rates
 - Tax policies (e.g., Opportunity zones), local services (e.g., Head Start programs), ...
- For such “tagging” applications, observed outcomes are of direct interest in standard optimal tax models [Akerlof 1978, Nichols 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

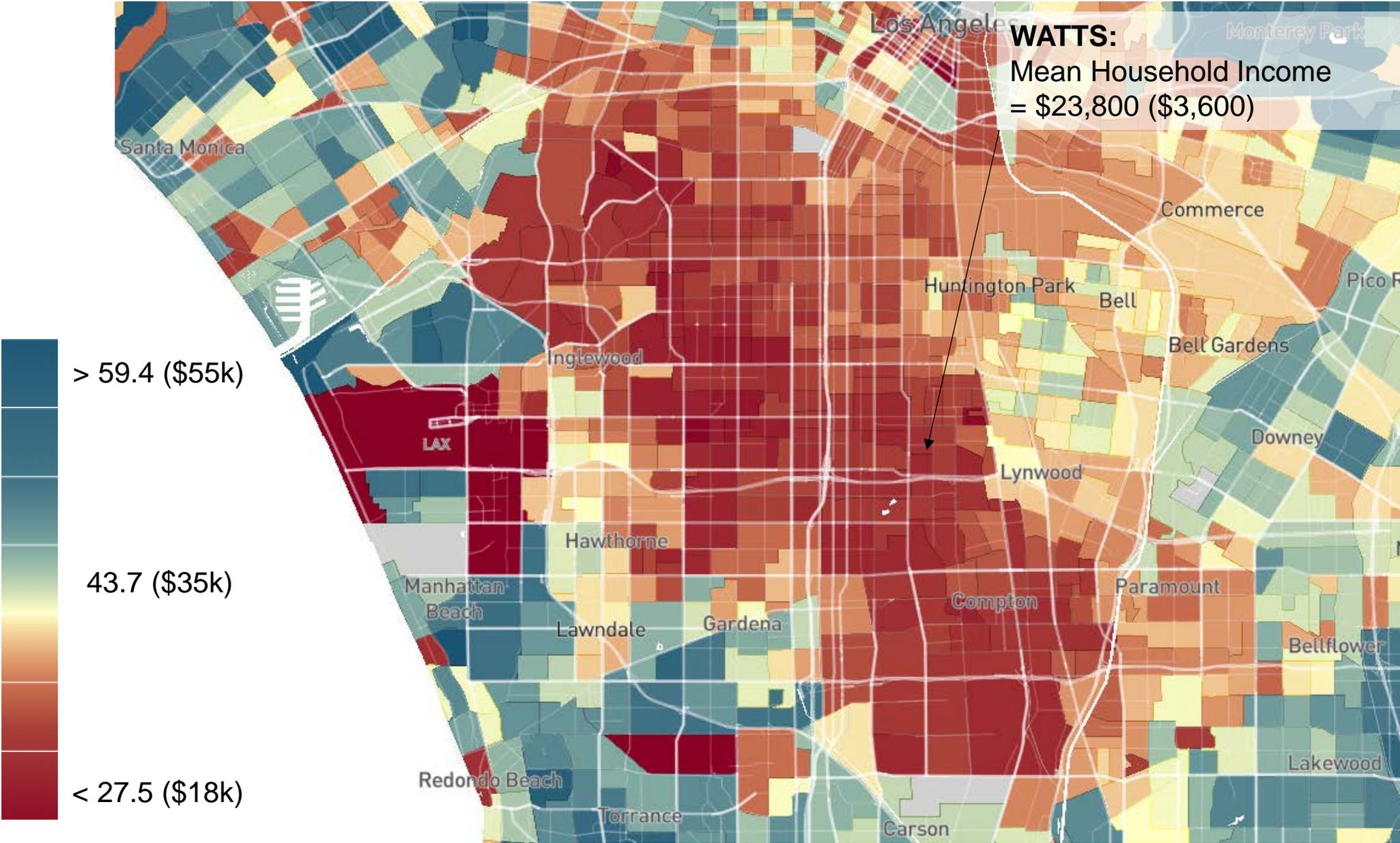
Average Household Income for Children with Parents Earning \$27,000 (25th percentile)



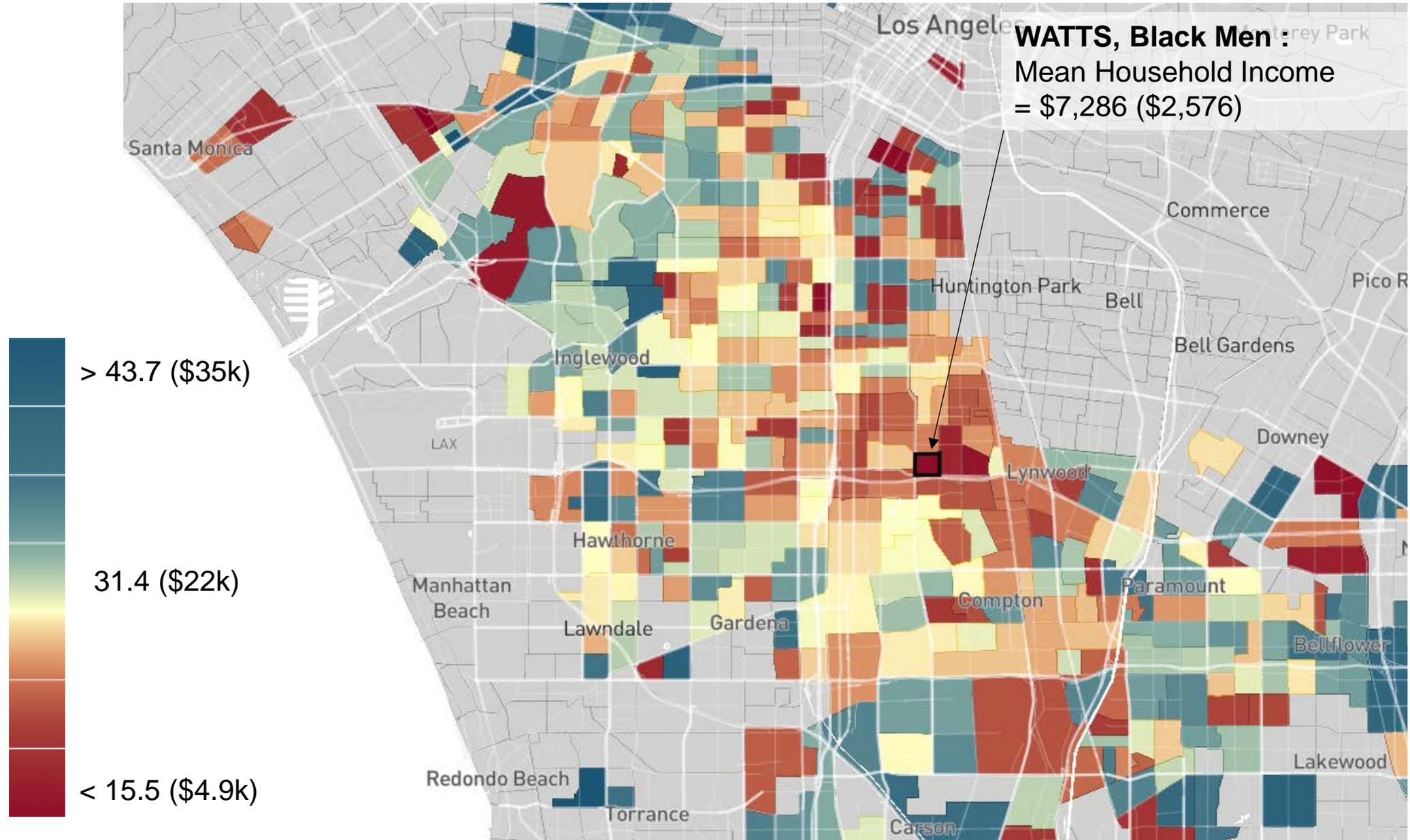
Mean Household Income for Children in Los Angeles with Parents Earning \$27,000 (25th percentile)



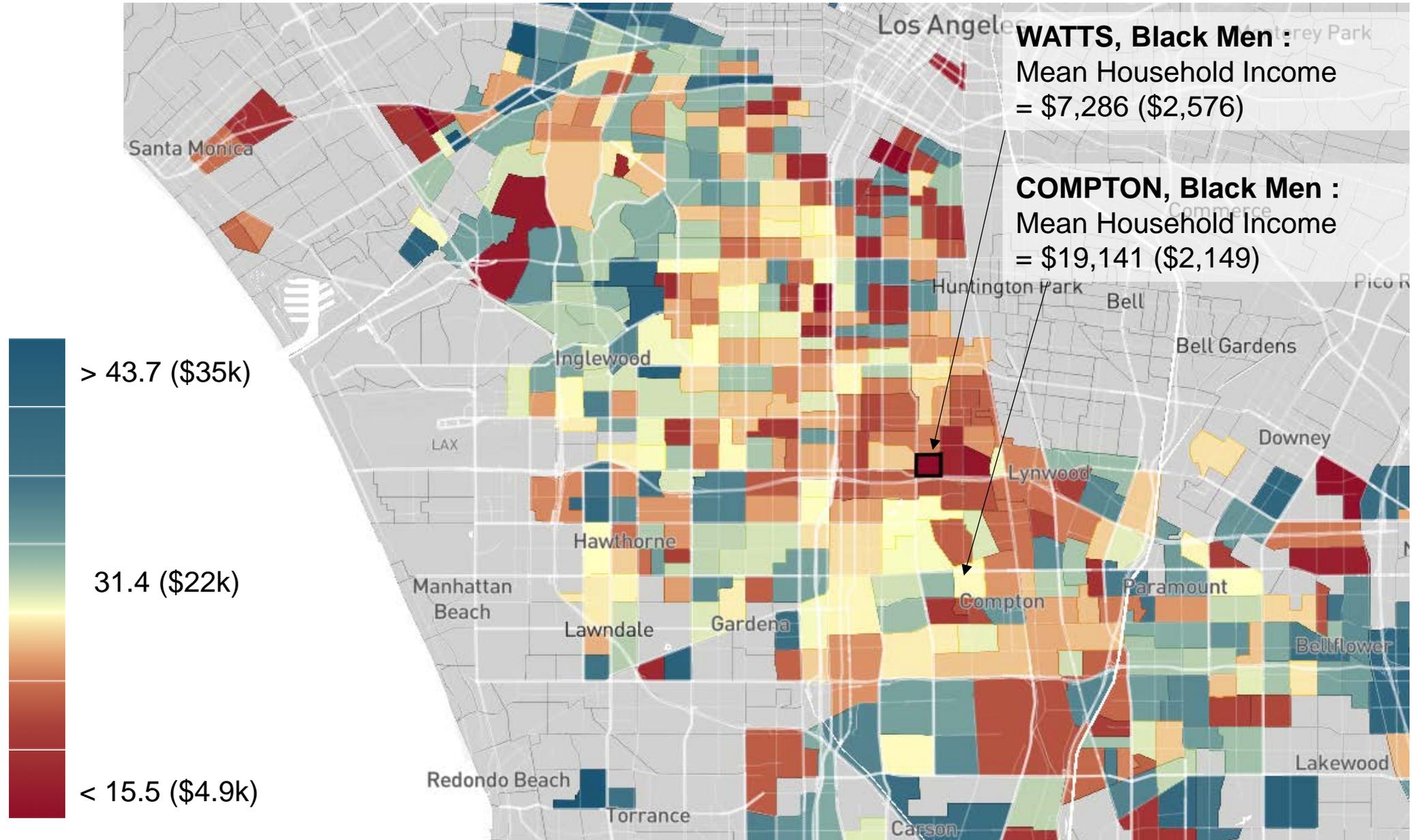
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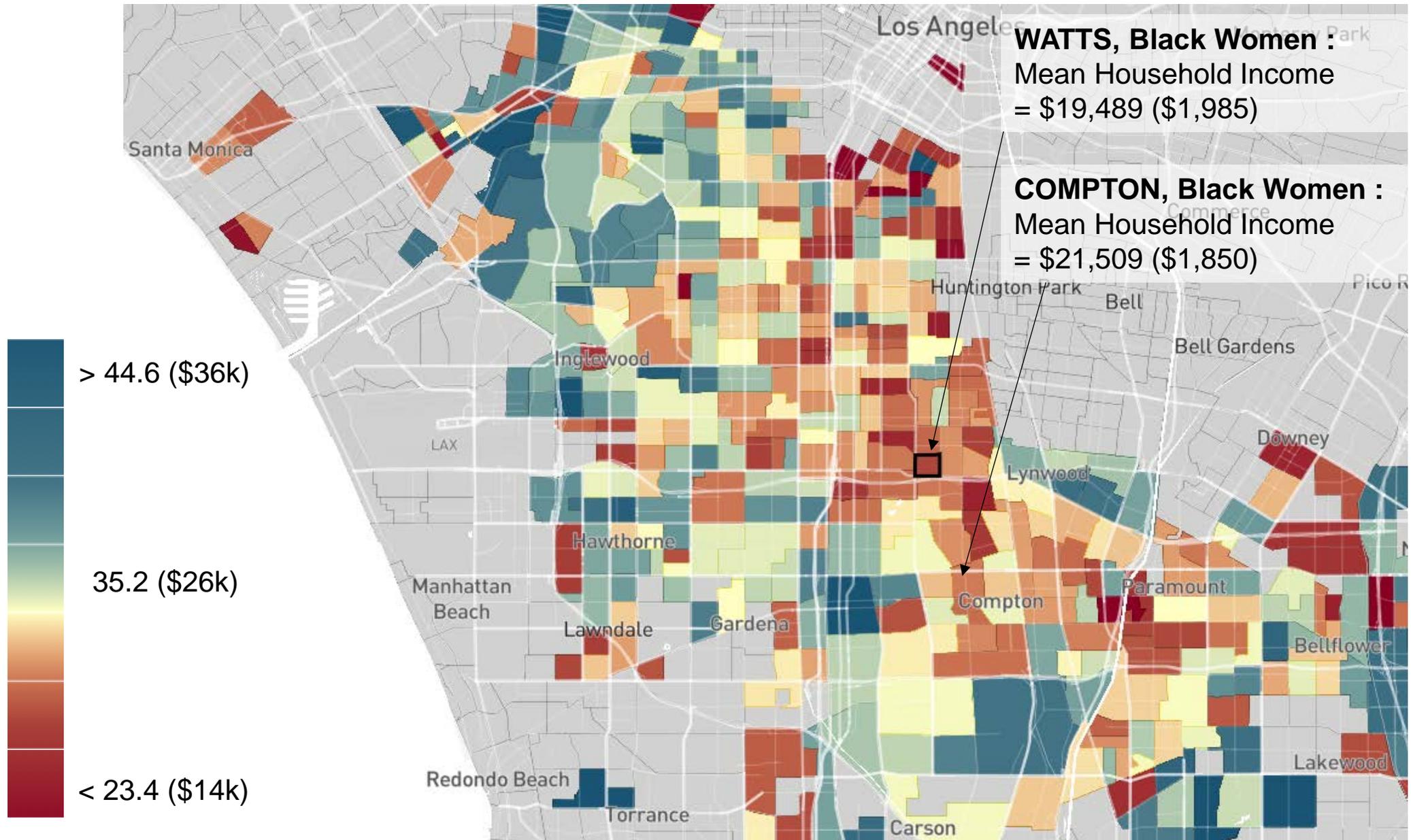
Mean Household Income for Black Men in Los Angeles with Parents Earning \$27,000 (25th percentile)



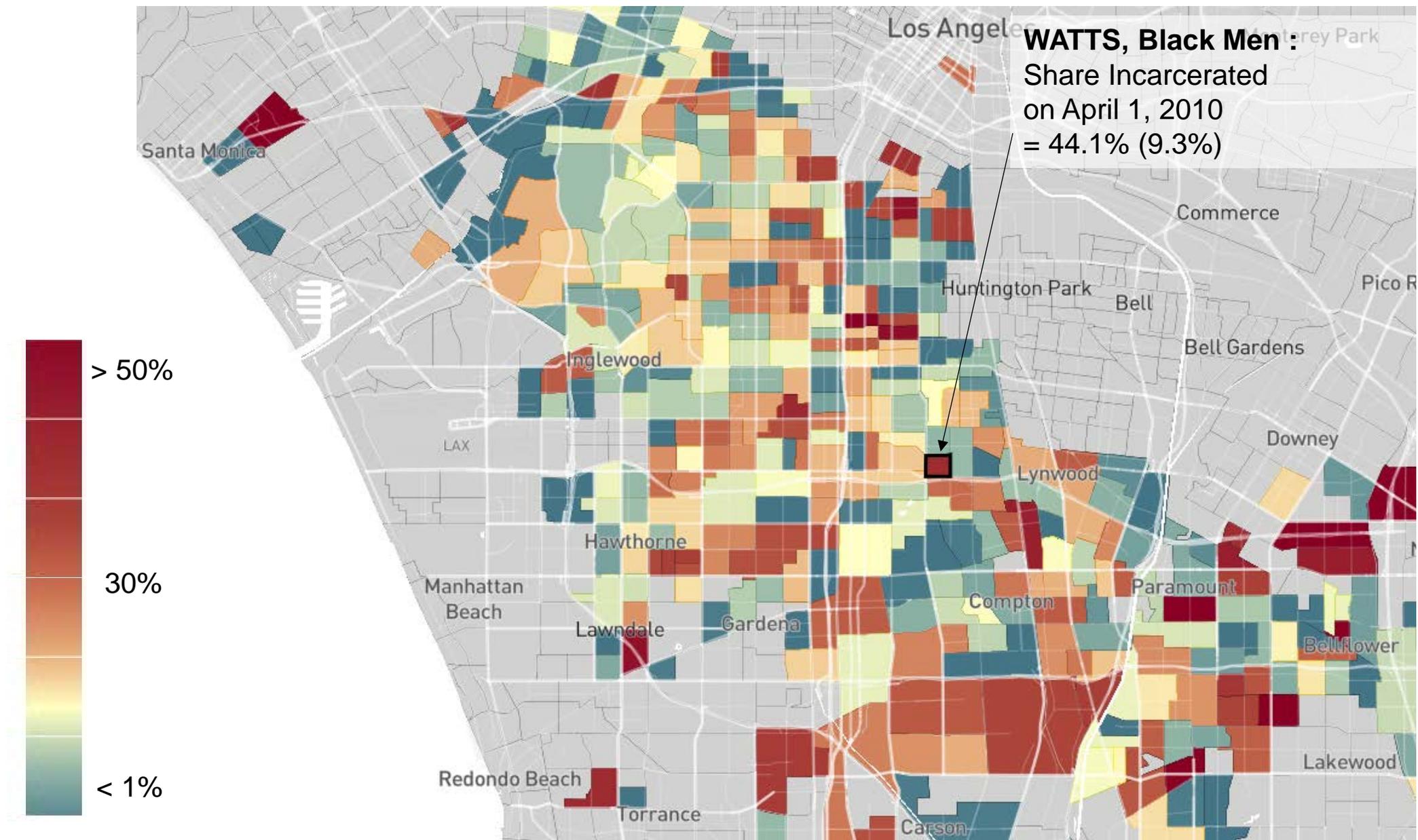
Mean Household Income for Black Men in Los Angeles with Parents Earning \$27,000 (25th percentile)



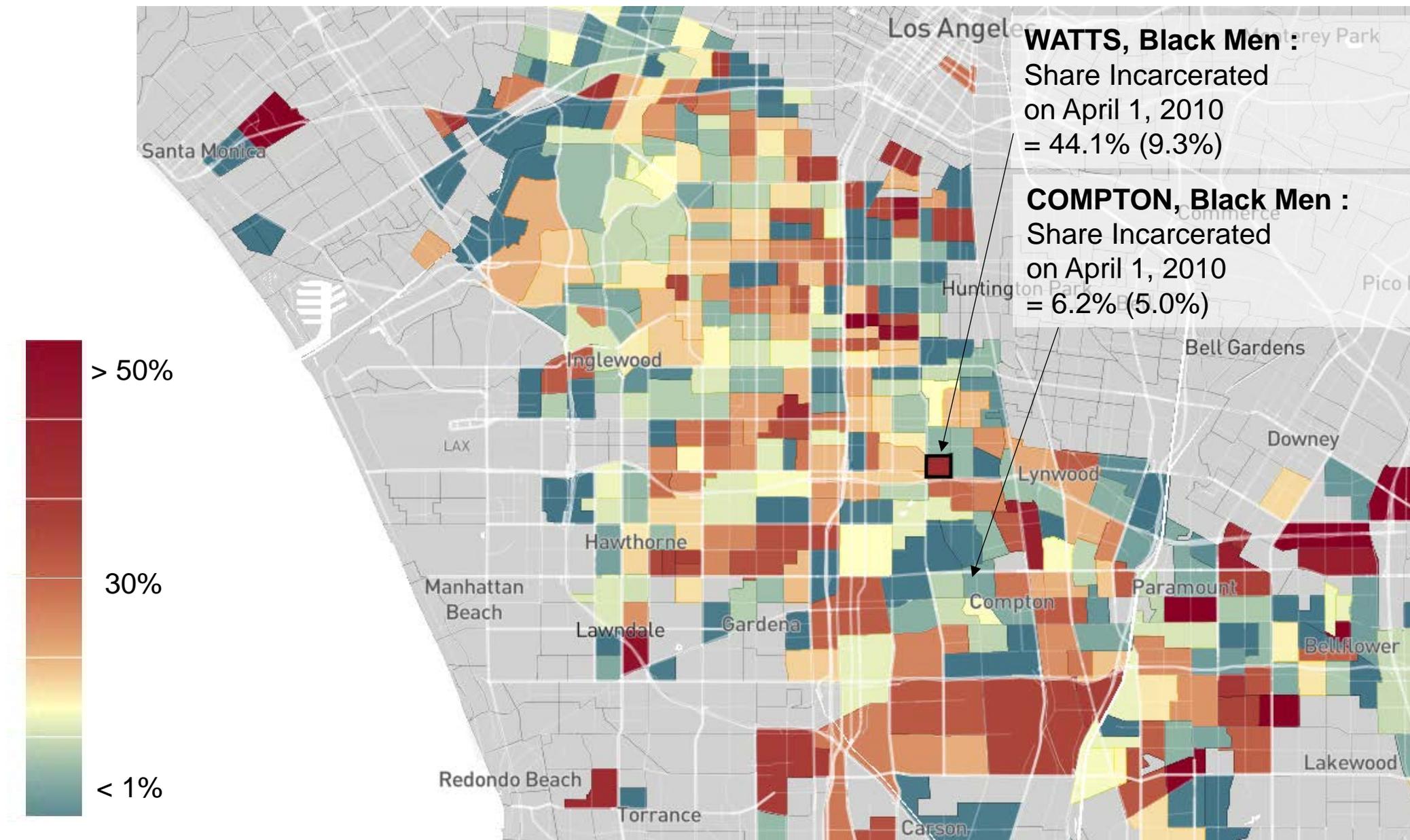
Mean Individual Income for Black Women in Los Angeles with Parents Earning \$27,000 (25th percentile)



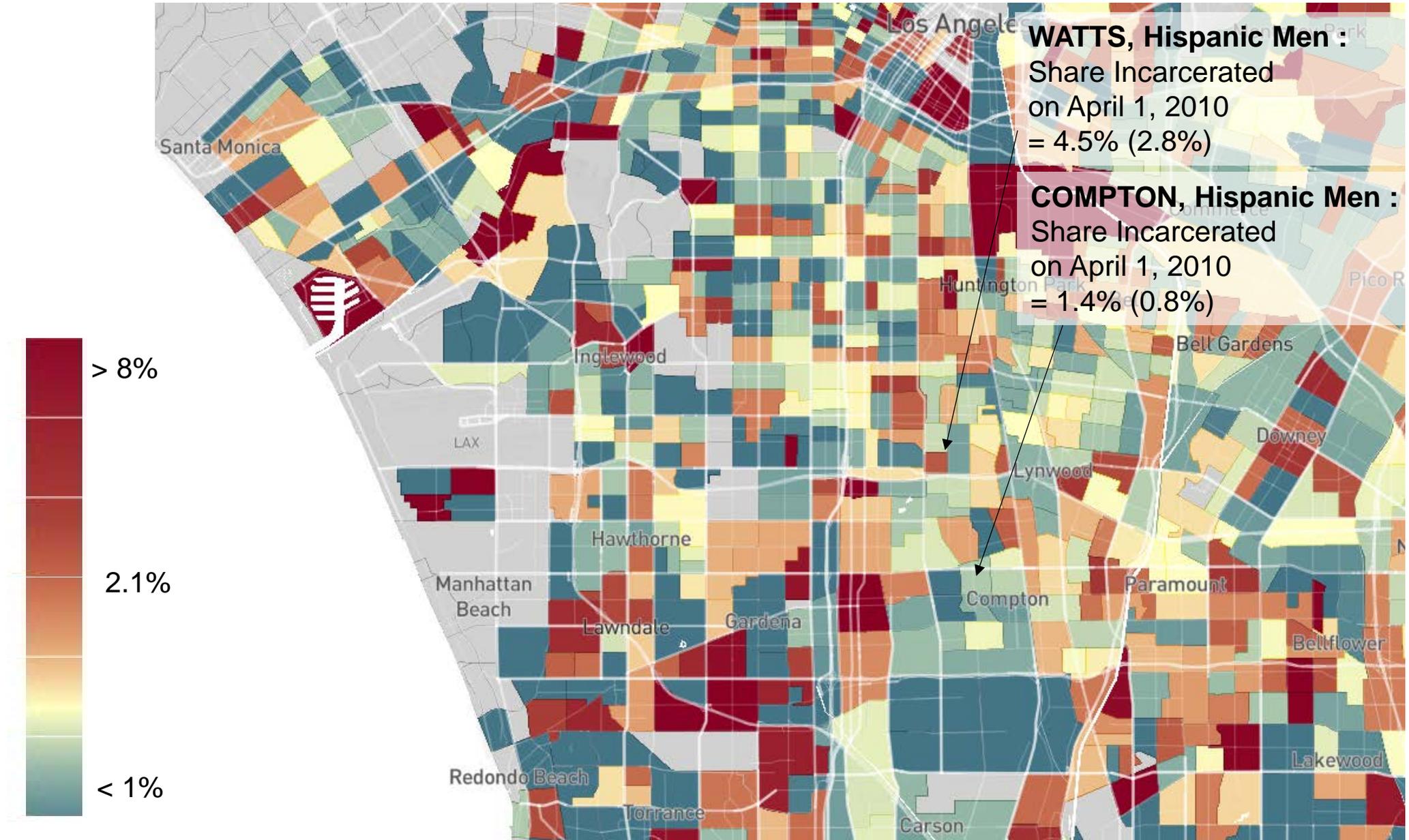
Incarceration Rates for Black Men in Los Angeles with Parents Earning < \$2,200 (1st percentile)



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

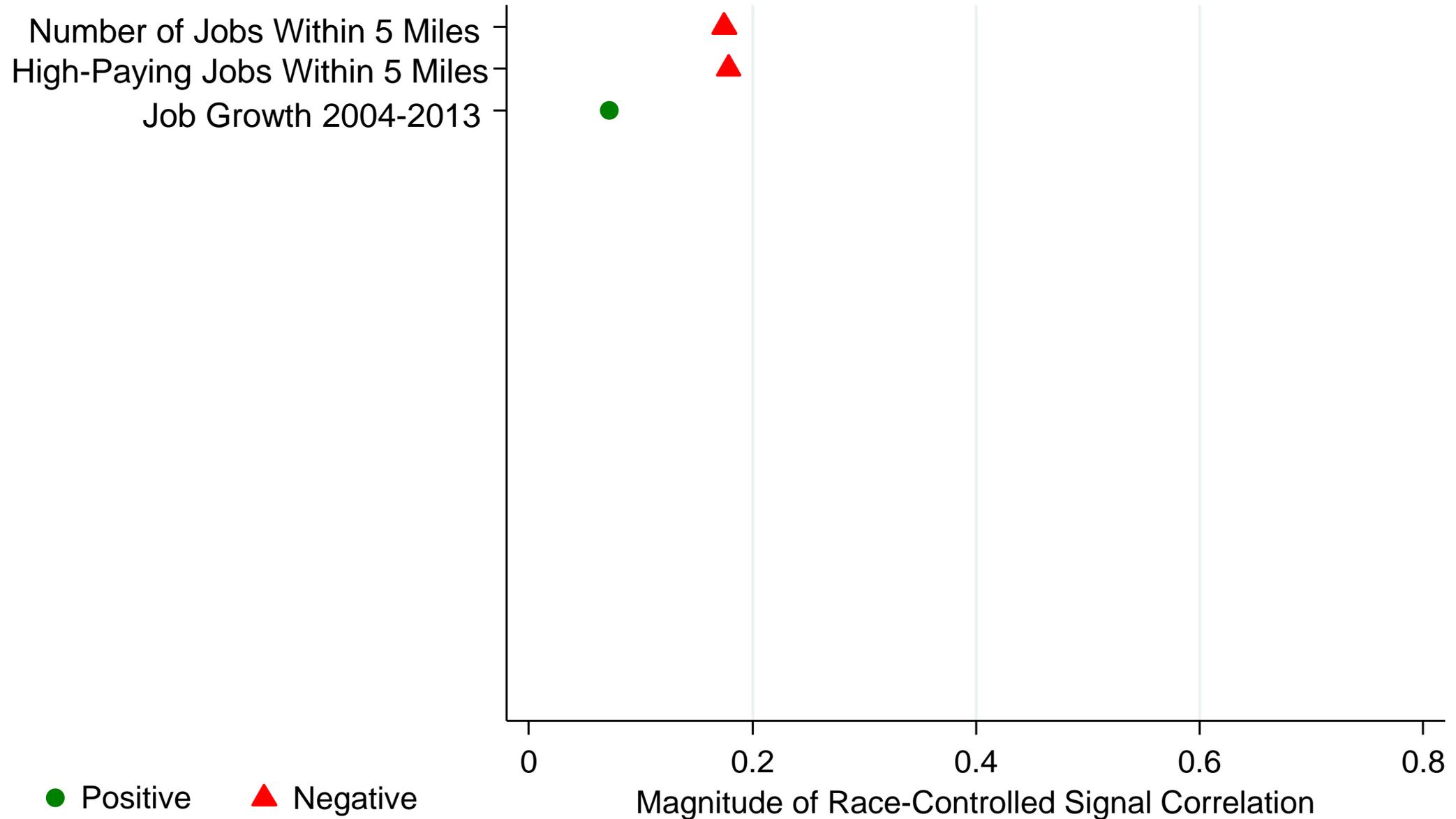


Incarceration Rates for Hispanic Men in Los Angeles with Parents Earning < \$2,200 (1st percentile)



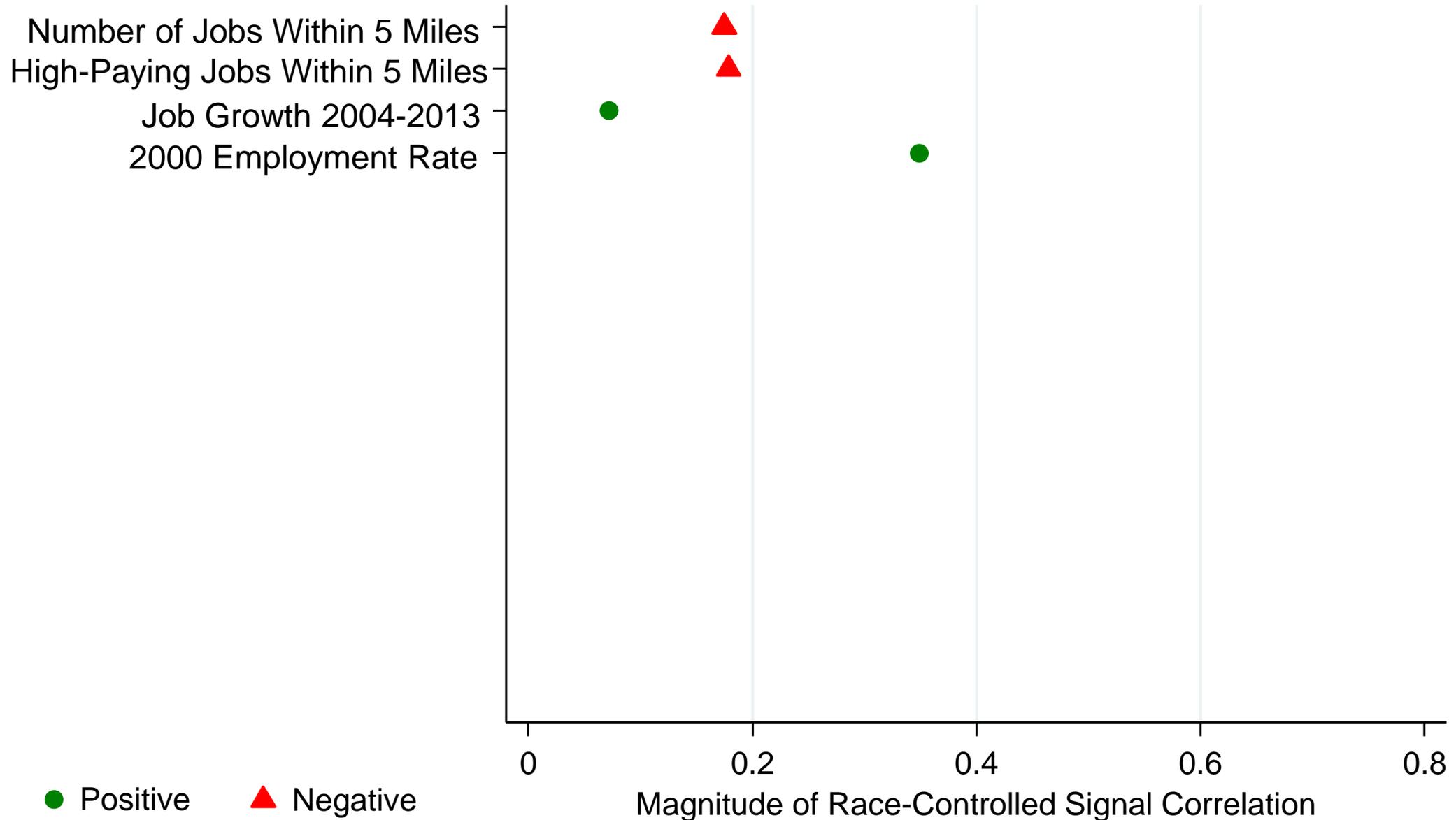
Correlations between Tract-Level Covariates and Household Income Rank

Race-Adjusted, Parent Income at 25th Percentile



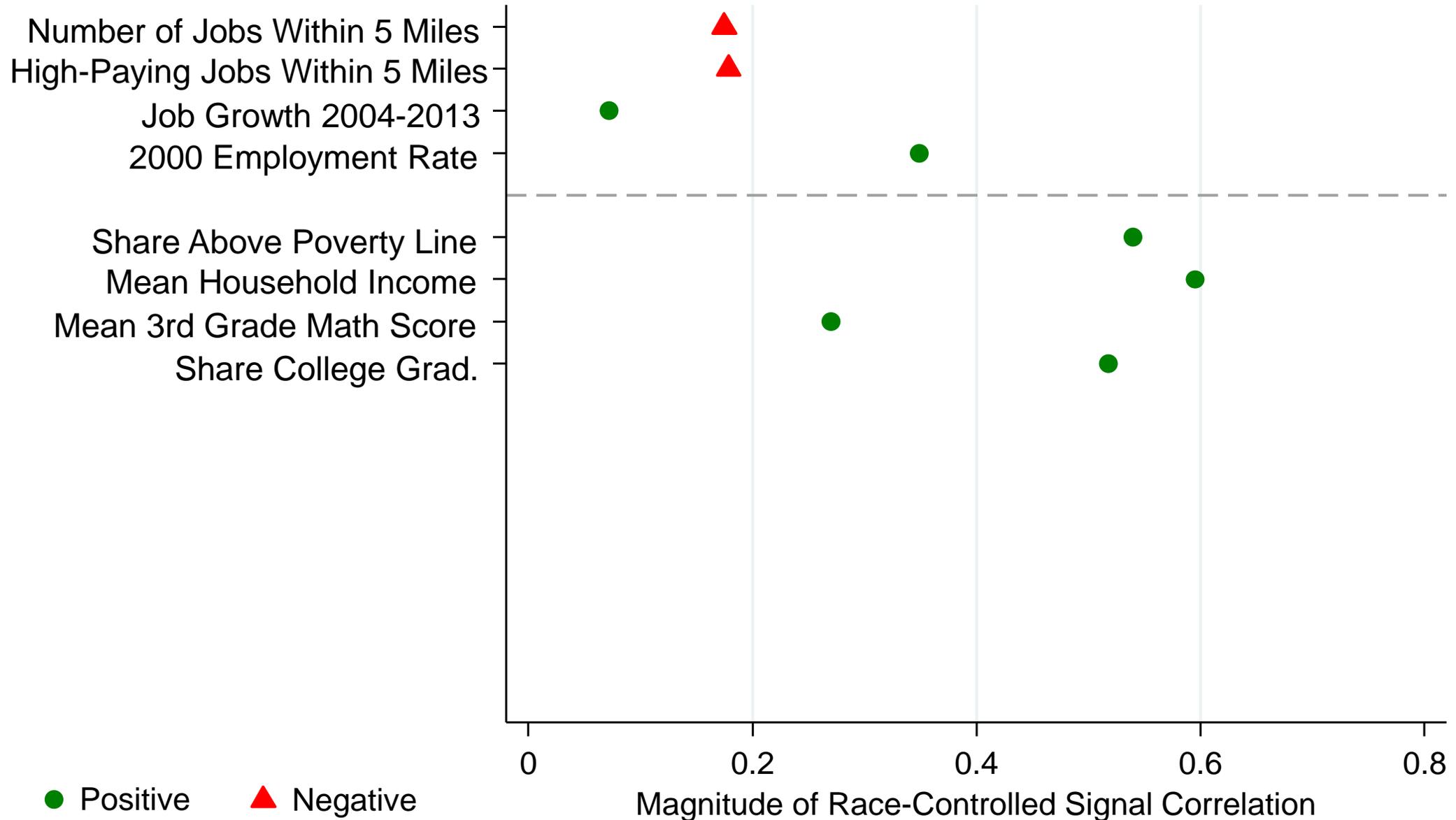
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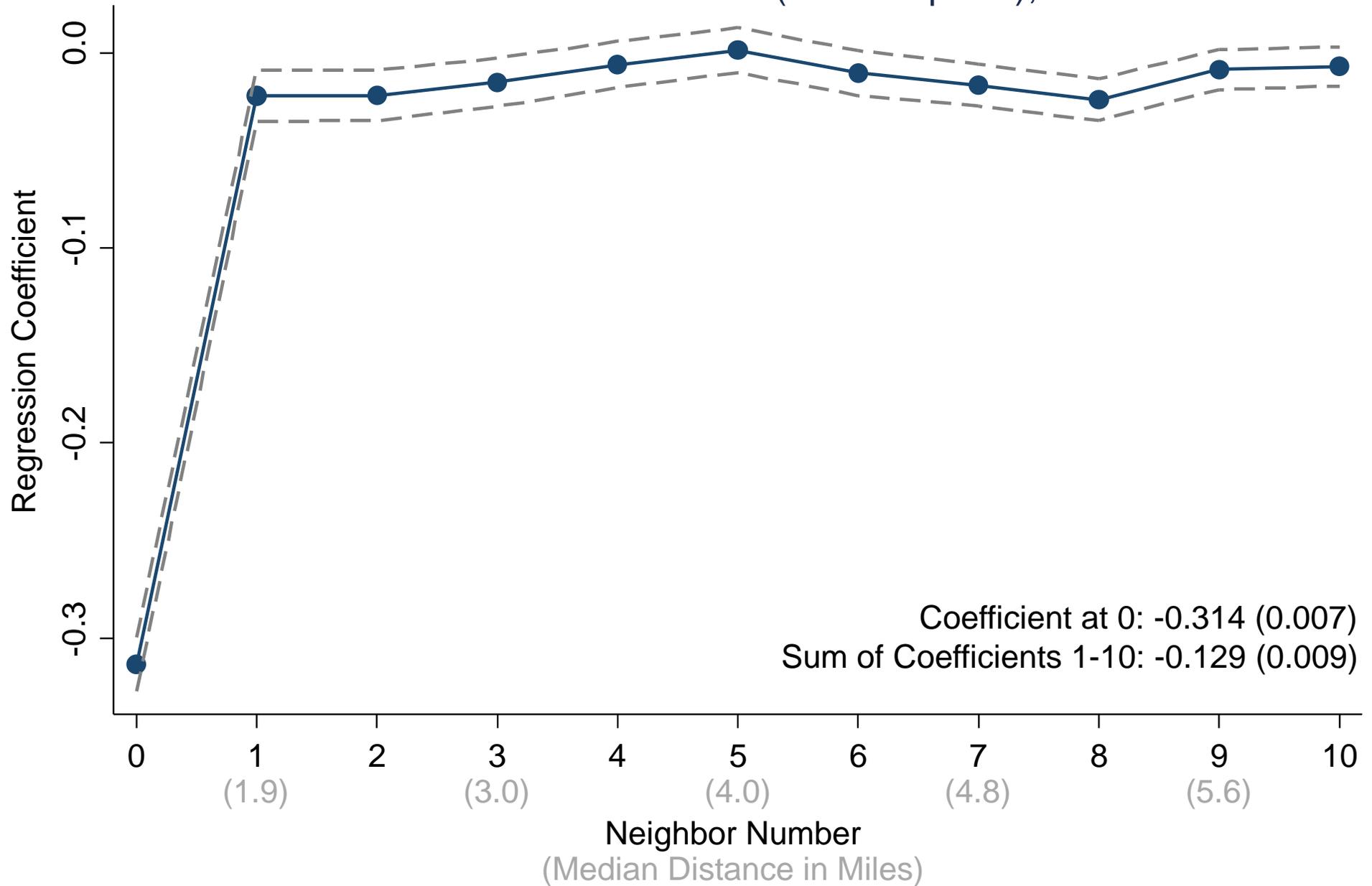
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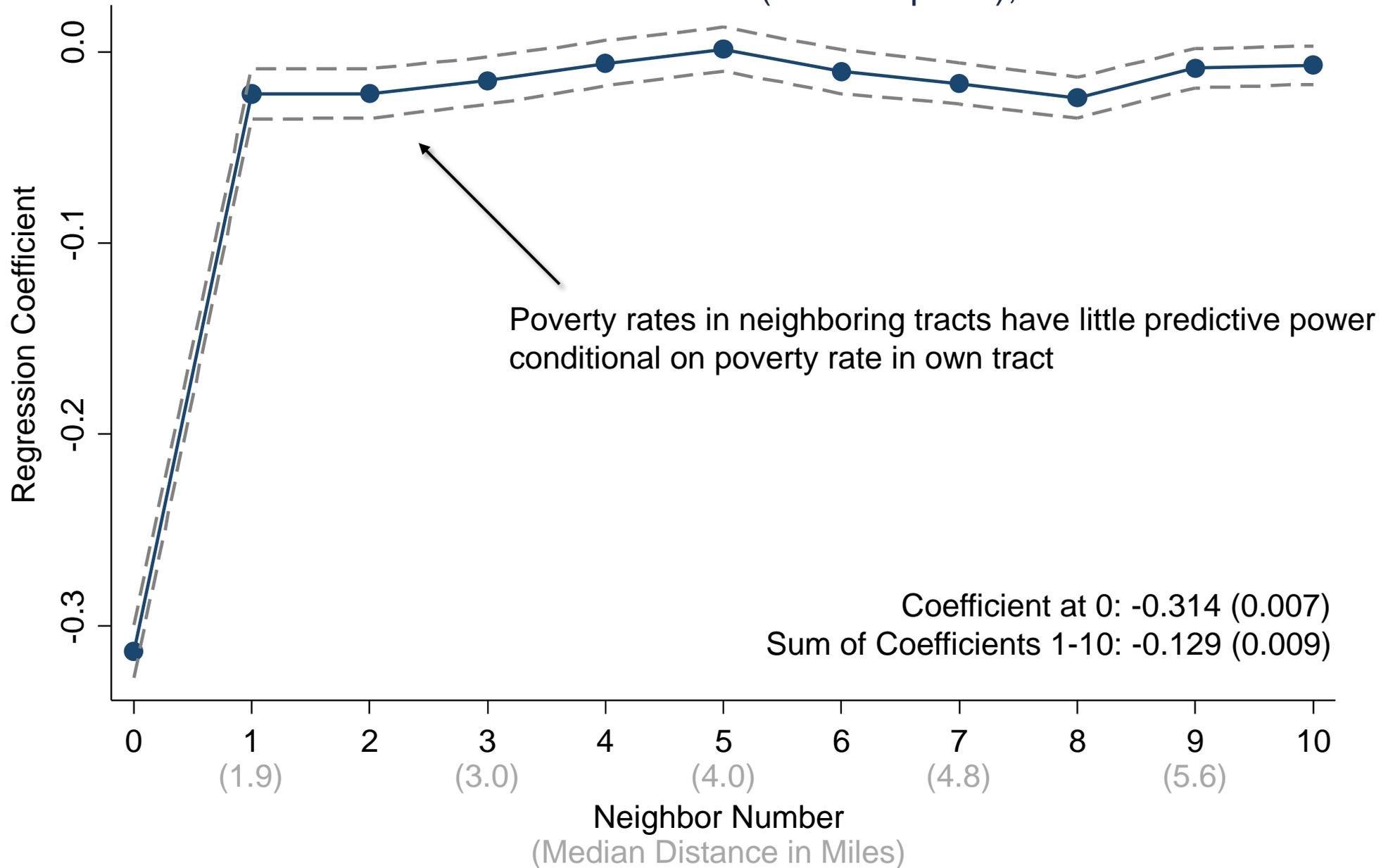
Spatial Decay of Correlation with Tract-Level Poverty Rate

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



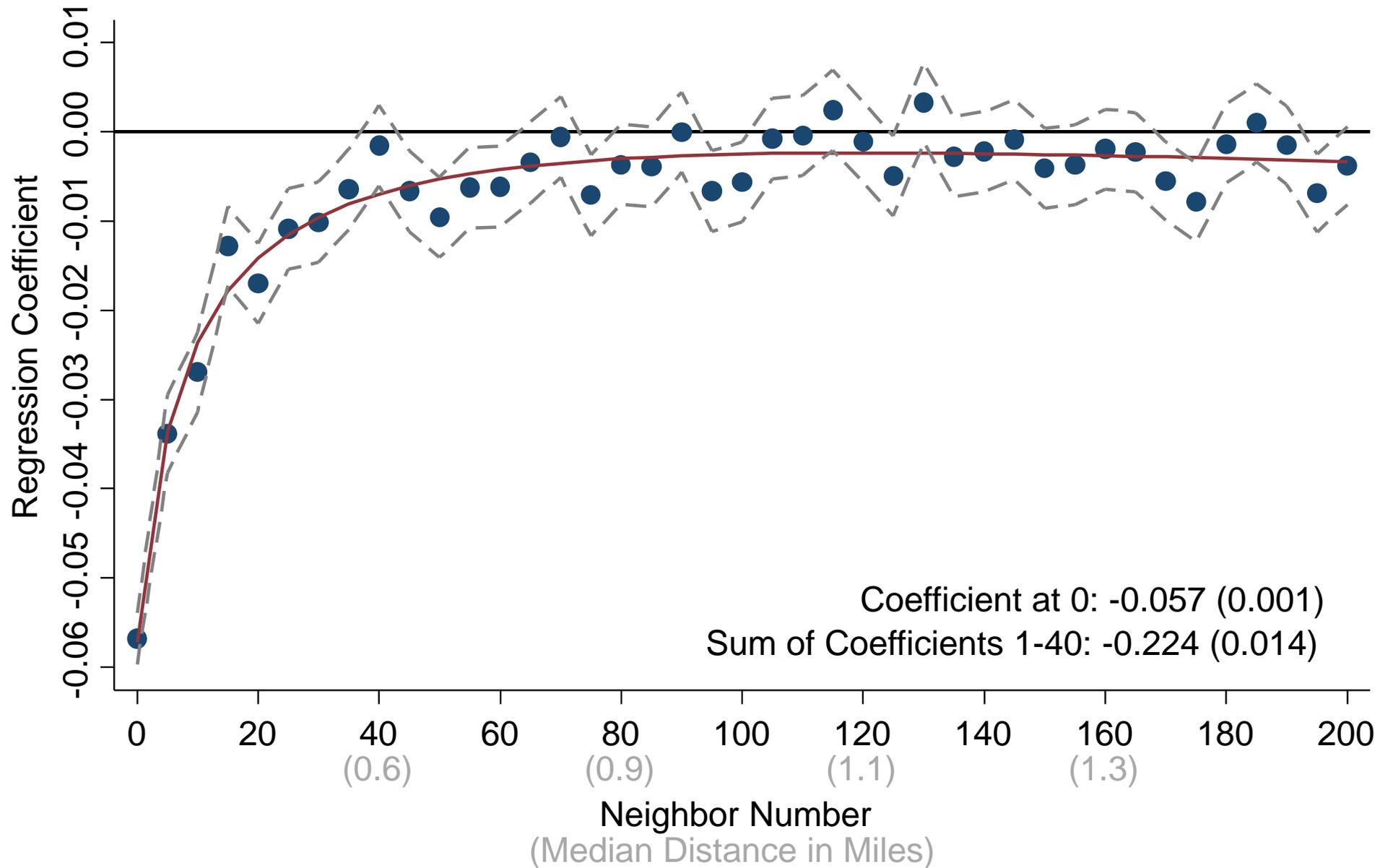
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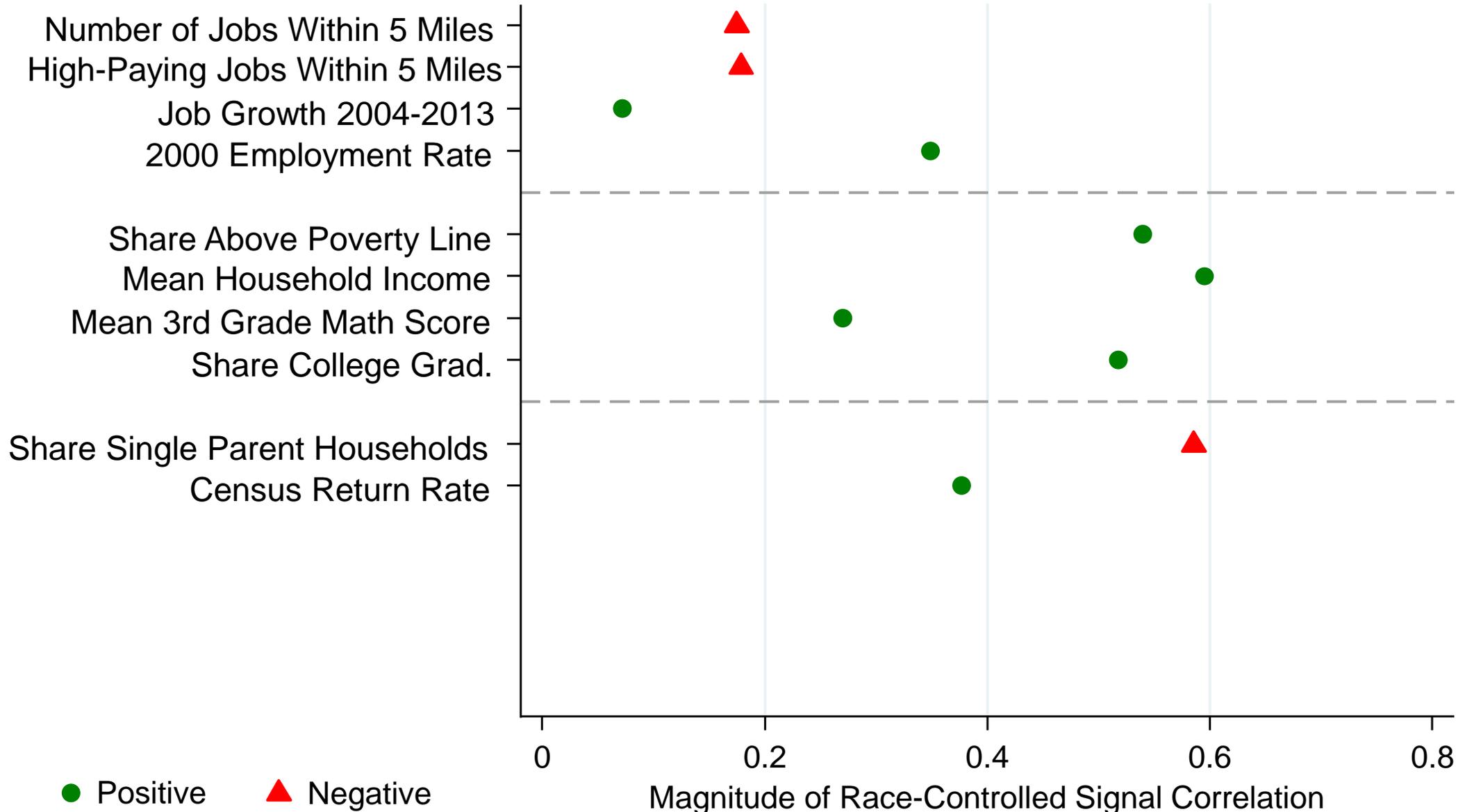
Spatial Decay of Correlation with Block-Level Poverty Rate

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



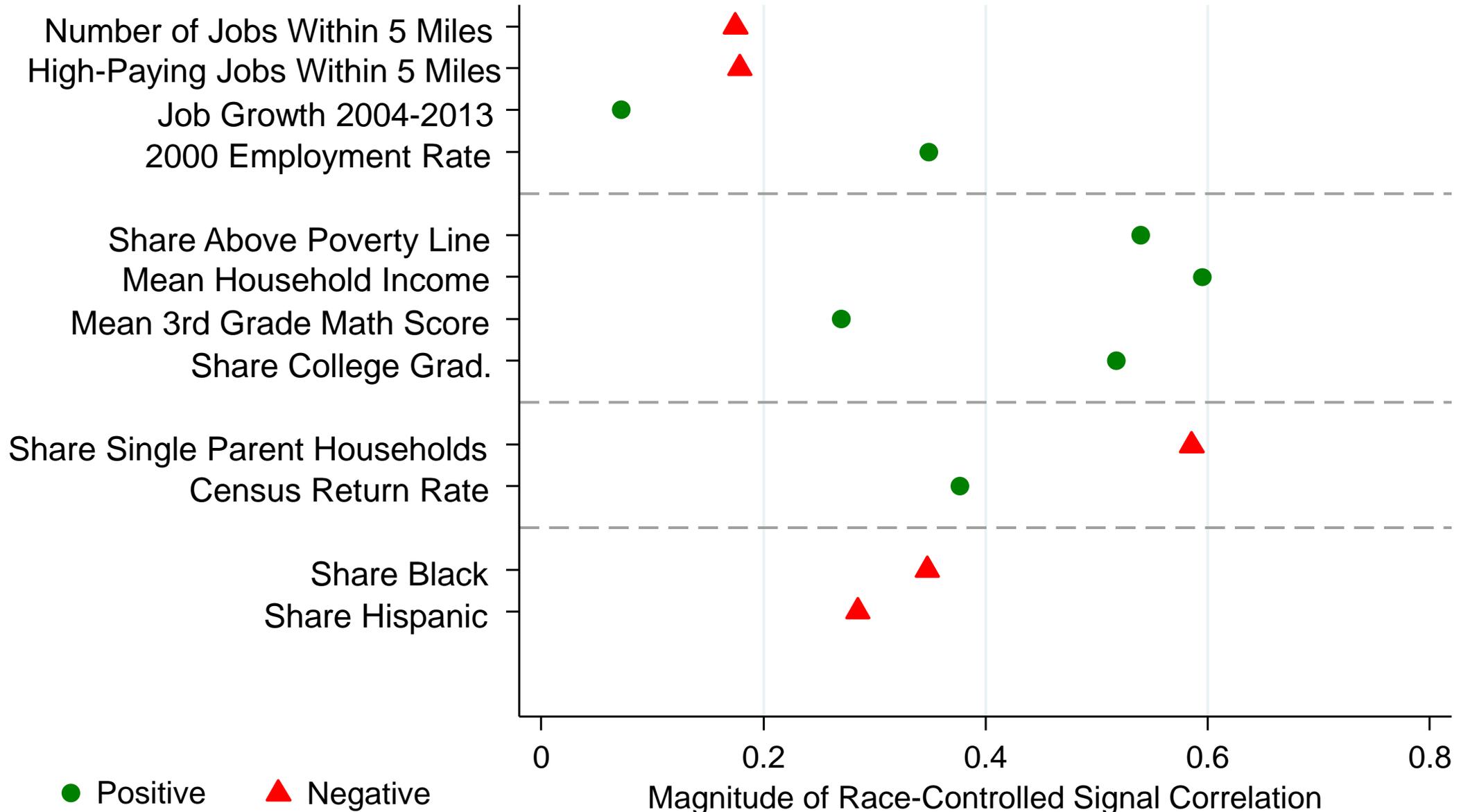
Correlations between Tract-Level Covariates and Household Income Rank

Race-Adjusted, Parent Income at 25th Percentile



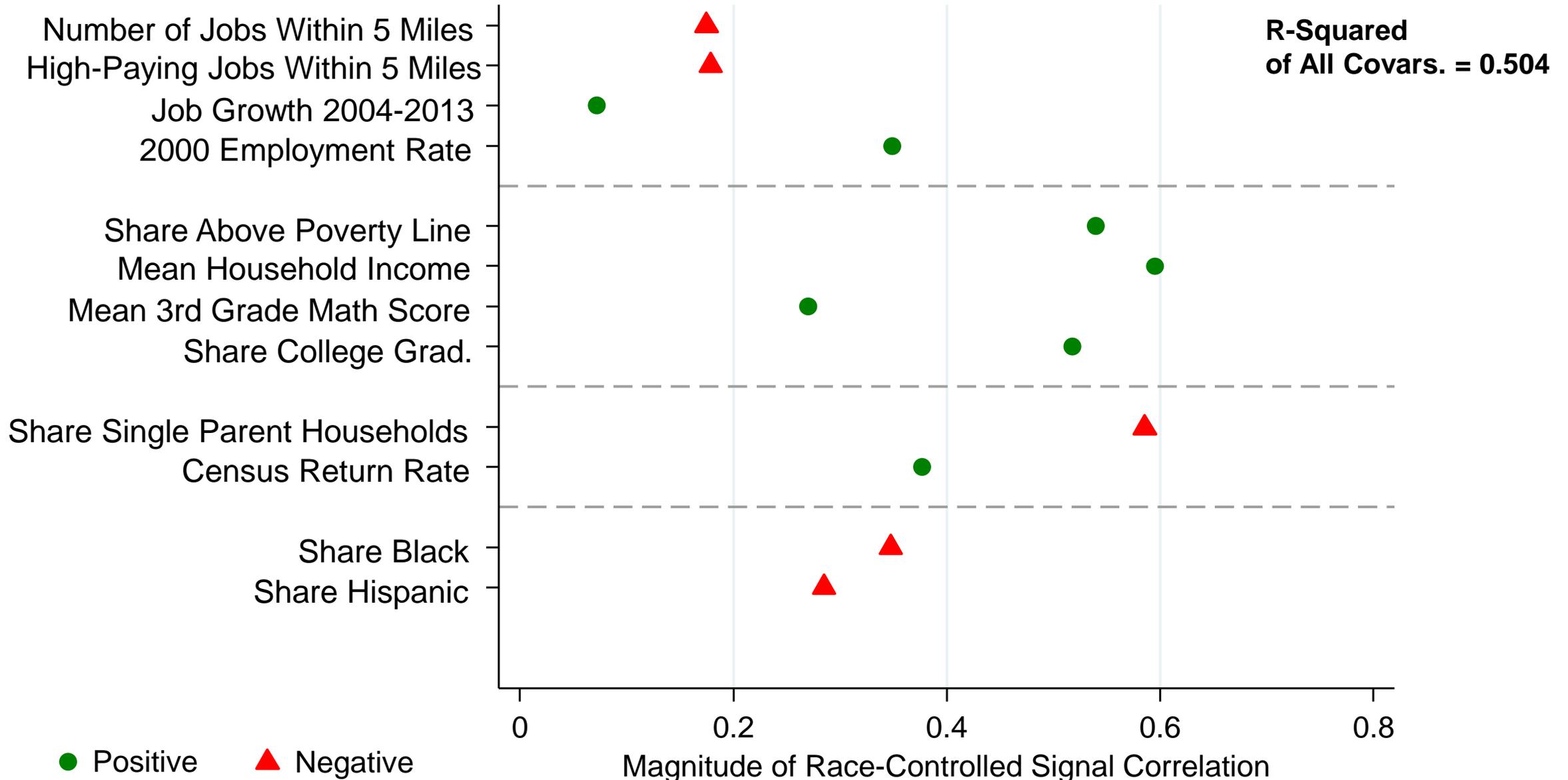
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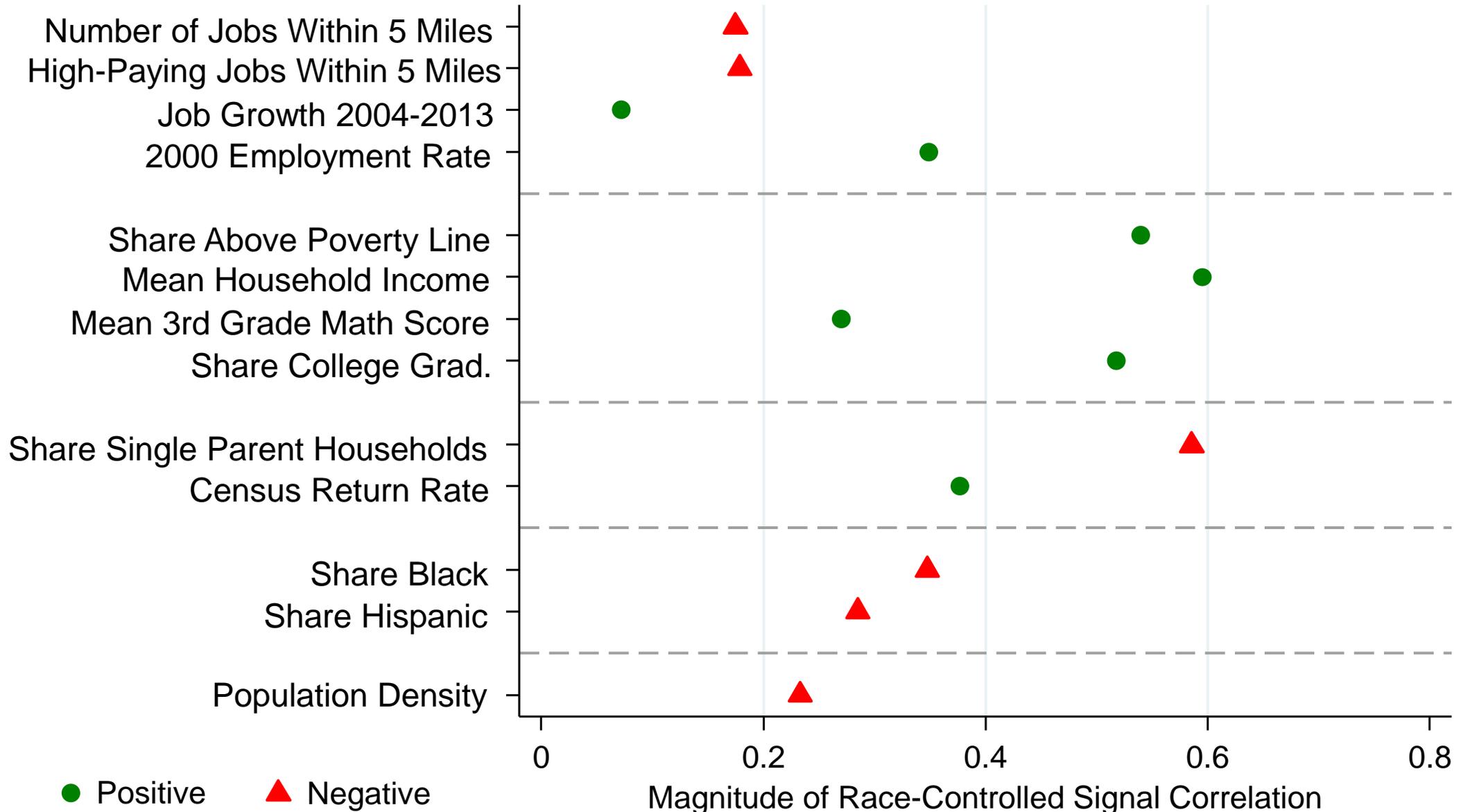
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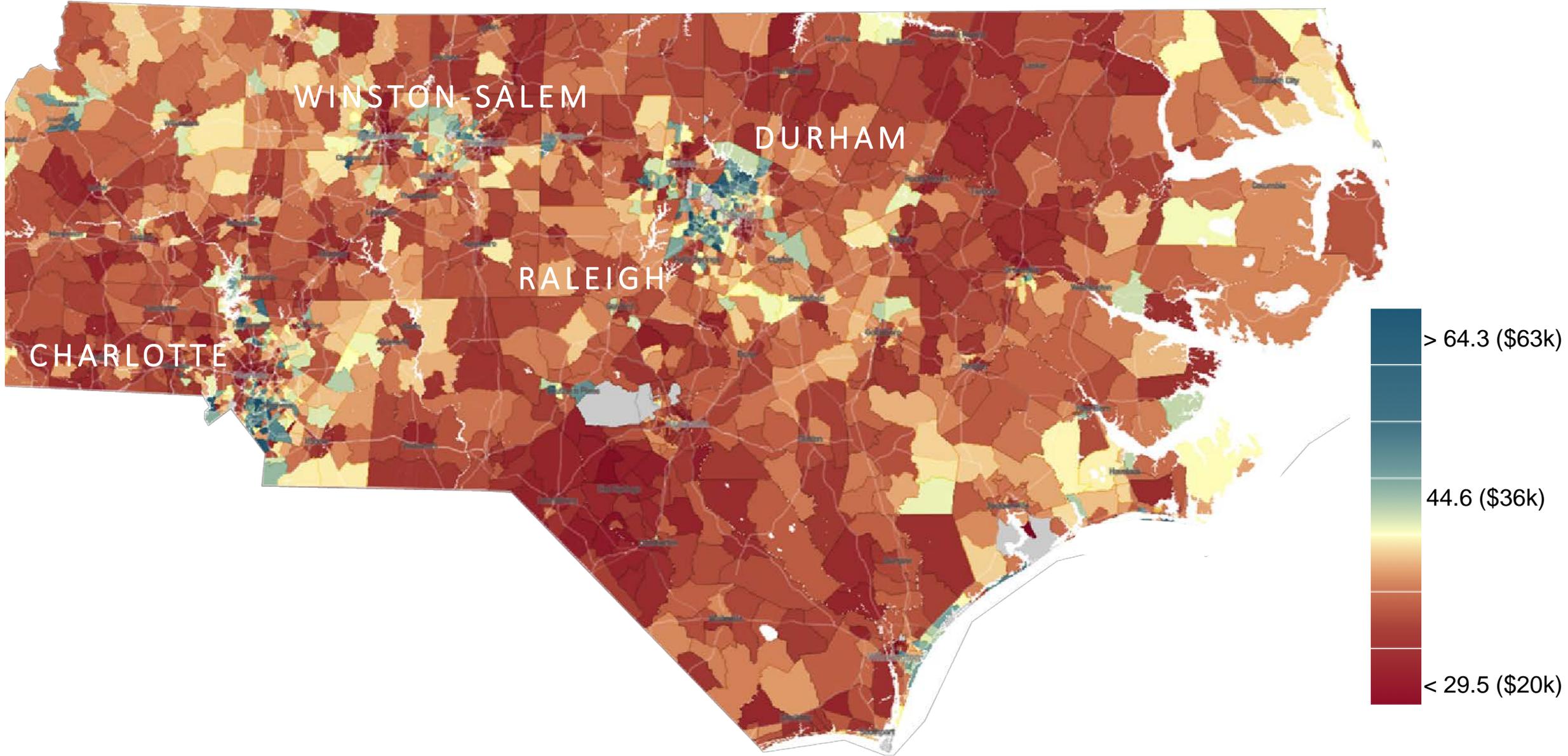
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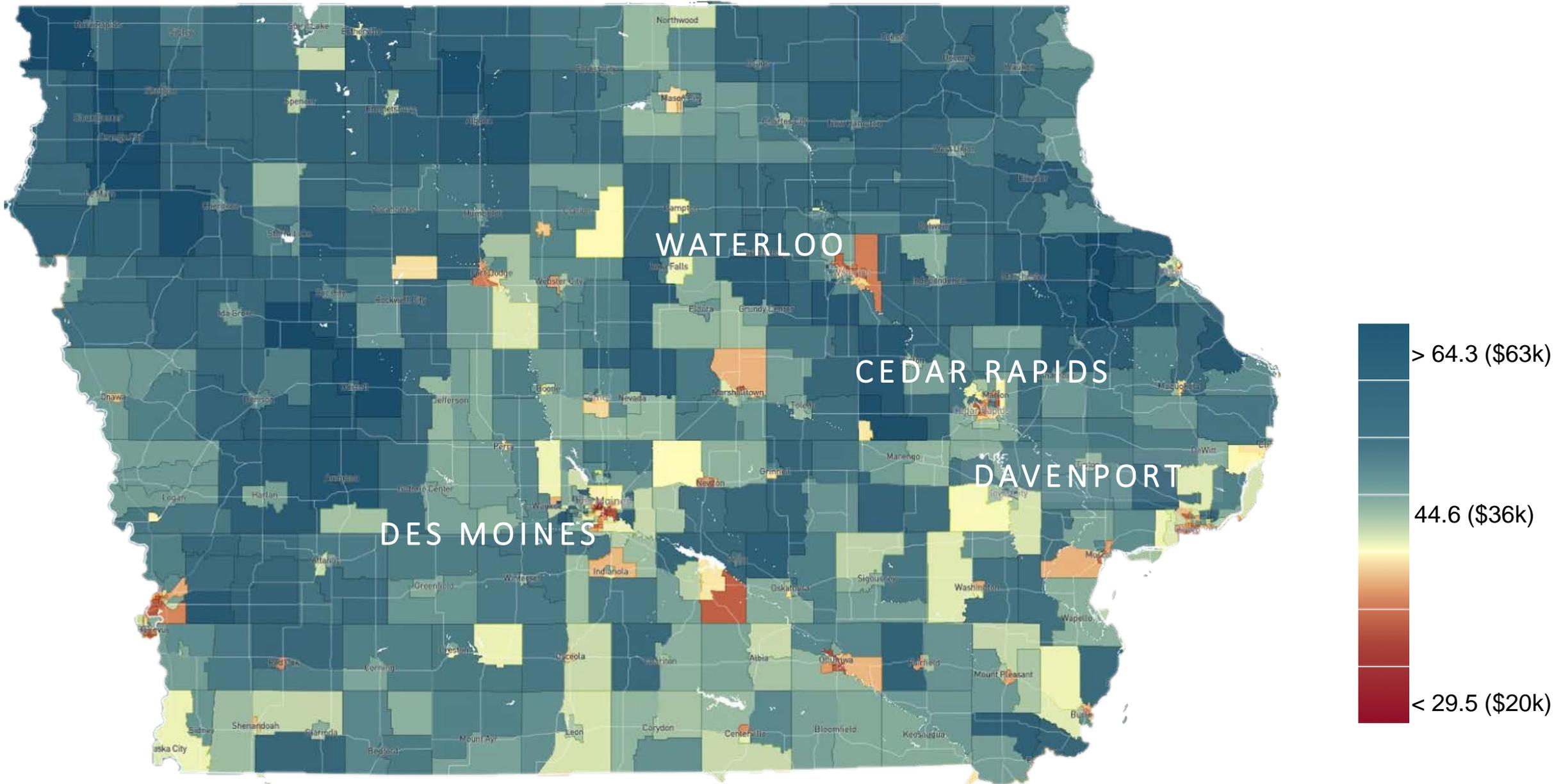
Do Cities Offer Greater Opportunities for Upward Mobility?

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



Are Historical Measures of Social Mobility Still Relevant Today?

- Tract-level estimates of children's appear to provide new information that could be helpful in identifying areas where opportunity is most lacking
 - But are they still relevant today? Yes, on average, for two reasons:
 1. Correlation of mean outcomes across tracts within CZs is high across cohorts
 - 90% signal correlation between 1980 cohort and 1990 cohort outcomes across tract (excluding cohort-specific shocks, which are not predictable)
 2. Historical outcomes are **better** predictors than other observables

The Opportunity Atlas via Two Applications

1 Observational Variation and Targeting

2 Causal Effects and Neighborhood Choice

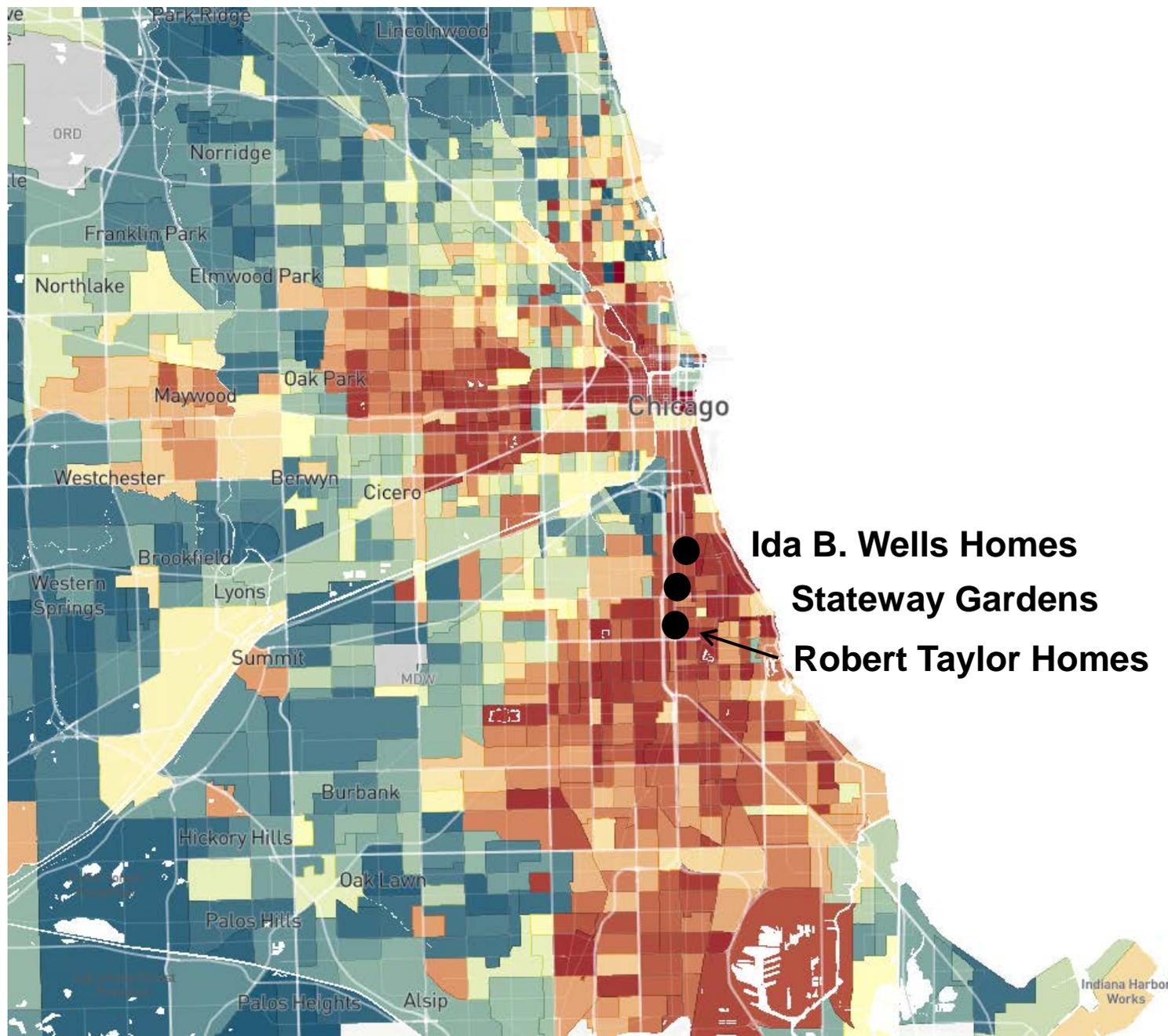
Neighborhood Choice and Causal Effects of Place

- 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

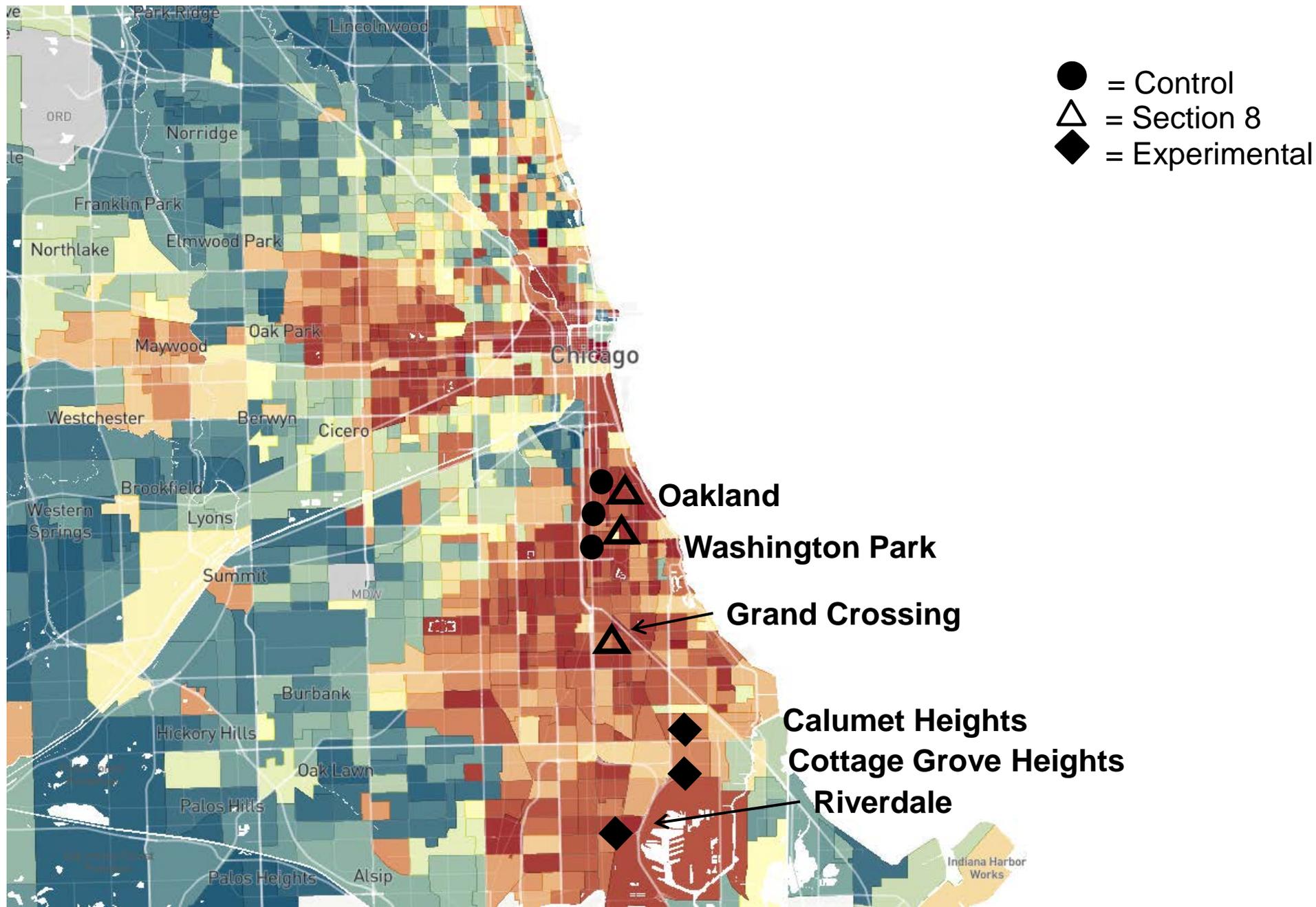
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago



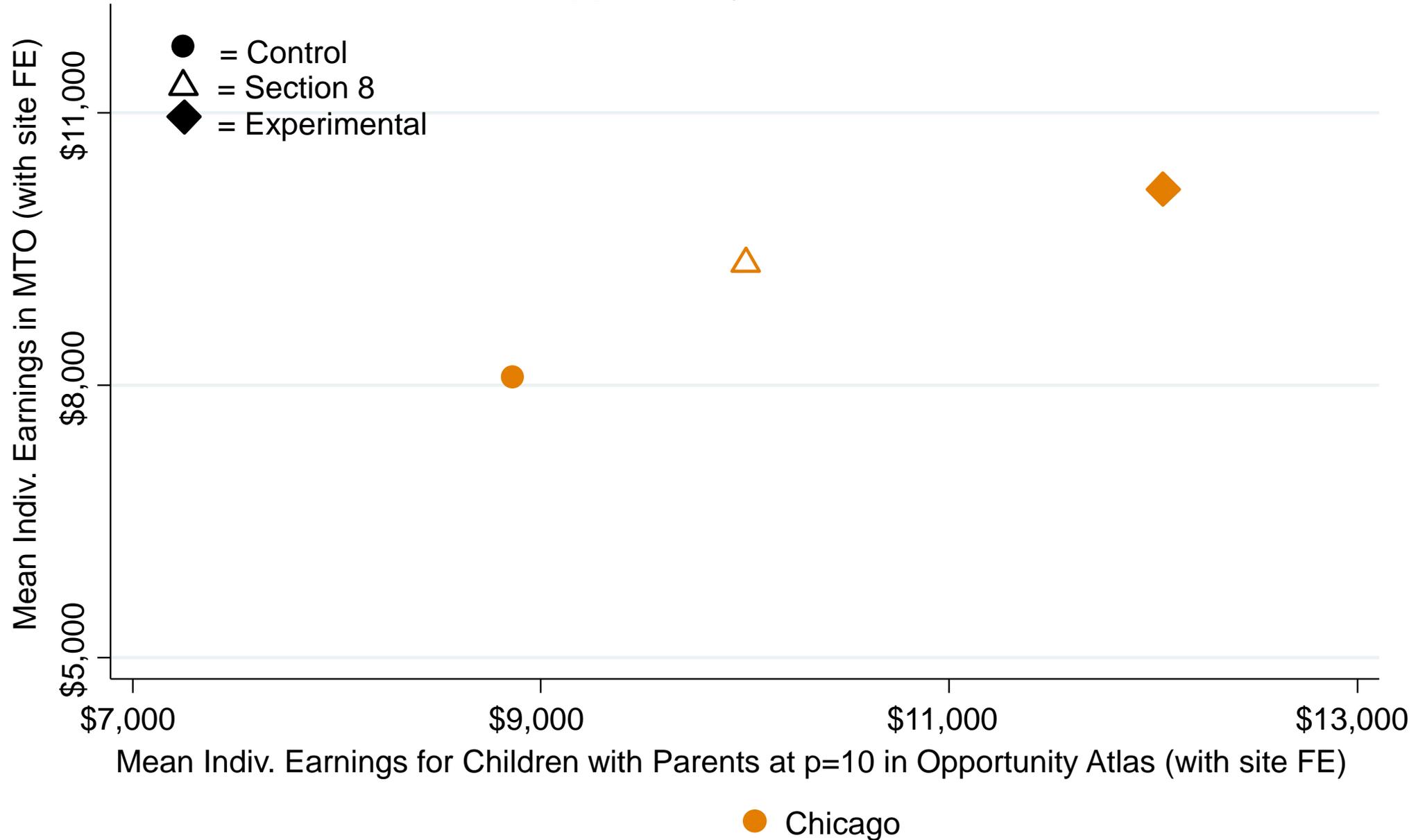
- = Control
- △ = Section 8
- ◆ = Experimental

Ida B. Wells Homes
Stateway Gardens
Robert Taylor Homes

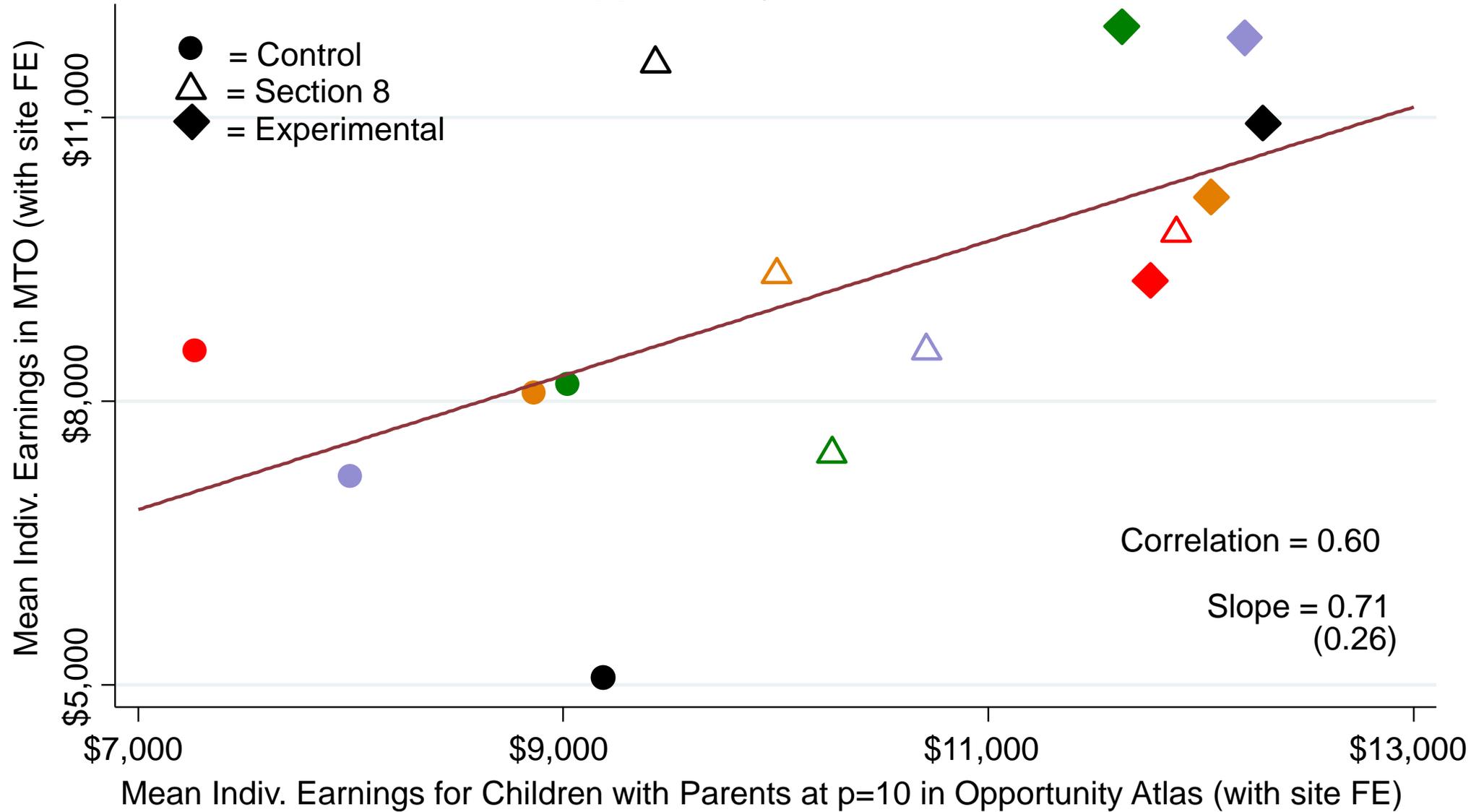
Moving To Opportunity Experiment: Origin and Destination Locations in Chicago



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



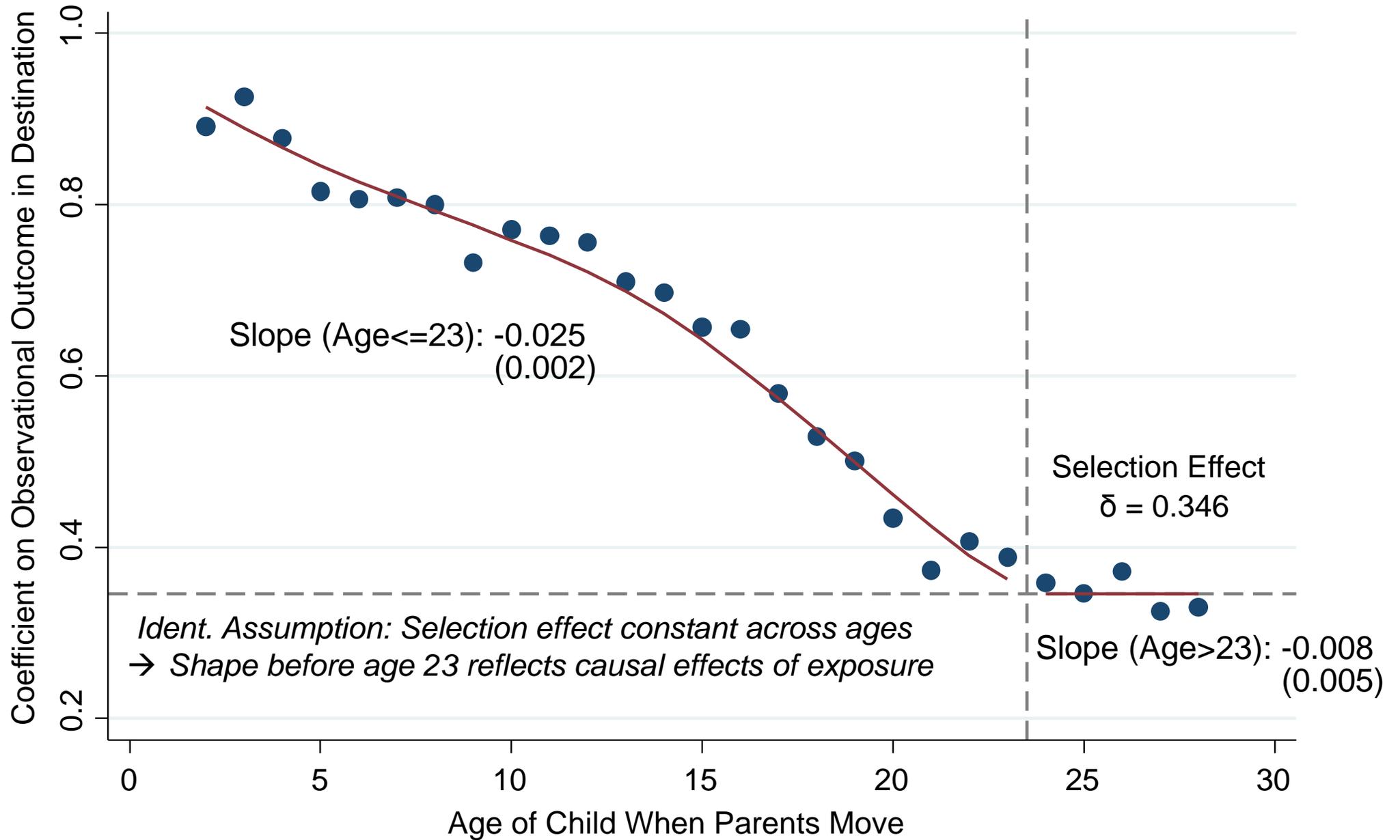
Earnings of Young Children in MTO Experiment vs. Observational Predictions from Opportunity Atlas



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)

Childhood Exposure Effects on Household Income Rank at Age 24



Identifying Causal Exposure Effects

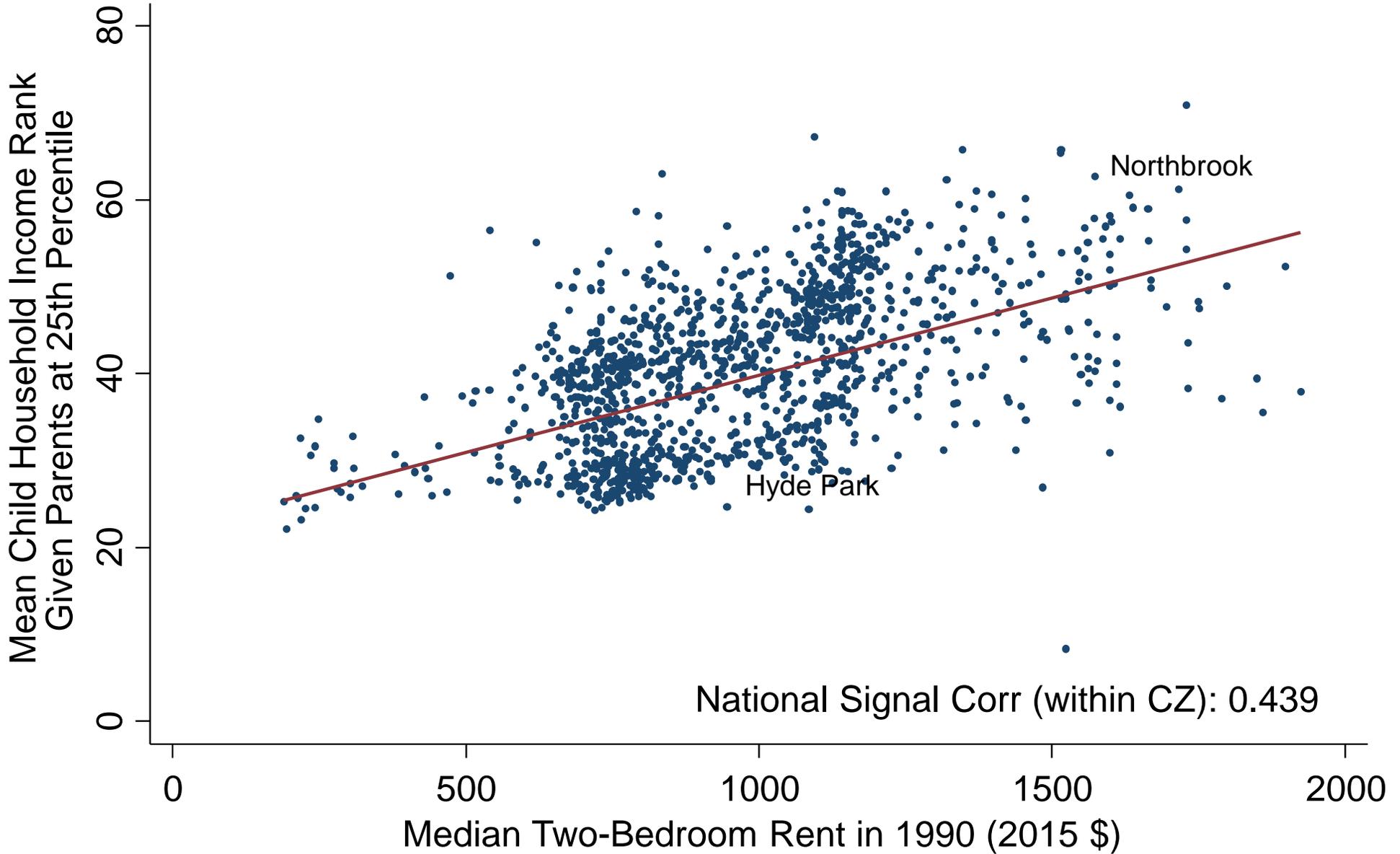
- Use two approaches to evaluate validity of key assumption, following Chetty and Hendren (2018):
 1. Sibling comparisons to control for family fixed effects
 2. Outcome-based placebo tests exploiting heterogeneity in place effects by gender, quantile, and outcome
 - Ex: moving to a place where boys have high earnings → son improves in proportion to exposure but daughter does not

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 → \$200K 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?

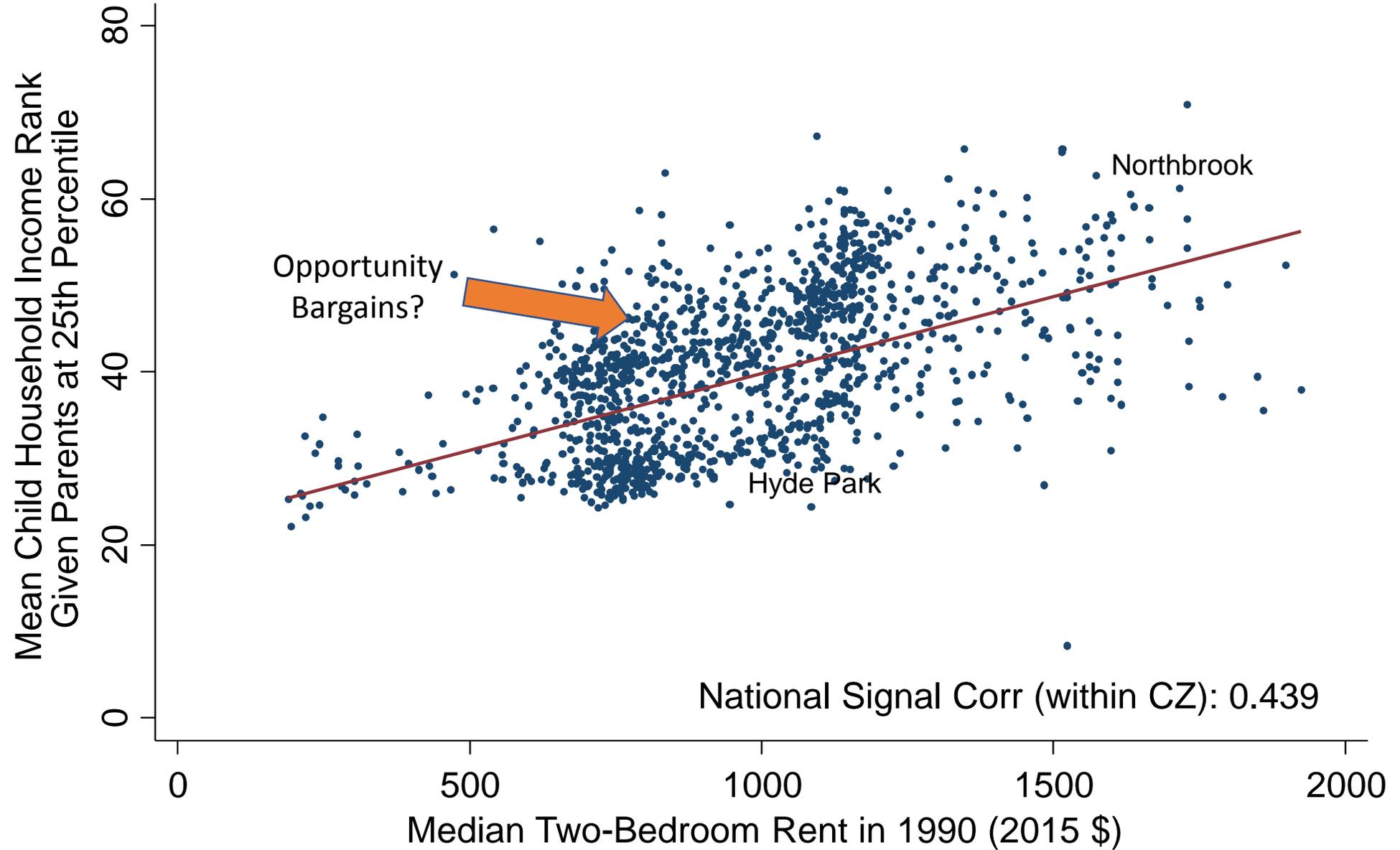
Children's Mean Income Ranks in Adulthood vs. Median Rents in Chicago, by Tract

Children with Parents at 25th Percentile



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

Children with Parents at 25th Percentile



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, e.g. longer commutes
 - Alternative explanation: lack of information or barriers such as discrimination [DeLuca et al 2016, Christensen and Timmins 2018]
- Key Question: if we relax the barriers families face to moving to higher opportunity neighborhoods, will they choose to move there?

Creating Moves to Opportunity in Seattle

Randomized trial to help families with vouchers move to “opportunity bargain” areas using three approaches:

- *Information + financial assistance*
- *Landlord recruitment*
- *Brokerage services*

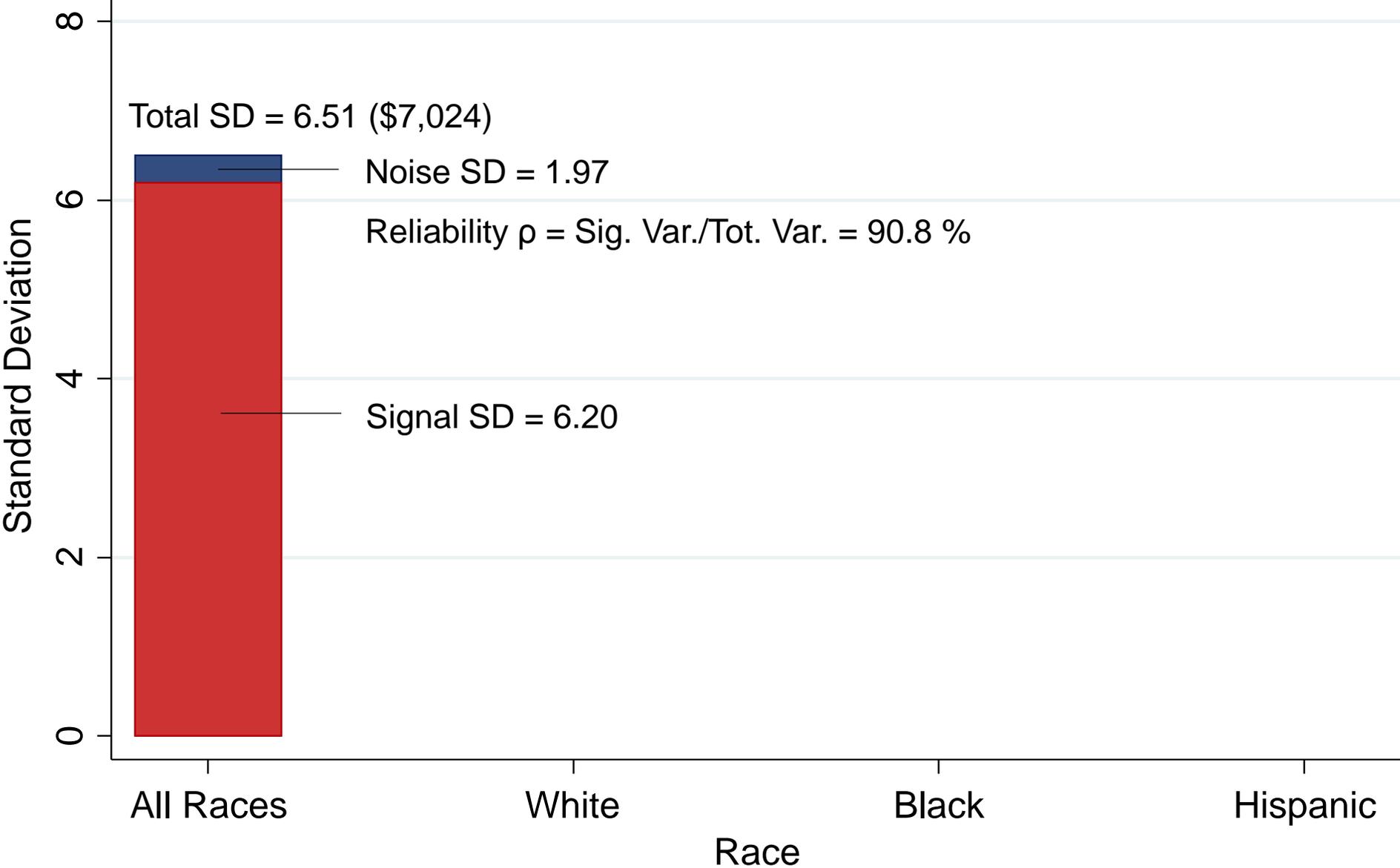


Supplementary Results

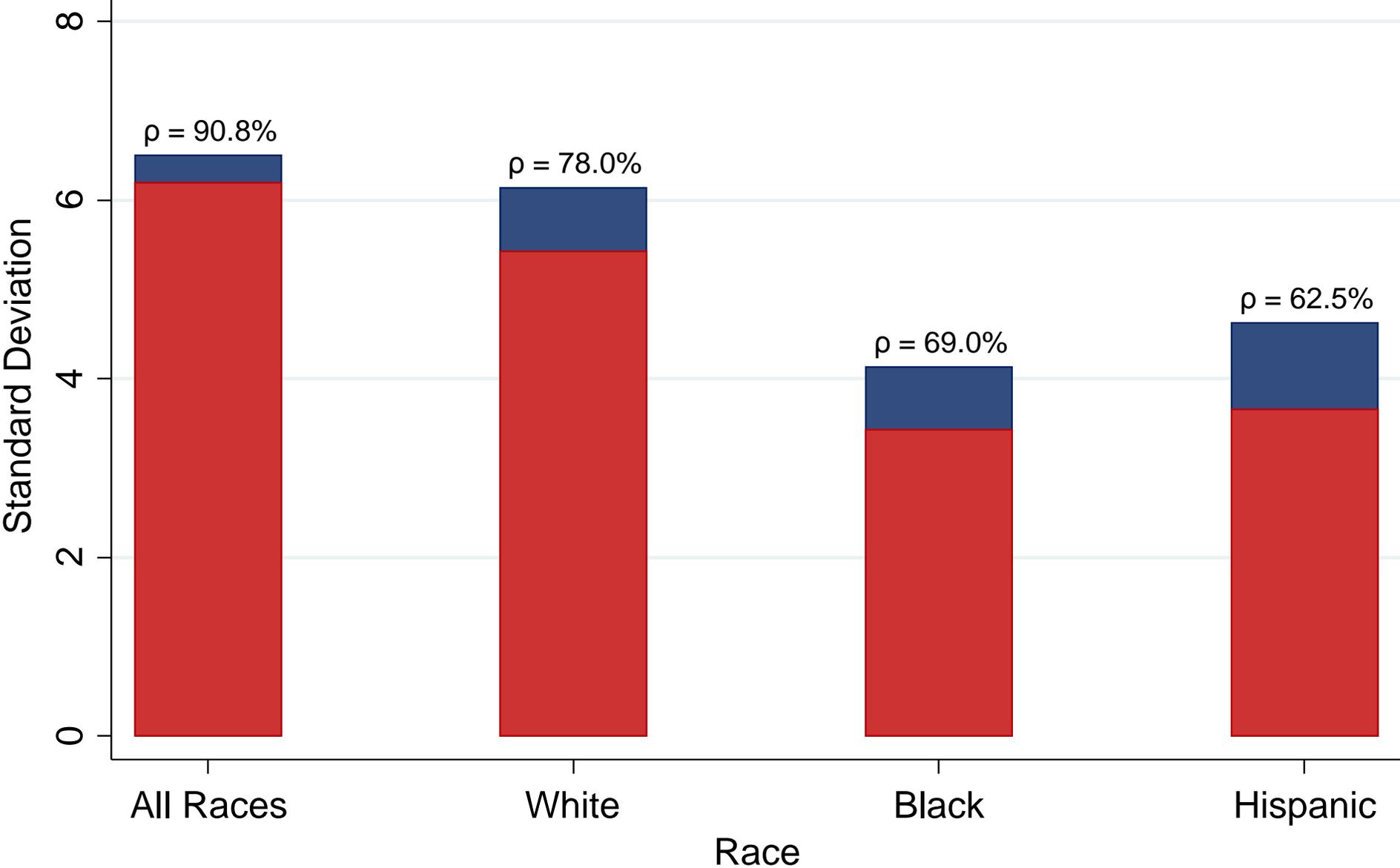
Reliability of Tract-Level Estimates

- 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

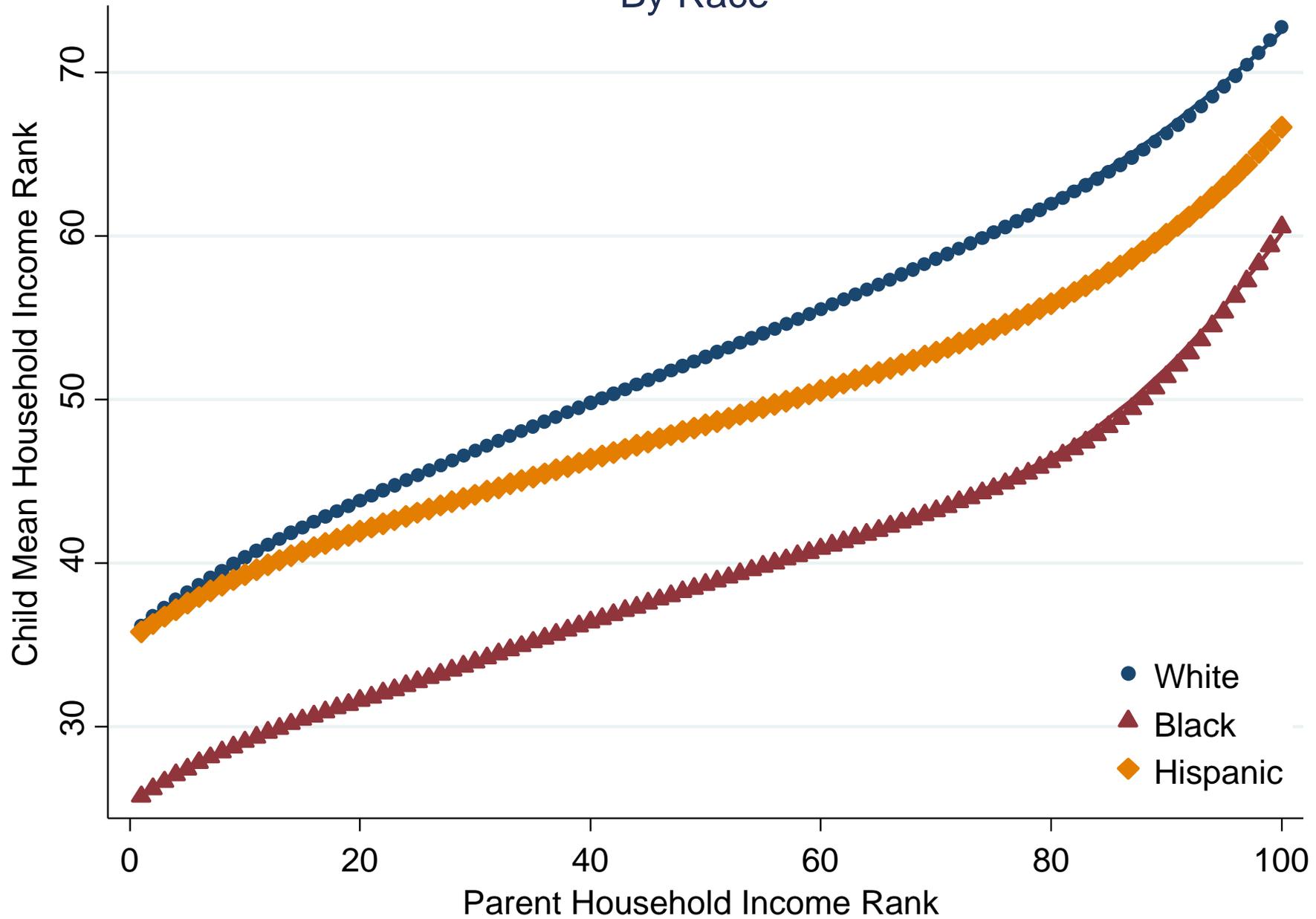
Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates For Children With Parents at 25th Percentile



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

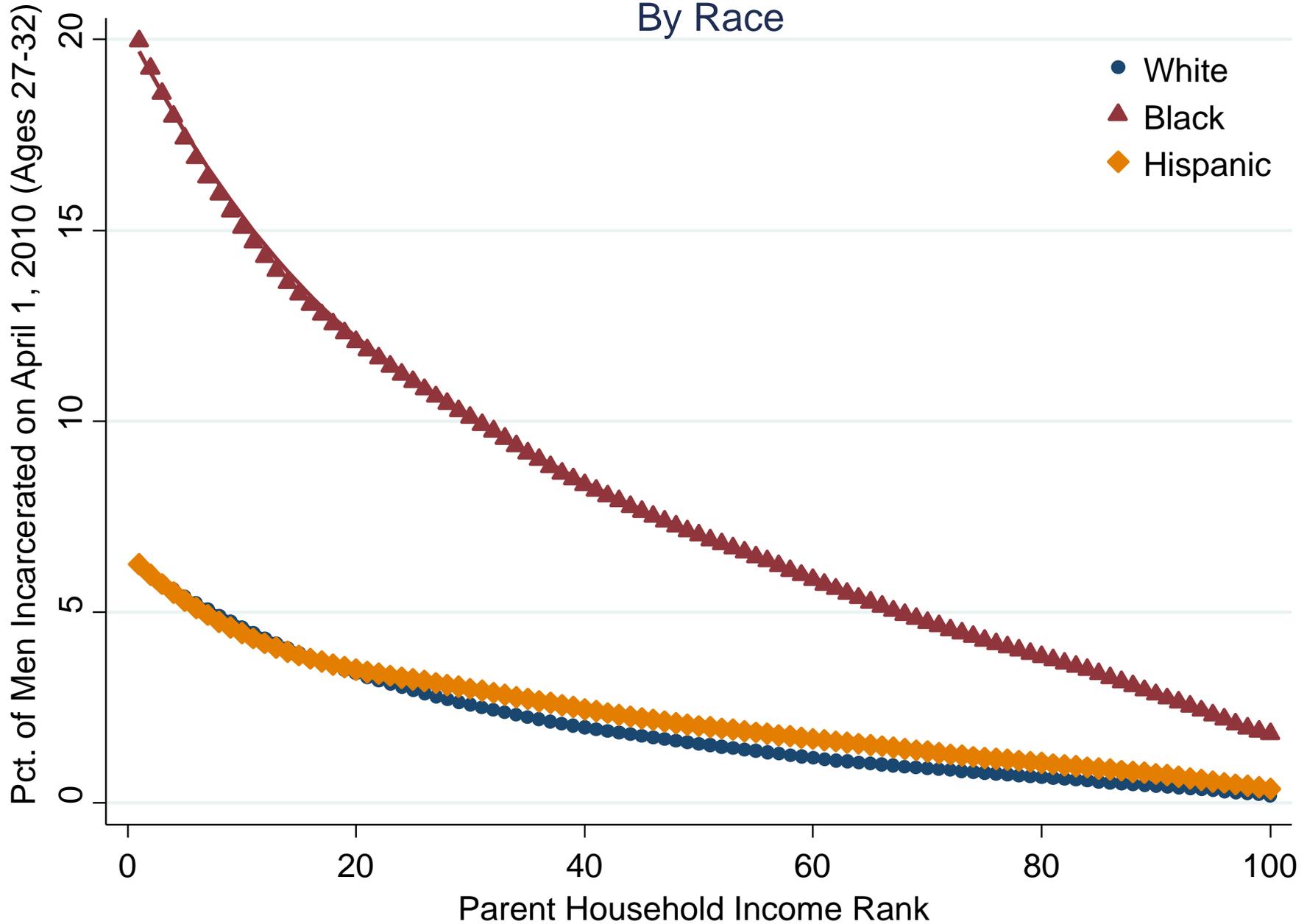


Mean Child Household Income Rank vs. Parent Household Income Rank By Race

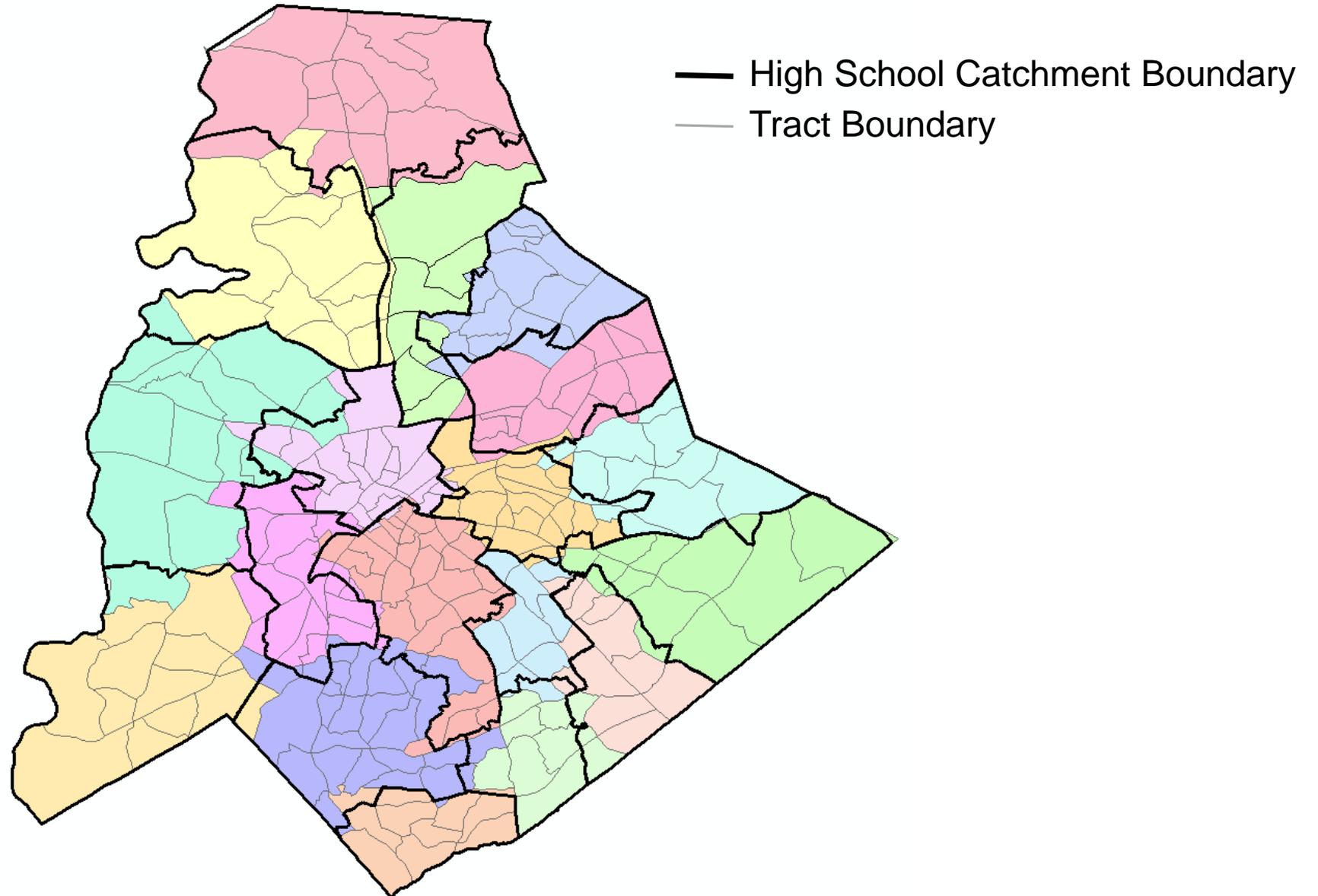


Incarceration Rates vs. Parent Household Income Rank

By Race

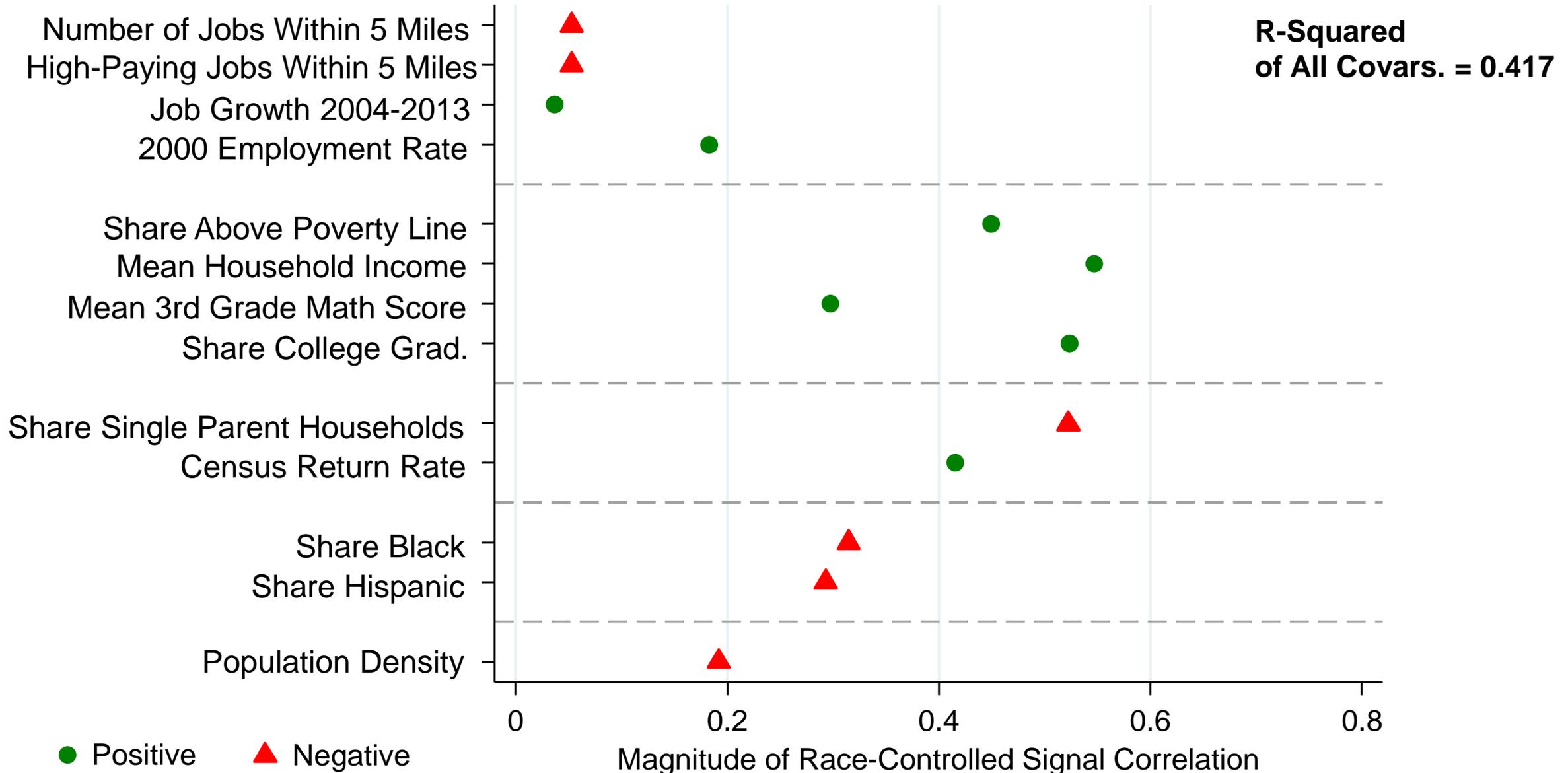


School Catchment Zones in Mecklenburg County: Boundaries vs. Assignment of Tracts to Catchment Zones

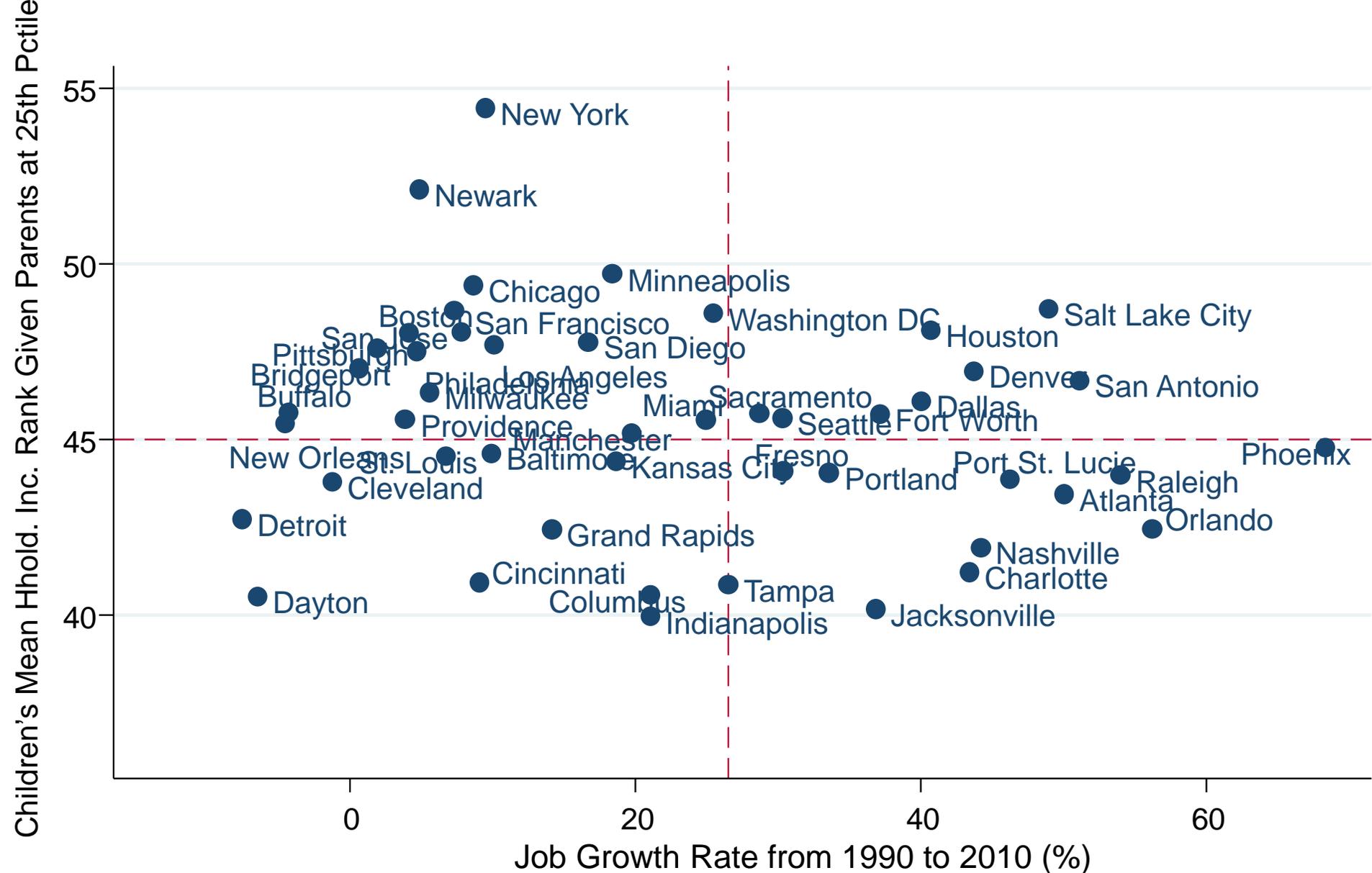


Correlations between Tract-Level Covariates and Household Income Rank

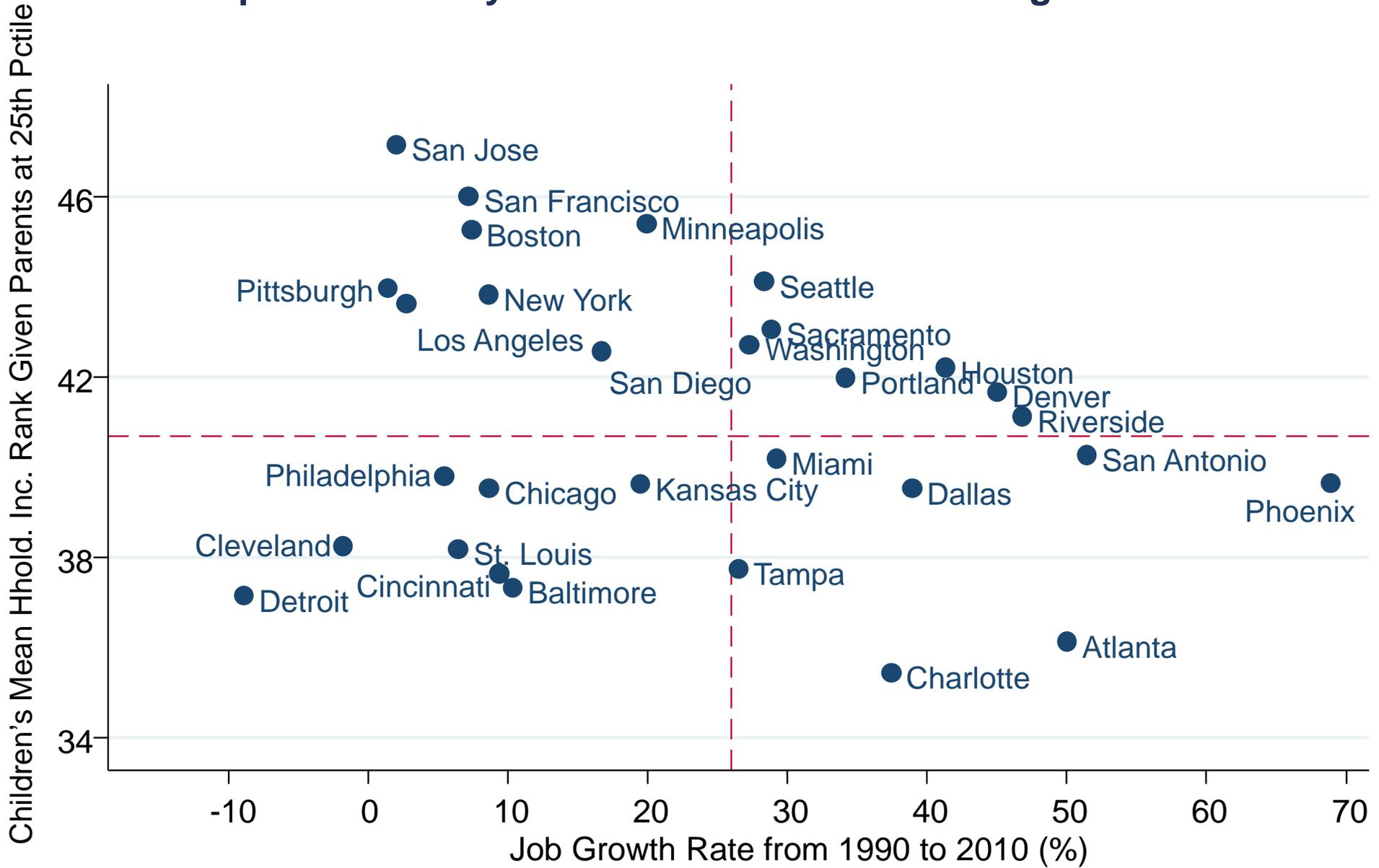
Race-Adjusted, Parent Income at 75th Percentile



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

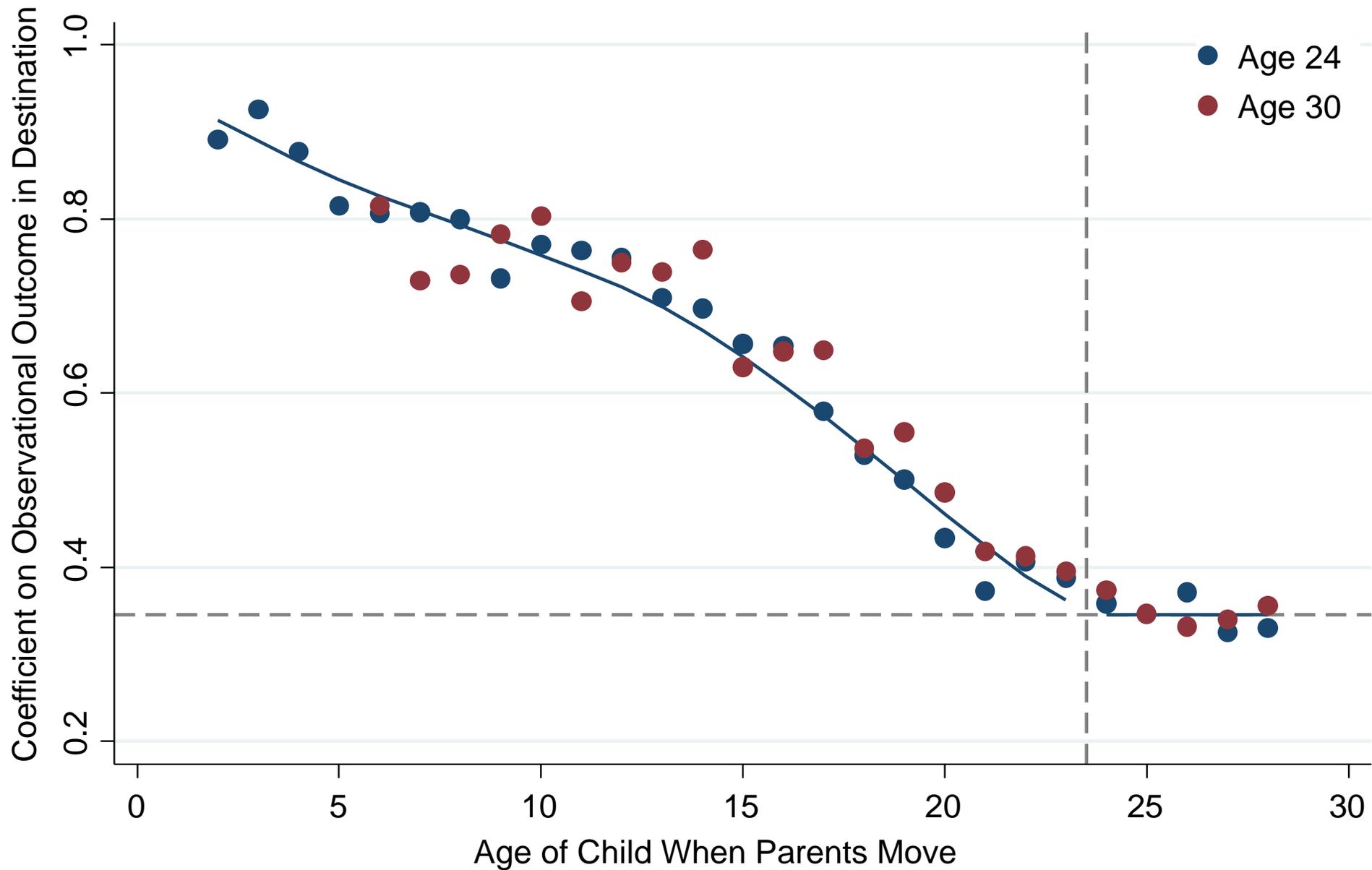


Upward Mobility vs. Job Growth in the 30 Largest MSAs

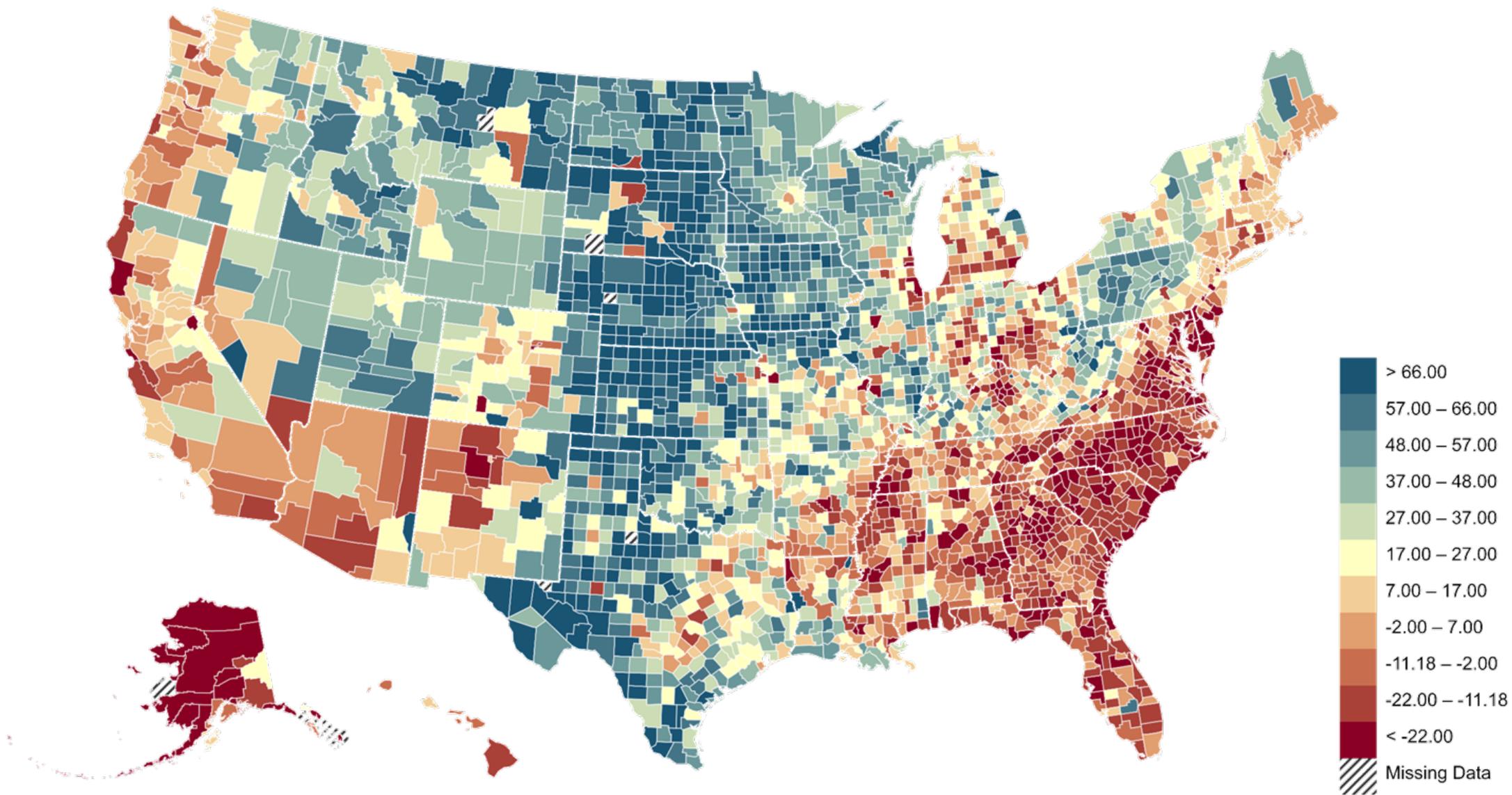


Correlation (across all MSAs): -0.07

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

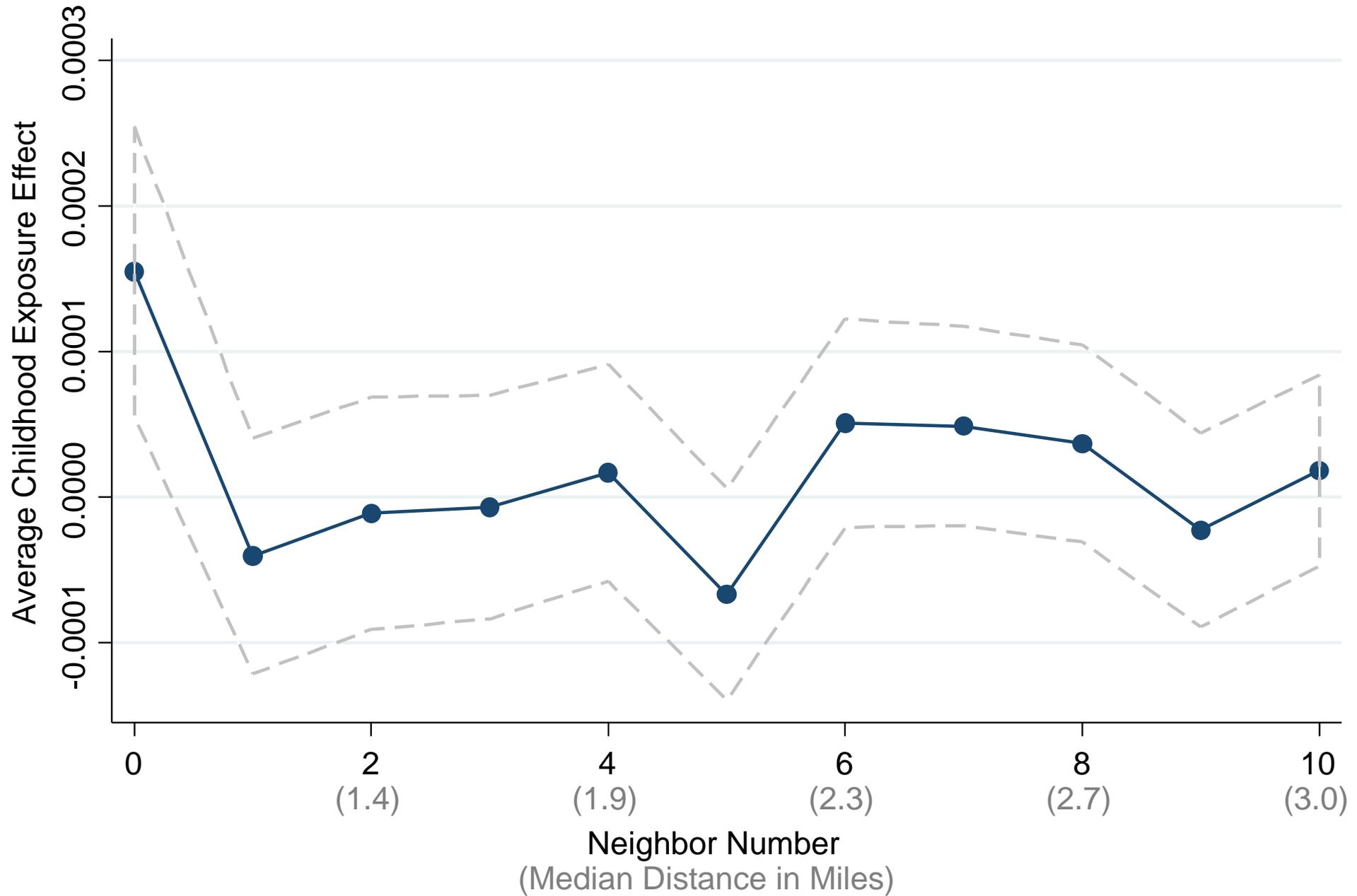
Childhood Exposure Effects on Household Income Rank at Age 24

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



Childhood Exposure Effects on Other Outcomes
For Female Children of All Races

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

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

Estimating Mean Outcomes by Tract

- 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
- Challenge: Not enough data to estimate these means non-parametrically for each group

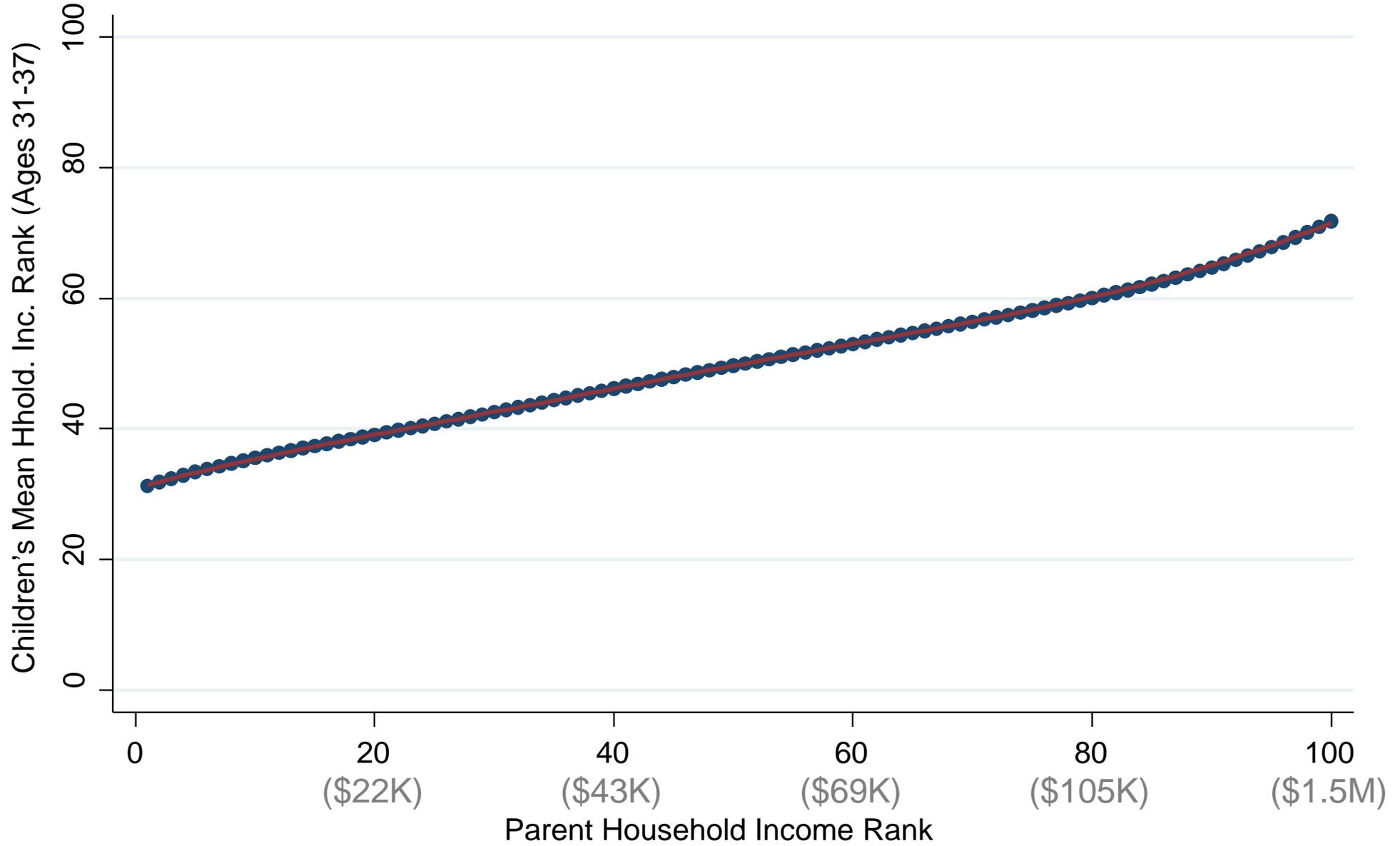
Estimating Mean Outcomes by Tract

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

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

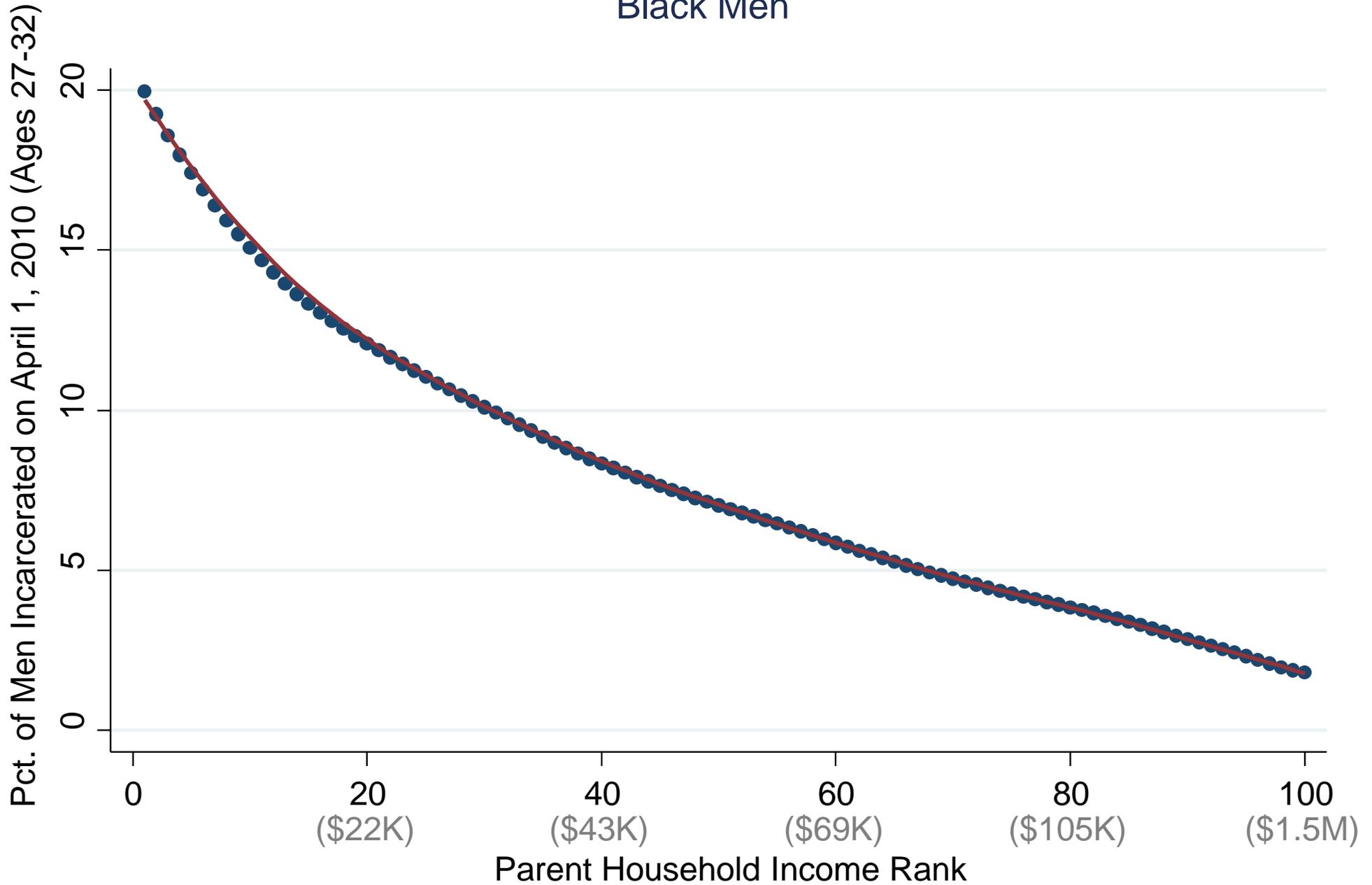
- Function f_{rg} estimated non-parametrically in national data, by race and gender

Mean Child Household Income Rank vs. Parent Household Income Rank



Incarceration Rates vs. Parent Household Income Rank

Black Men



Estimating Mean Outcomes by Tract

- 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:

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

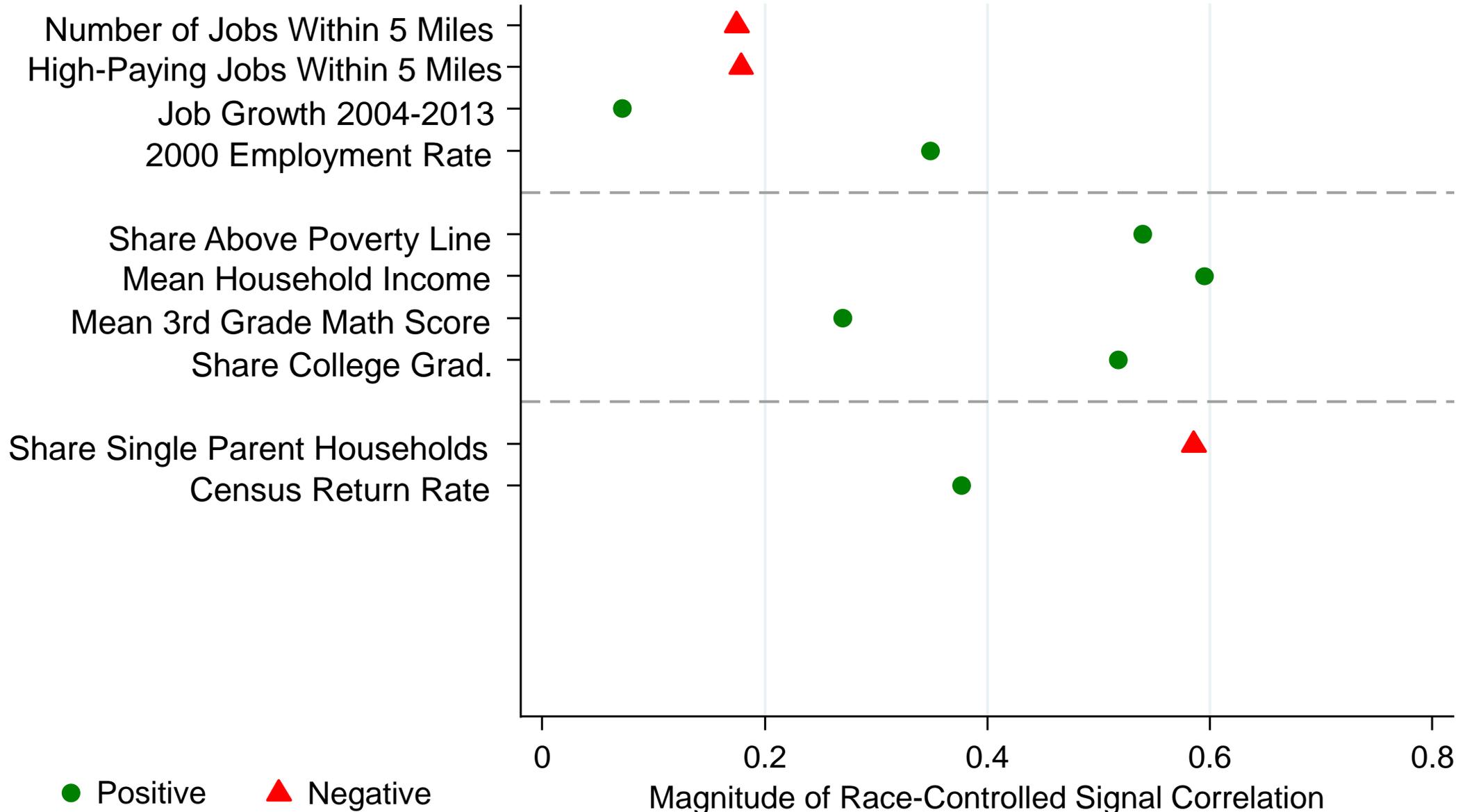
- Function f_{rg} estimated non-parametrically in national data, by race and gender
- In practice, many children move across tracts in childhood
 - Weight children in each tract-level regression by fraction of childhood (up to age 23) spent in that tract

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
- Translate mean rank outcomes back to dollar values based on income distribution of children in their mid-30s (in 2015) for ease of interpretation

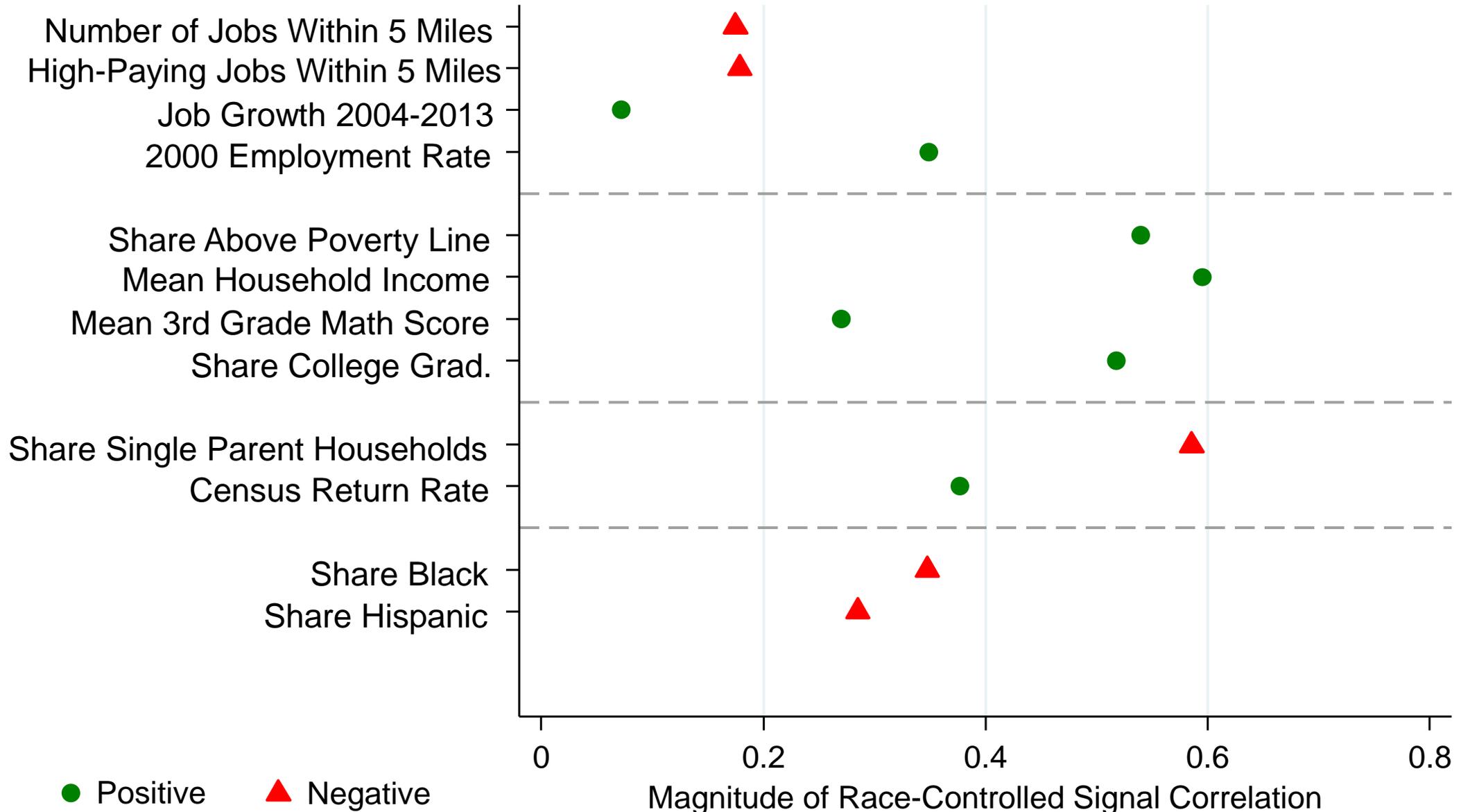
Correlations between Tract-Level Covariates and Household Income Rank

Race-Adjusted, Parent Income at 25th Percentile



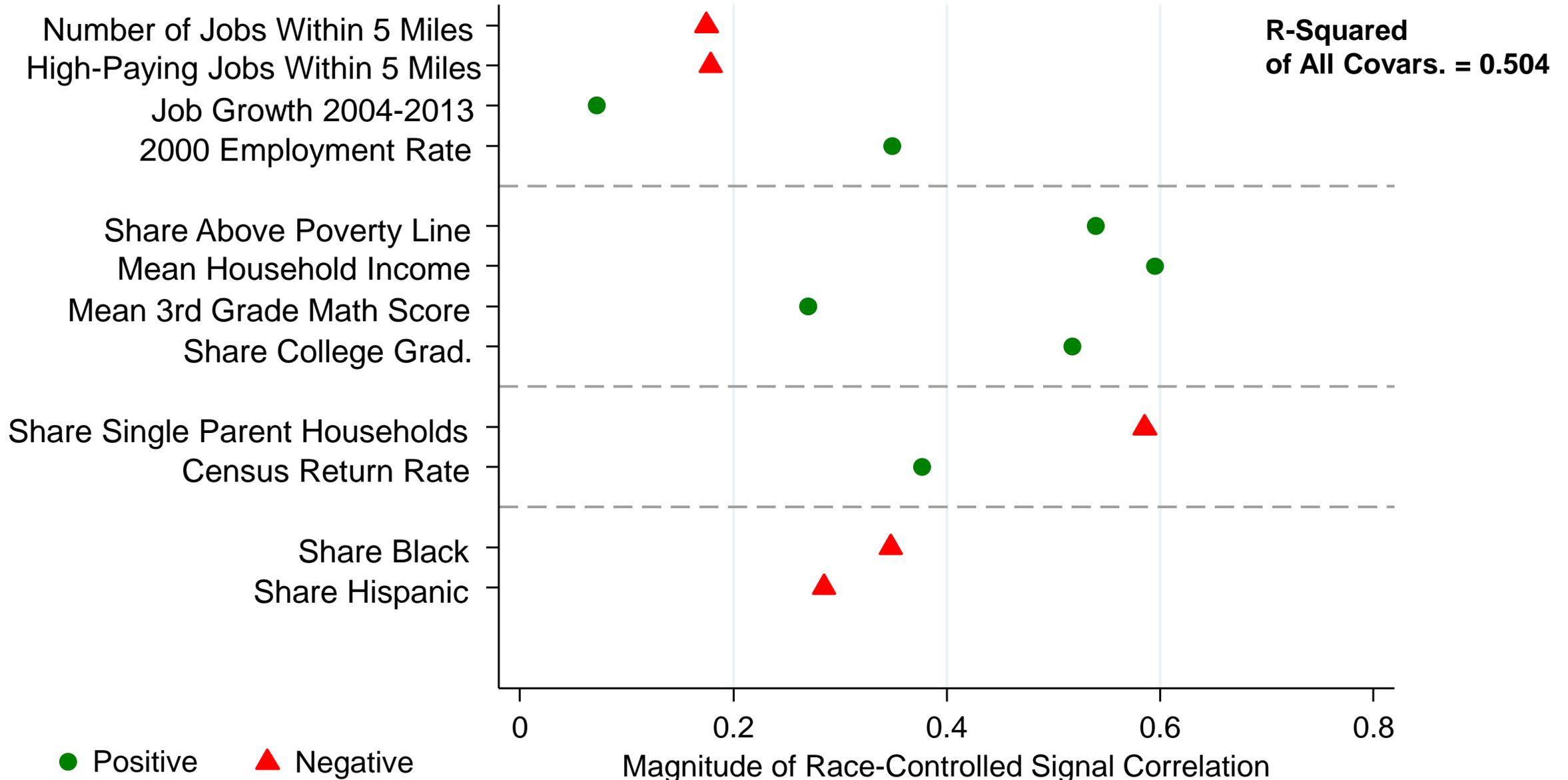
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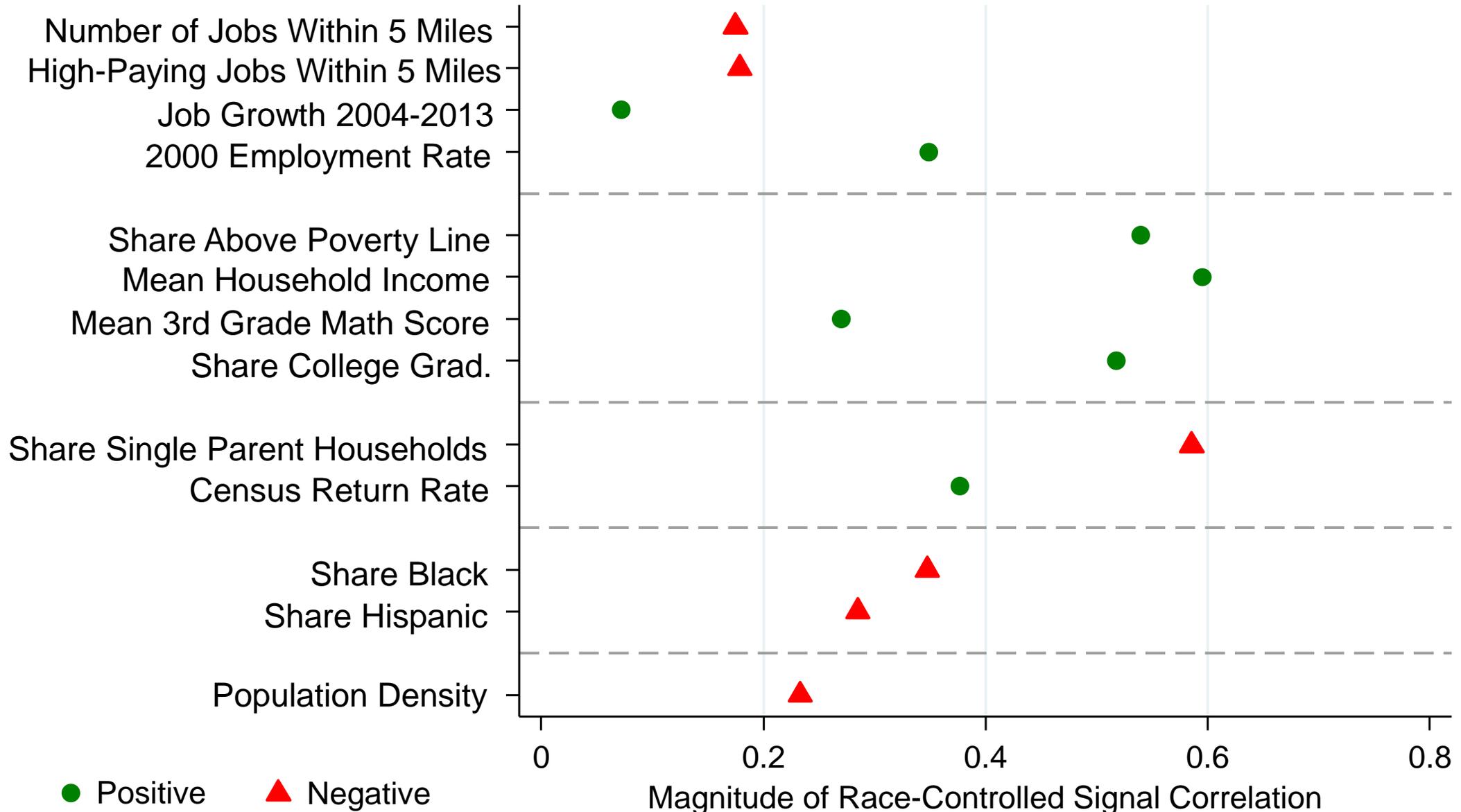
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Correlations between Tract-Level Covariates and Household Income Rank

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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

Targeting Place-Based Policies

- 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

Estimating Exposure Effects in Observational Data

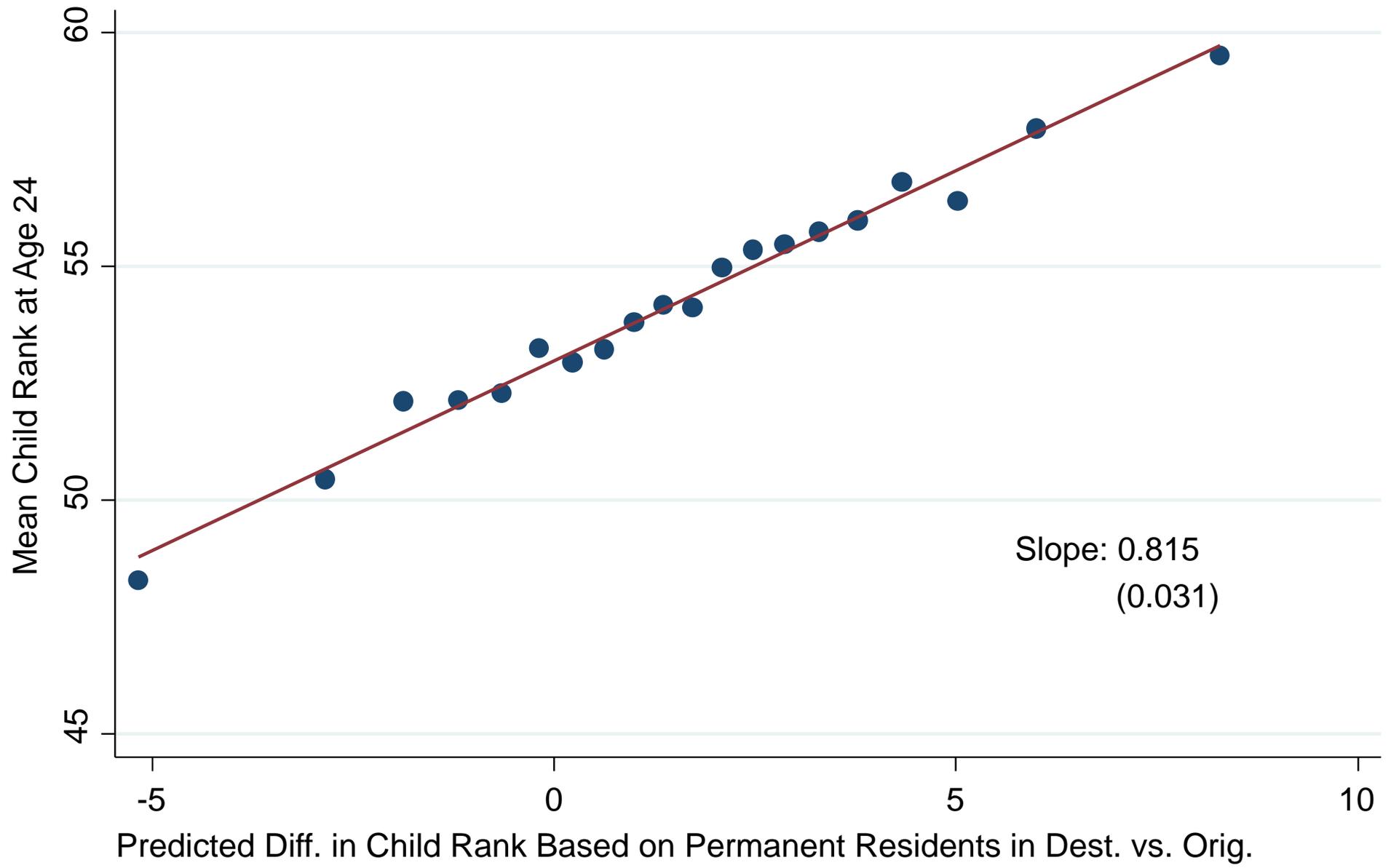
- To begin, consider families who move when child is exactly 5 years old
- Regress child's income rank in adulthood y_i on mean rank of children with same parental income level in destination:

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

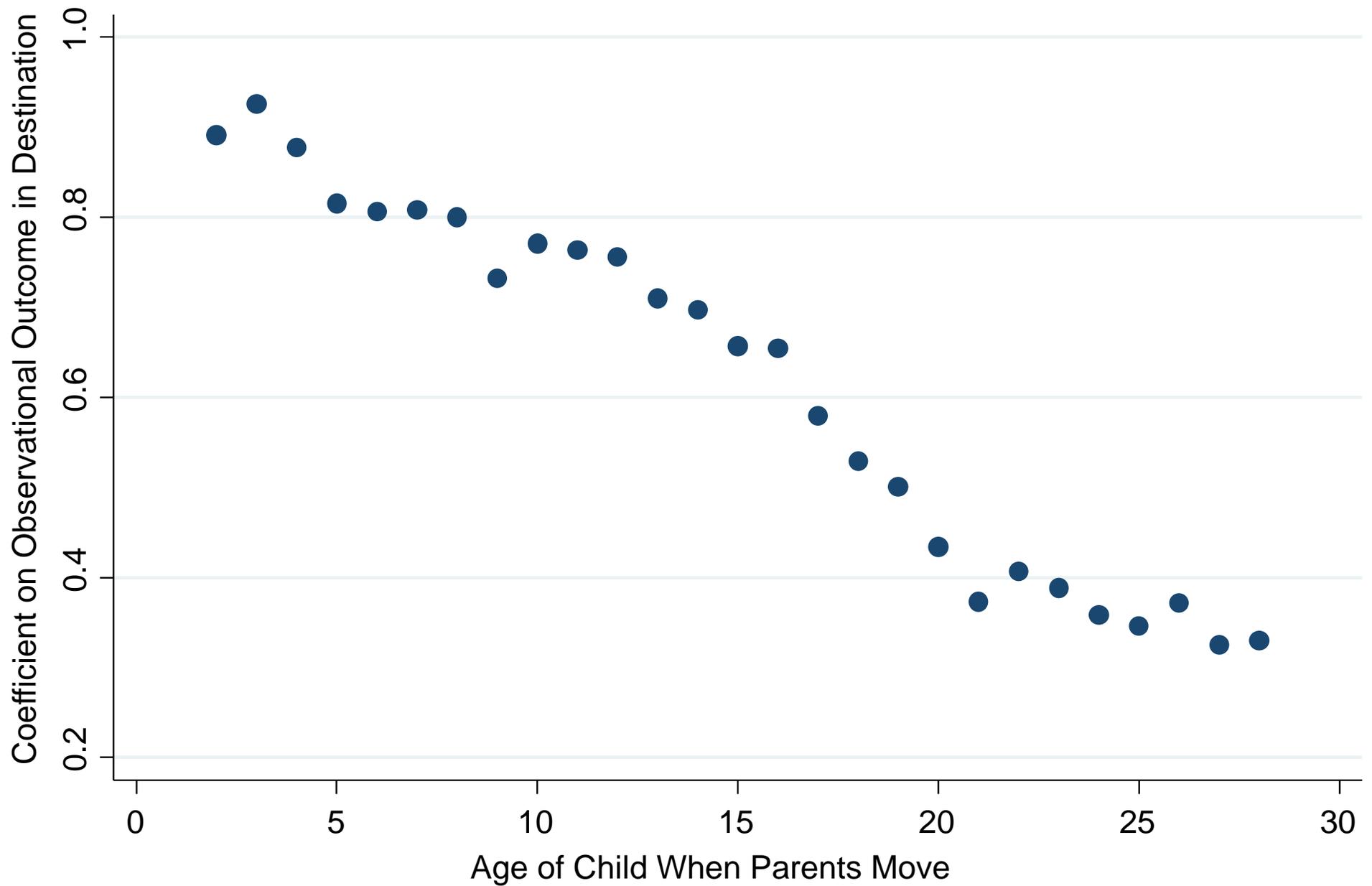
- Include parent decile (q) by origin (o) fixed effects to identify b_m purely from differences in destinations

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

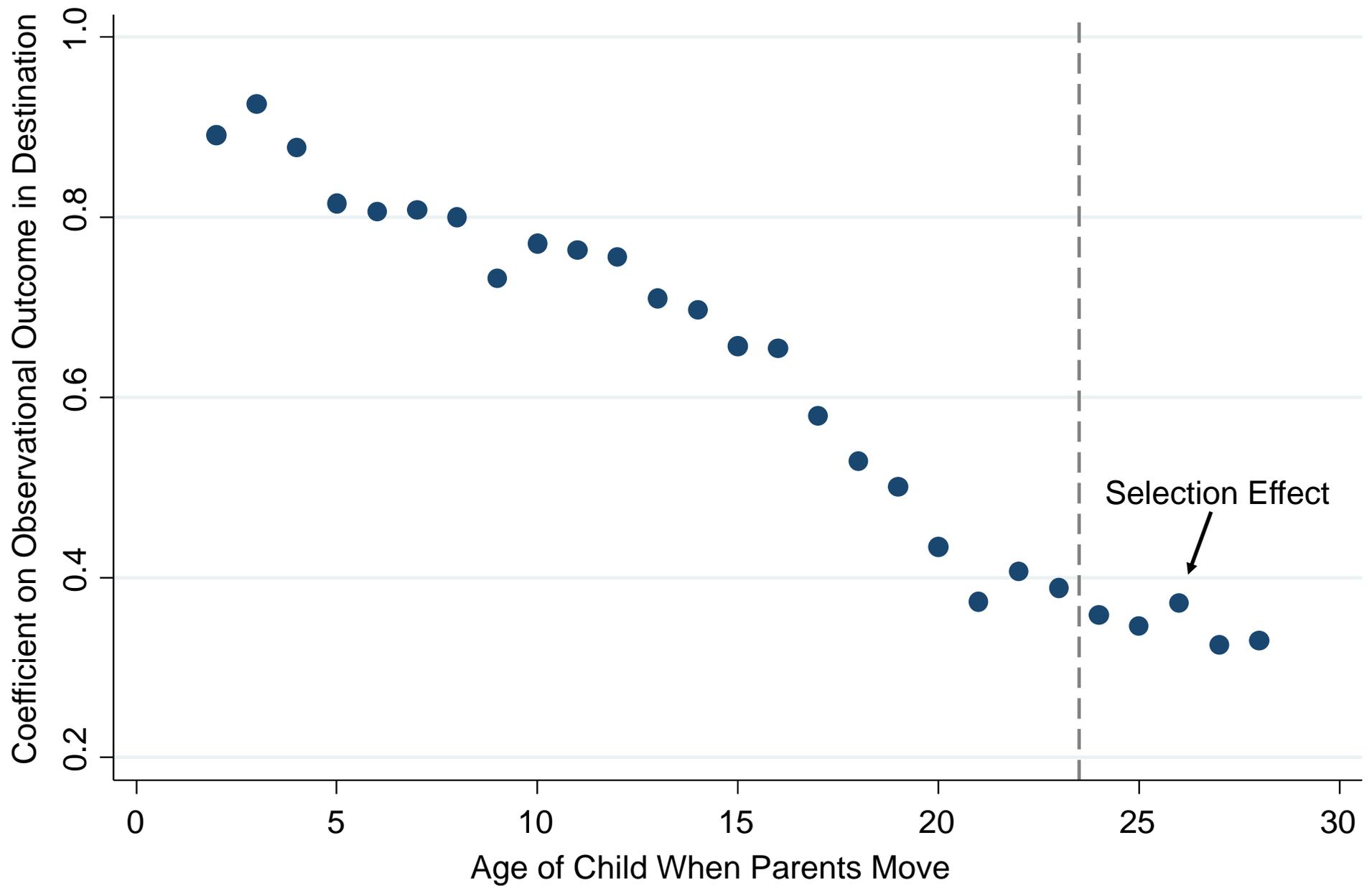
For Children Who Move at Age 5



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

