The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates

Raj Chetty and Nathaniel Hendren

Harvard University and NBER

May 2017

The opinions expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Internal Revenue Service or the U.S. Treasury Department. This work is a component of a larger project examining the effects of eliminating tax expenditures on the budget deficit and economic activity. Results reported here are contained in the SOI Working Paper "The Economic Impacts of Tax Expenditures: Evidence from Spatial Variation across the U.S.," approved under IRS contract TIRNO-12-P-00374.

Causal Effects of Each County

- First paper establishes that neighborhoods matter on average, but it does not tell us which places are good or what their characteristics are

- **Second paper:** "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates"
  - Estimate the causal effect of each county on children's earnings
  - Estimate ~3,000 treatment effects (one per county) instead of one average exposure effect as in first paper

Estimating County Fixed Effects

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

- Intuition for identification: suppose children who move from Manhattan to Queens at younger ages earn more as adults

  - Can infer that Queens has positive exposure effects relative to Manhattan

Estimating County Fixed Effects

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

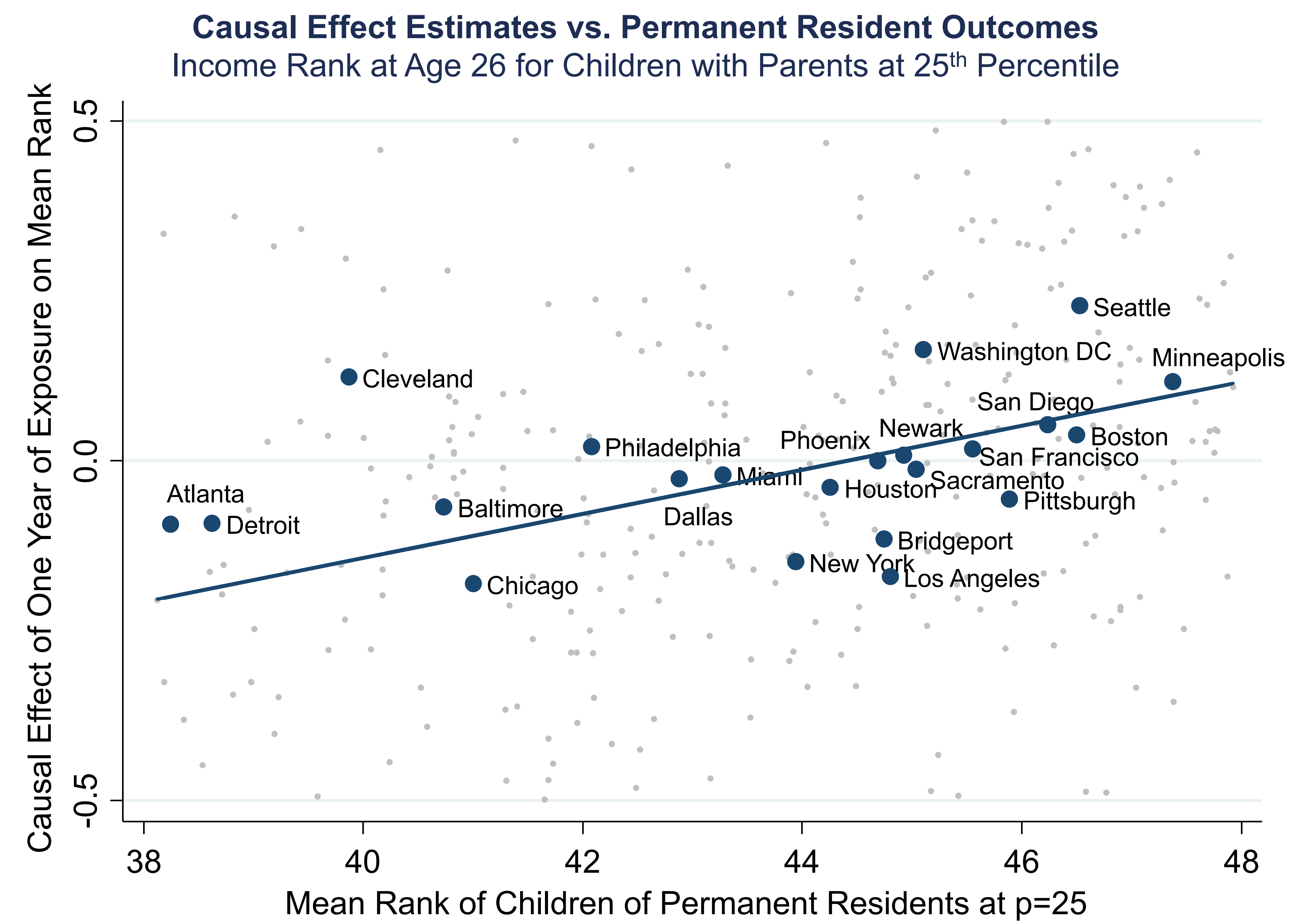
$$y_i = \underbrace{(T_c - m)}_{\text{Exposure}} \left[\underbrace{\mu_d 1\{d(i) = d\}}_{\text{Dest. FE}} - \underbrace{\mu_o 1\{o(i) = o\}}_{\text{Orig. FE.}} \right] + \underbrace{\alpha_{odps}}_{\text{orig x Dest FE}} + \eta_i$$

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

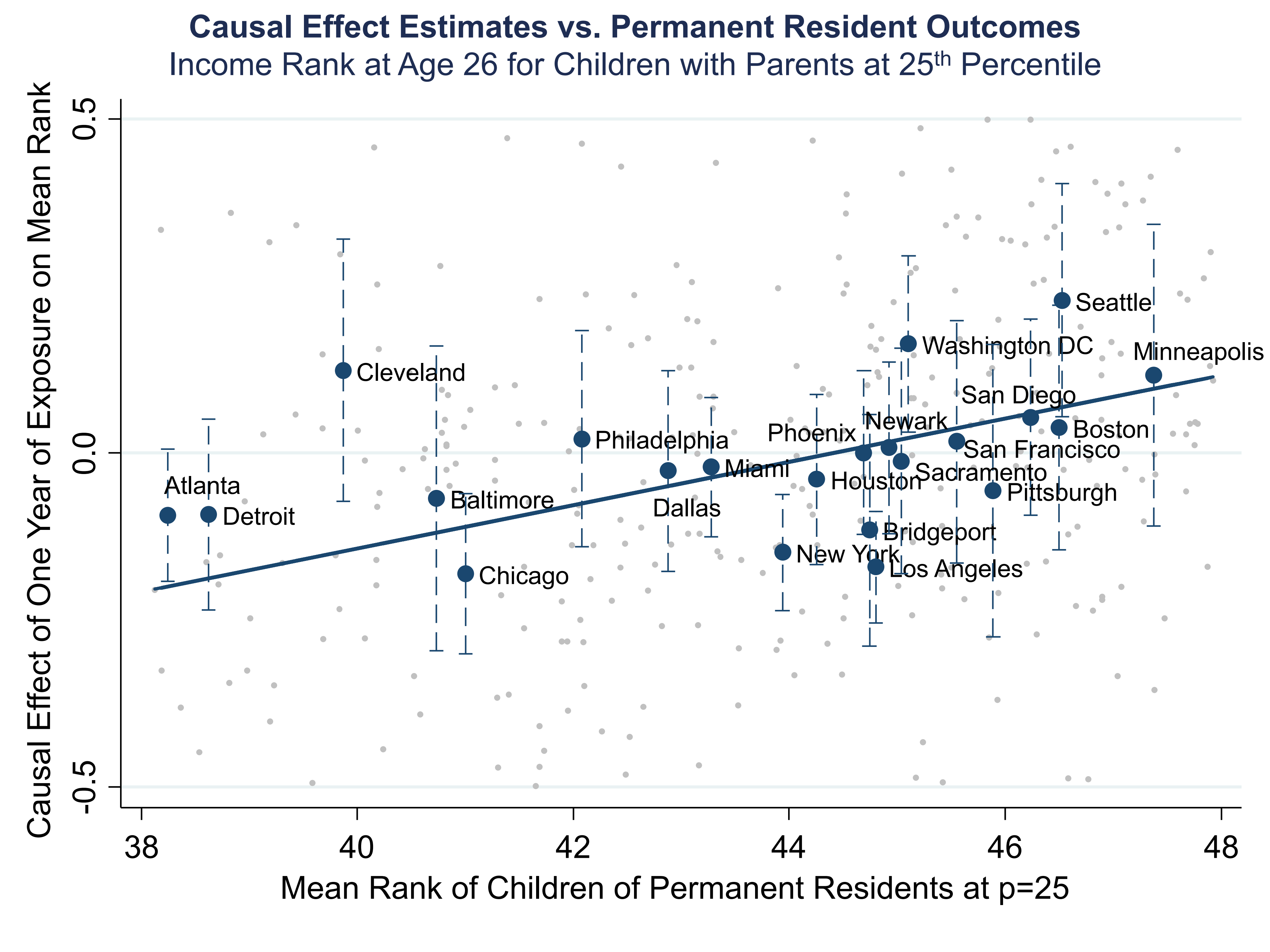
$$\mu_c = \mu_c^0 + \mu_c^P p$$

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

$$\alpha_{odps} = \left(\alpha_{od}^0 + \alpha_{od}^P p + \psi_{od}^0 s + \psi_{od}^1 s^2 + \psi_{od}^2 sp + \psi_{od}^3 s^2 p\right)$$

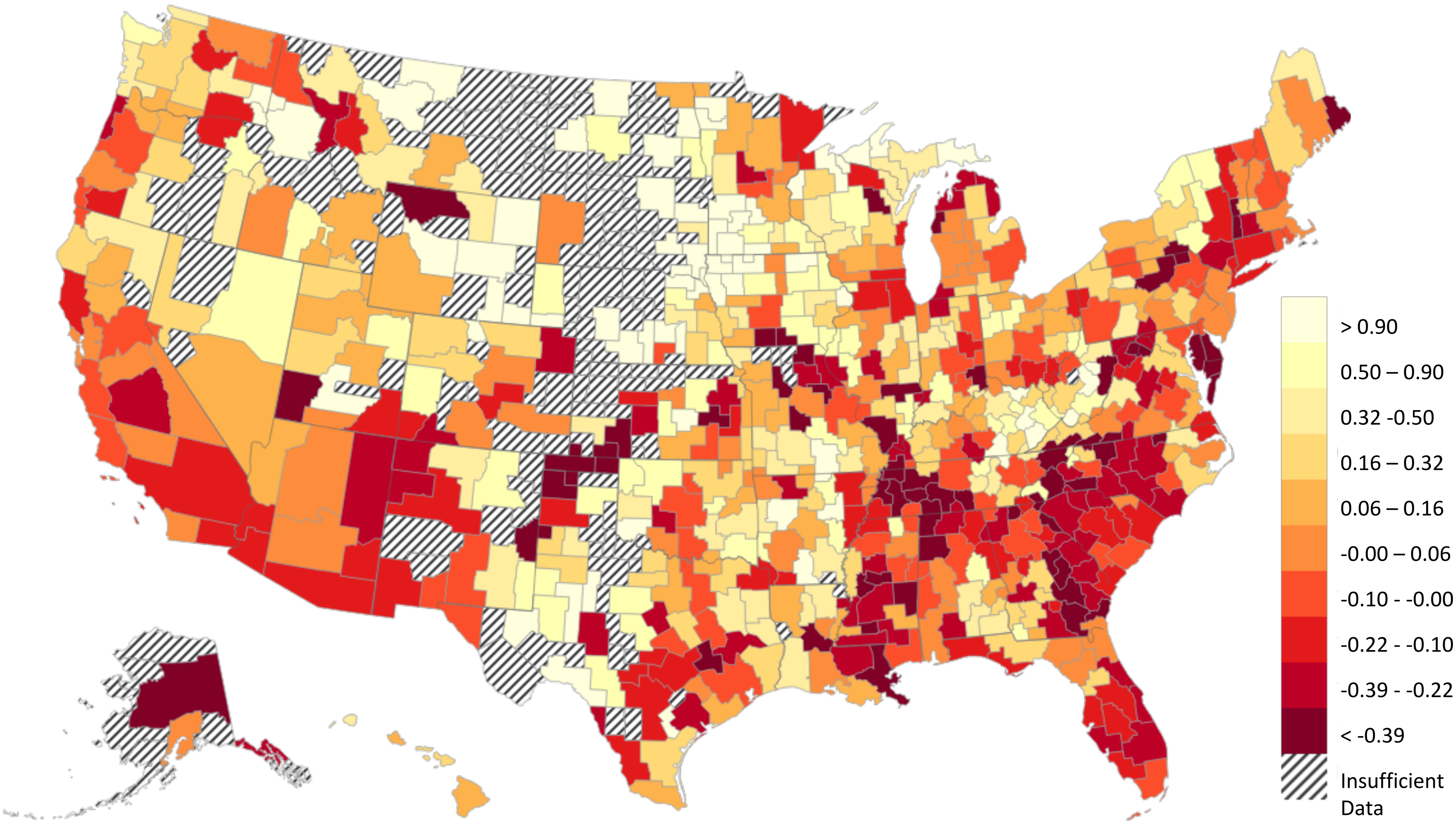


Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of One Year of Exposure on Mean Rank
Mean Rank of Children of Permanent Residents at p=25
0.5
0.0
-0.5
38
40
42
44
46
48
Seattle
Washington DC
Minneapolis
Cleveland
San Diego
Newark
Phoenix
Boston
Philadelphia
San Francisco
Miami
Sacramento
Houston
Atlanta
Pittsburgh
Baltimore
Detroit
Dallas
Bridgeport
New York
Los Angeles
Chicago


Causal Effect Estimates vs. Permanent Resident Outcomes
Income Rank at Age 26 for Children with Parents at 25th Percentile
Causal Effect of One Year of Exposure on Mean Rank
Mean Rank of Children of Permanent Residents at p=25
0.5
0.0
-0.5
38
40
42
44
46
48
Atlanta
Detroit
Cleveland
Baltimore
Chicago
Philadelphia
Dallas
Miami
Phoenix
Houston
New York
Newark
Bridgeport
Los Angeles
Sacramento
Washington DC
San Diego
San Francisco
Pittsburgh
Seattle
Boston
Minneapolis

CZ Fixed Effect Estimates for Child's Income Rank at Age 26

For Children with Parents at 25th Percentile of Income Distribution



Note: Estimates represent annual exposure effects on child's rank in income distribution at age 26

Three Objectives

- Use fixed effect estimates for three purposes:

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

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

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

Objective 1: Magnitude of Place Effects

- Estimate signal variance of place effects
  - To interpret units, note that 1 pctile ~= 3% change in earnings
- For children with parents at 25th percentile: 1 SD better county from birth → 10% earnings gain
- For children with parents at 75th percentile: 1 SD better county from birth → 6% earnings gain
- Correlation of place effects for p25 and p75 across counties is +0.3
    - Places that are better for the poor are not worse for the rich

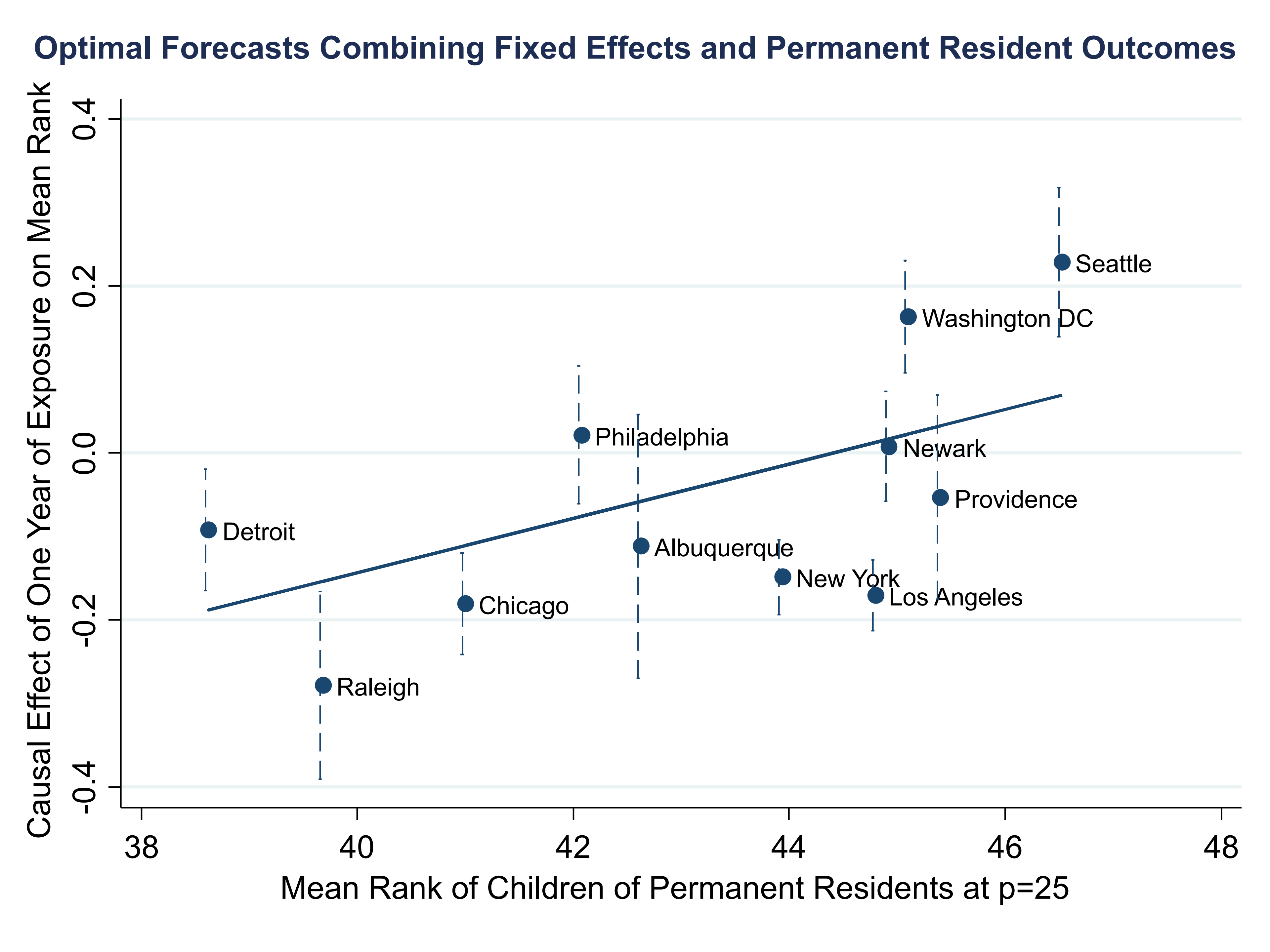
Objective 2: Forecasts of Best and Worst Areas

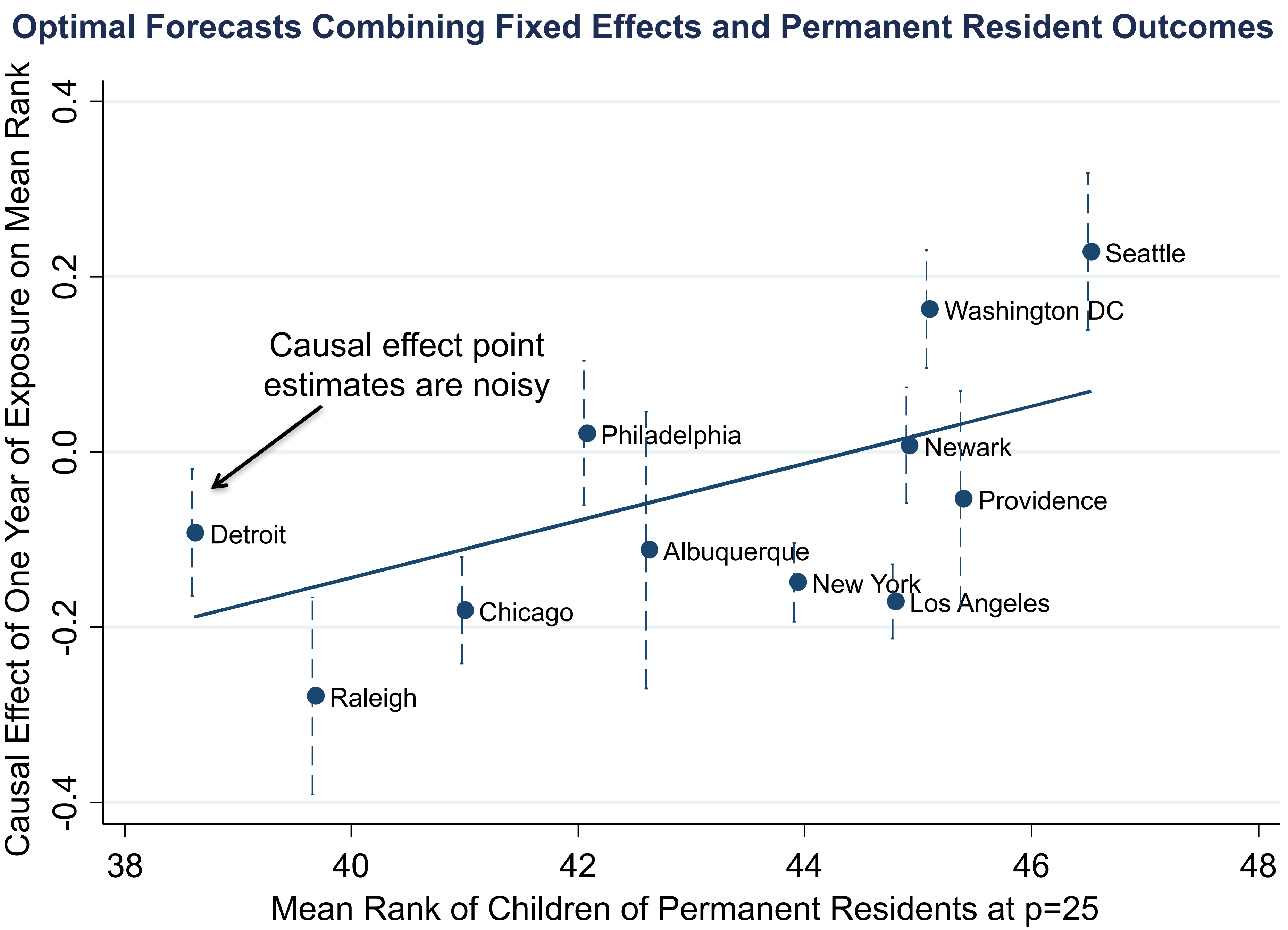
- What are the best and worst places to grow up?

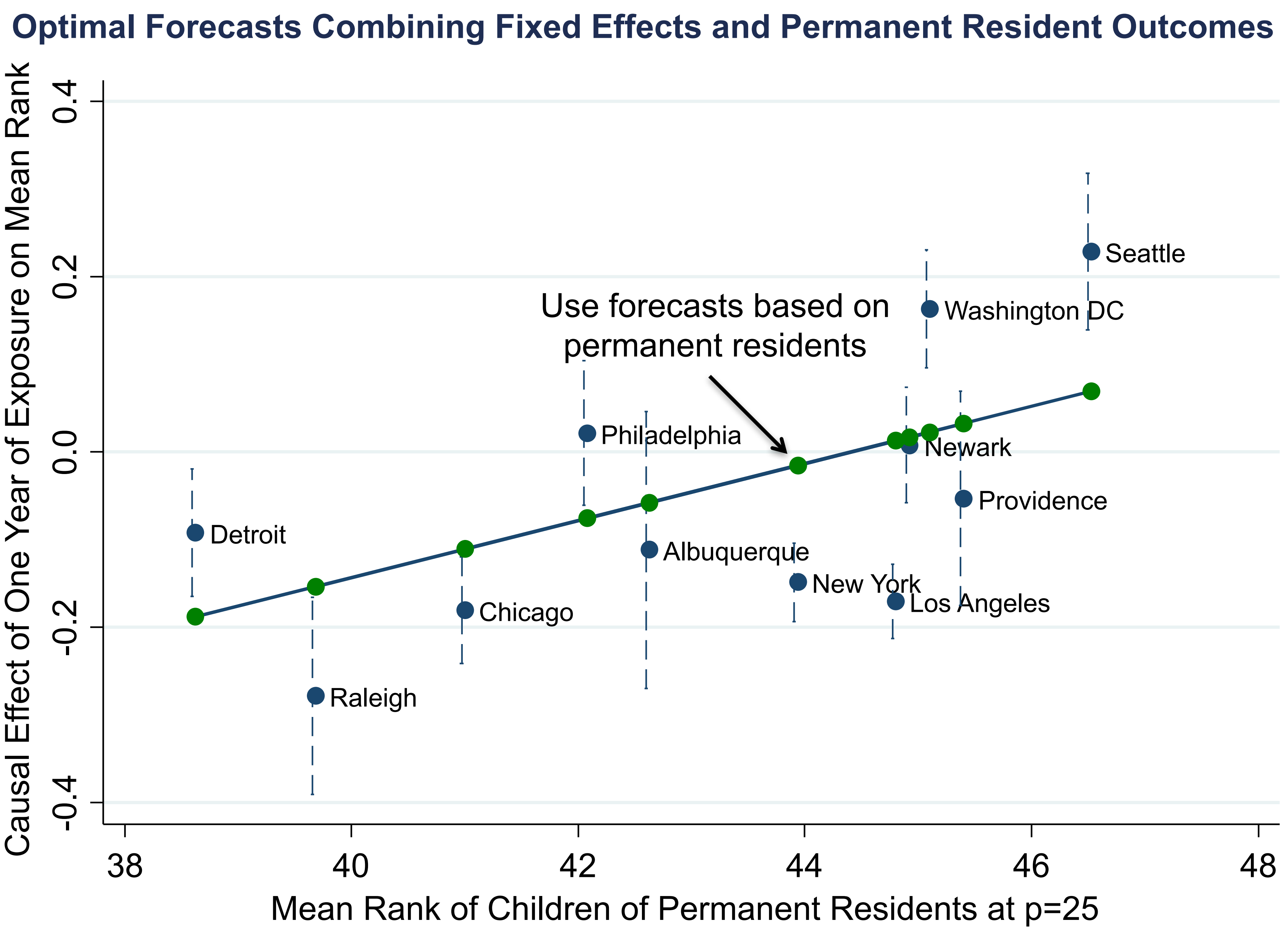
- Construct forecasts that minimize mean-squared-error of predicted impact for a family moving to a new area

- Raw fixed effect estimates have high MSE because of sampling error

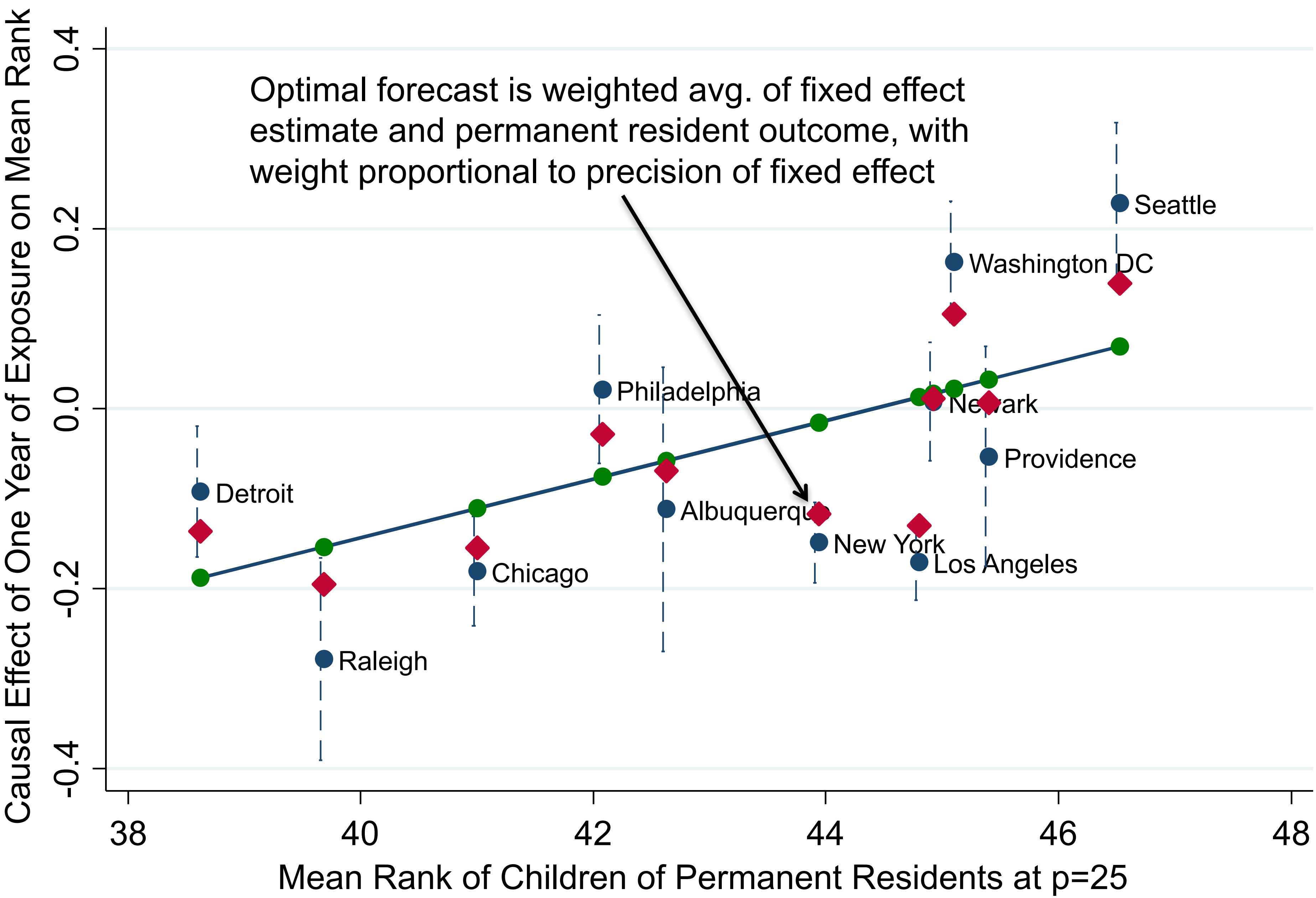
- Reduce MSE by combining fixed effects (unbiased, but imprecise) with permanent resident outcomes (biased, but precise)


Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Causal Effect of One Year of Exposure on Mean Rank
Mean Rank of Children of Permanent Residents at p=25
0.4
0.2
0.0
-0.2
-0.4
38
40
42
44
46
48
Seattle
Washington DC
Philadelphia
Newark
Providence
Detroit
Albuquerque
New York
Los Angeles
Chicago
Raleigh

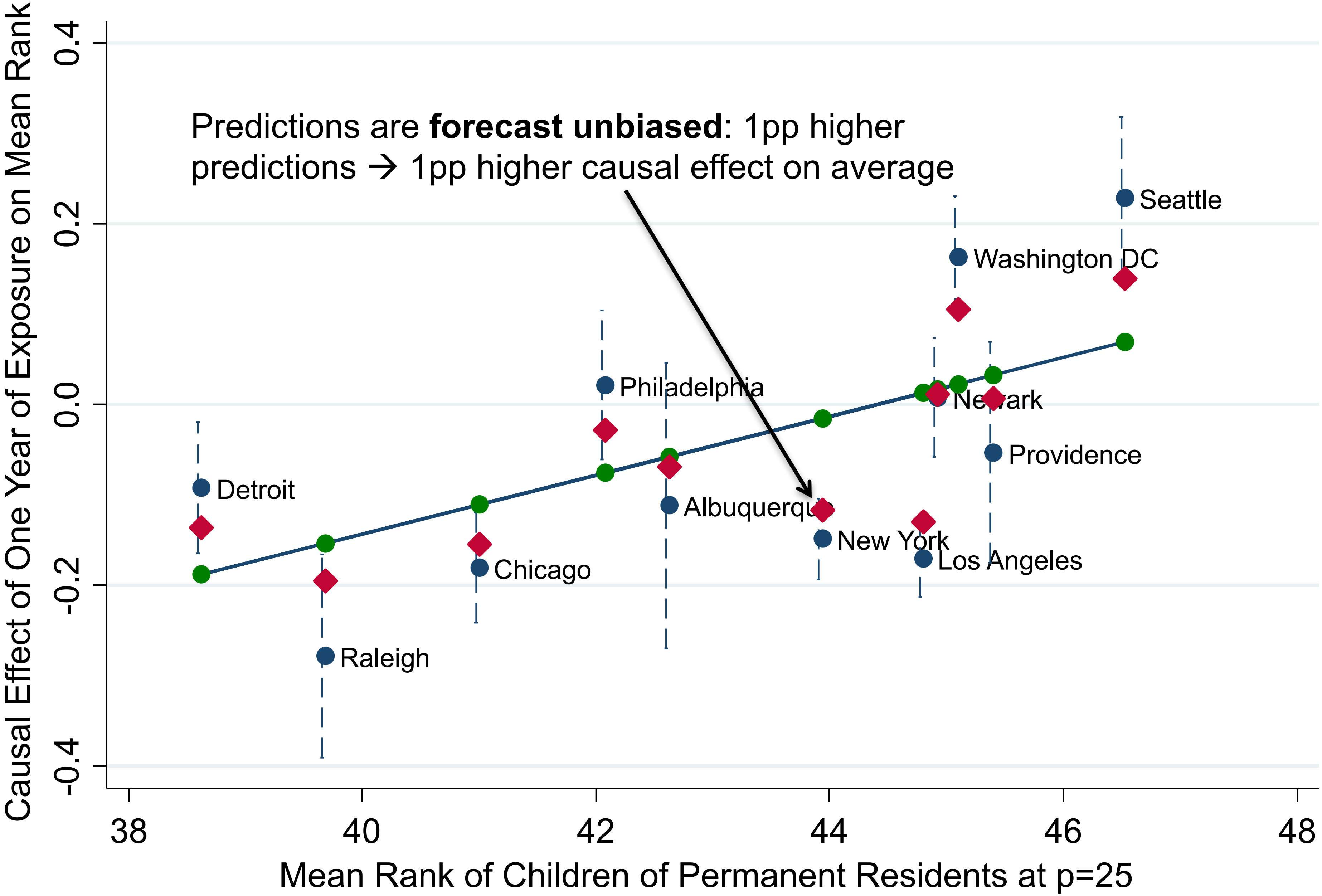

Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Causal effect point
estimates are noisy
Seattle
Washington DC
Philadelphia
Newark
Providence
Detroit
Albuquerque
New York
Los Angeles
Chicago
Raleigh
Causal Effect of One Year of Exposure on Mean Rank
Mean Rank of Children of Permanent Residents at p=25
0.4
0.2
0.0
-0.2
-0.4
38
40
42
44
46
48


Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes
Causal Effect of One Year of Exposure on Mean Rank
Mean Rank of Children of Permanent Residents at p=25
-0.4
-0.2
0.0
0.2
0.4
38
40
42
44
46
48
Use forecasts based on
permanent residents
Seattle
Washington DC
Philadelphia
Newark
Providence
Detroit
Albuquerque
New York
Los Angeles
Chicago
Raleigh

Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes

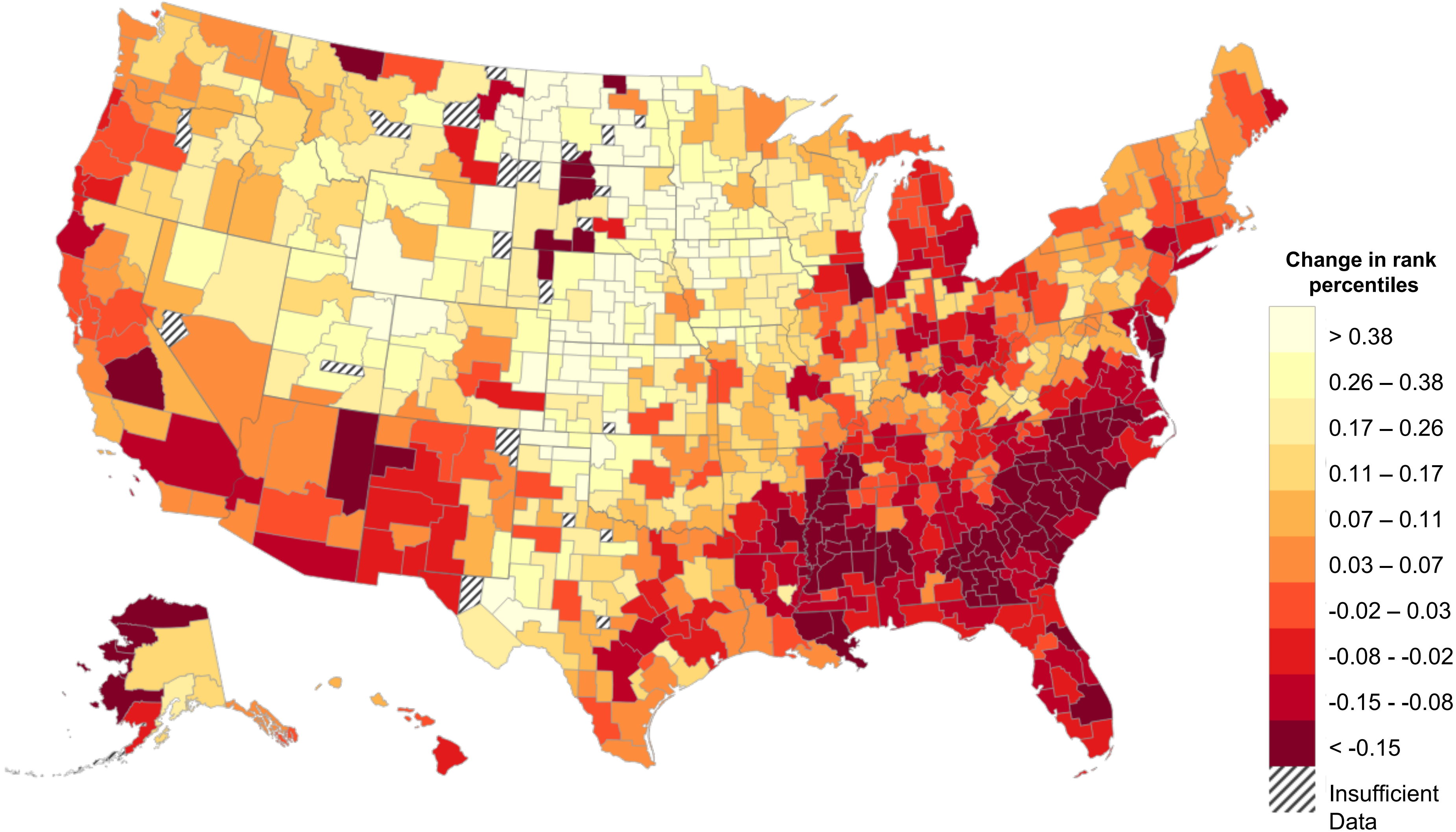


Optimal Forecasts Combining Fixed Effects and Permanent Resident Outcomes



Predicted Exposure Effects on Child's Income Rank at Age 26 by CZ

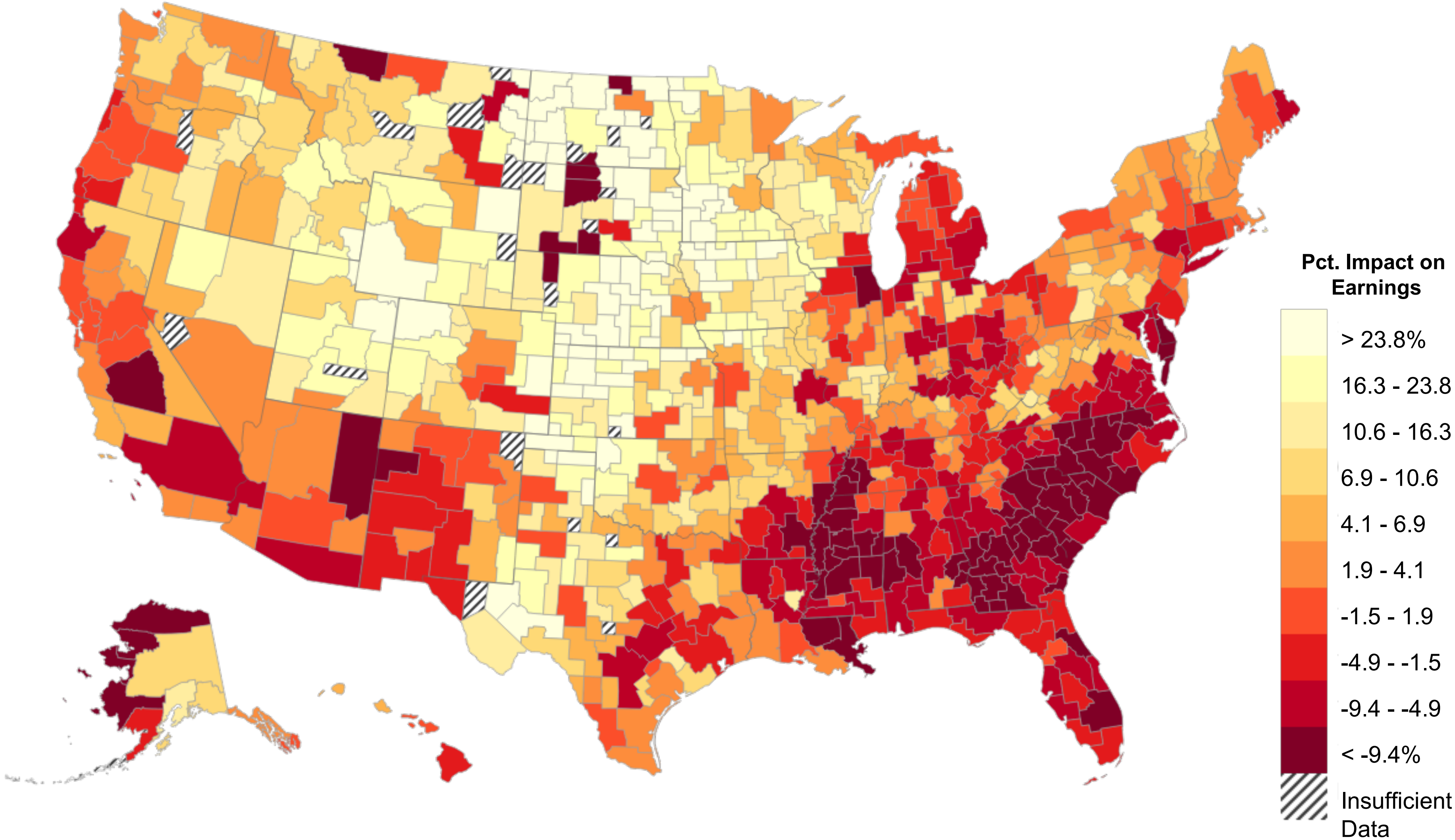
For Children with Parents at 25th Percentile of Income Distribution



Note: Estimates represent change in rank from spending one more year of childhood in CZ

Predicted Exposure Effects on Child's Income Level at Age 26 by CZ

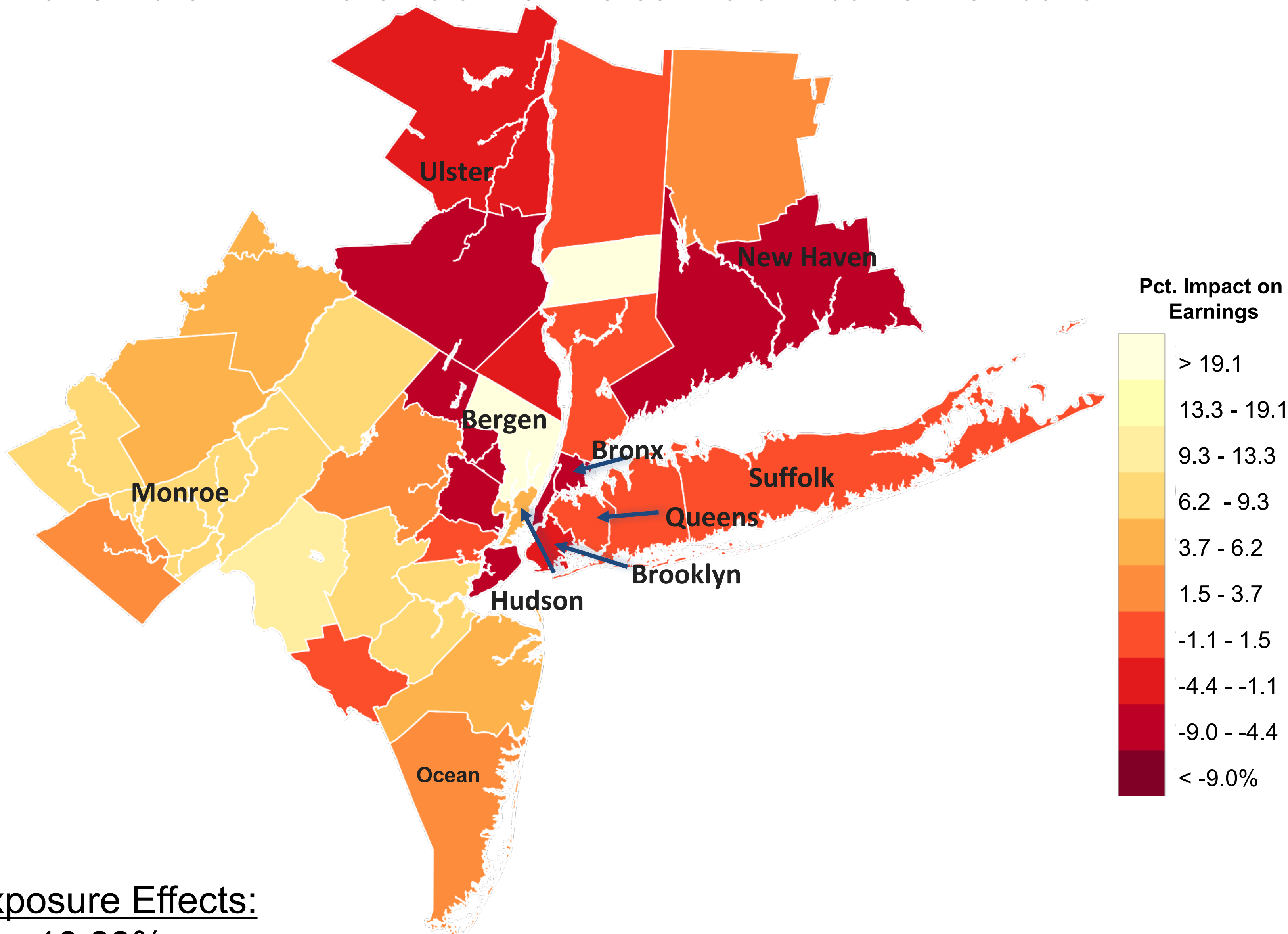
For Children with Parents at 25th Percentile of Income Distribution



Note: Estimates represent % change in earnings from growing up from birth (i.e. 20 years of childhood exposure) in CZ

Exposure Effects on Income in the New York CSA

For Children with Parents at 25th Percentile of Income Distribution



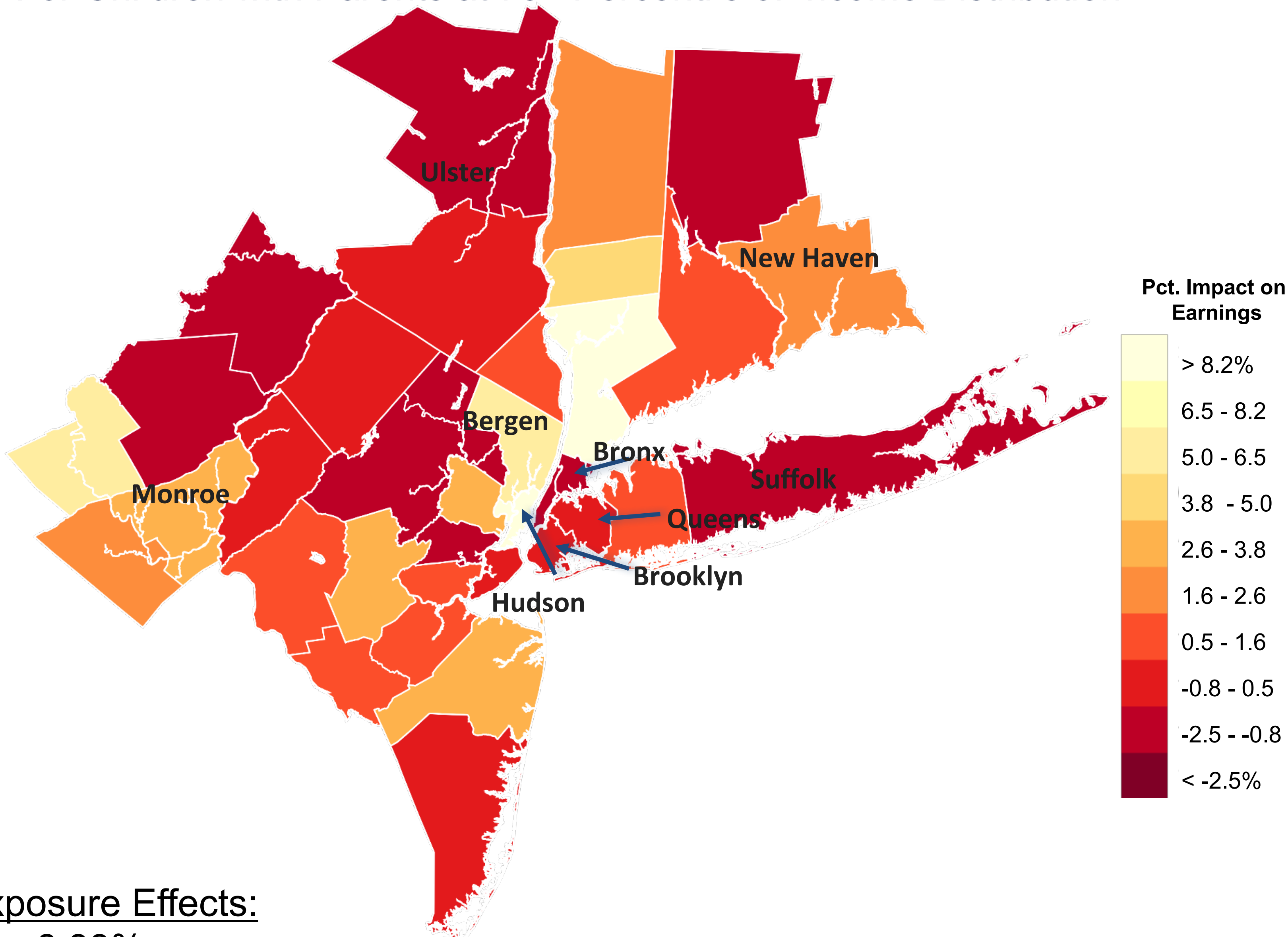
<u>Causal Exposure Effects:</u>

Bronx NY: - 10.89%

Bergen NJ: + 13.77%

Exposure Effects on Income in the New York CSA

For Children with Parents at 75th Percentile of Income Distribution



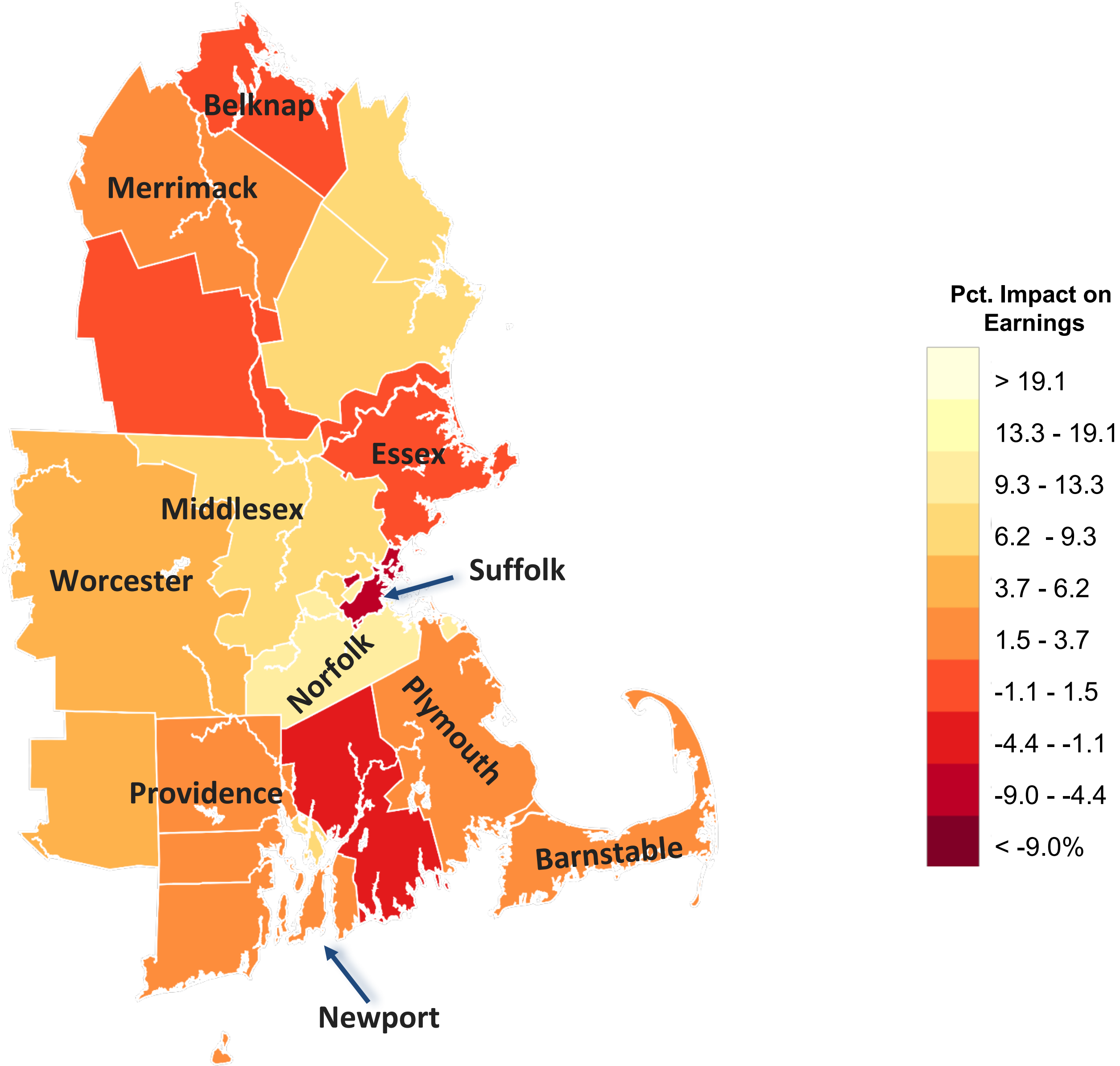
<u>Causal Exposure Effects:</u>

Bronx NY: - 8.33%

Bergen NJ: + 6.29%

Exposure Effects on Income in the Boston CSA

For Children with Parents at 25th Percentile of Income Distribution



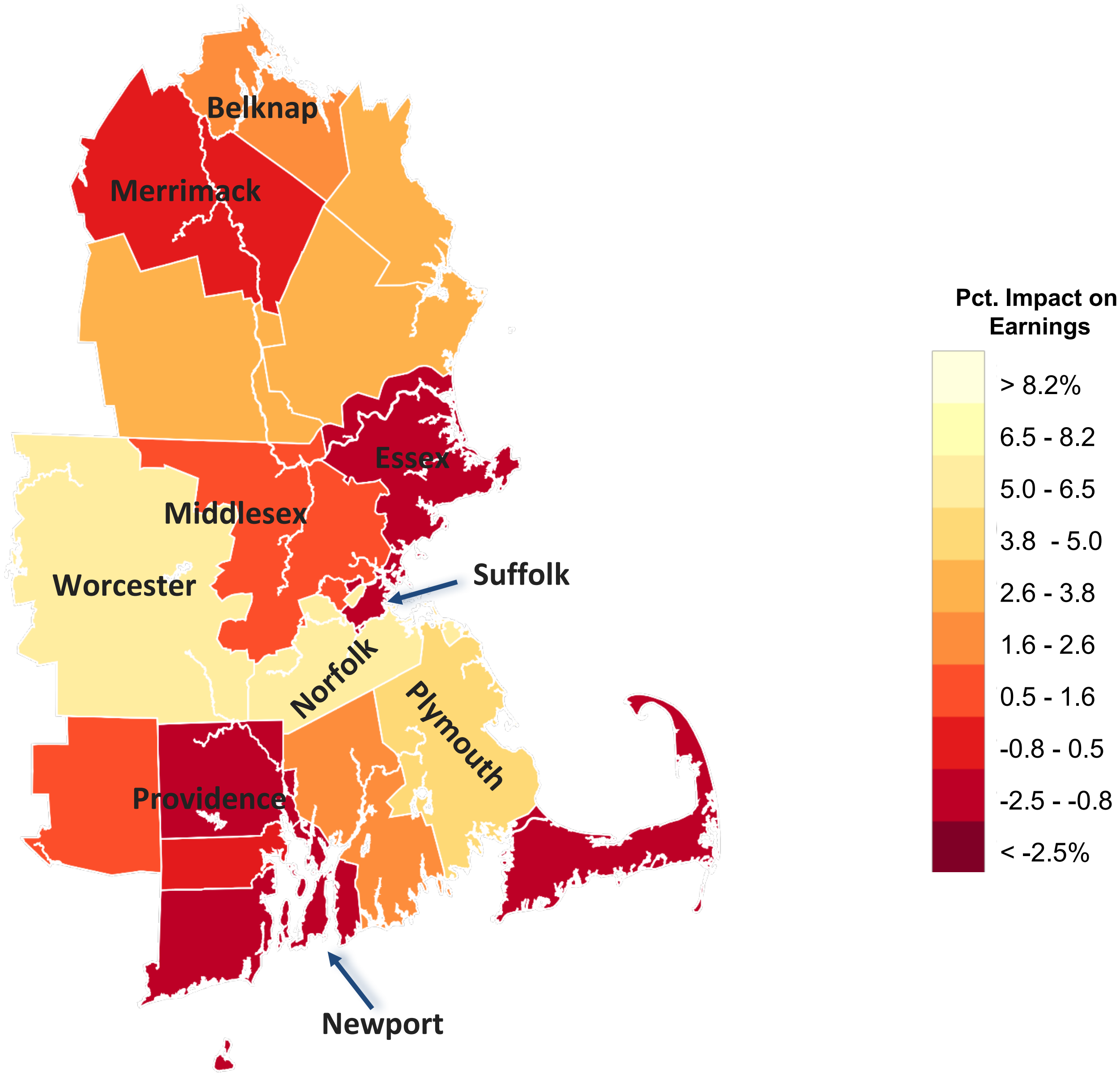
<u>Causal Exposure Effects:</u>

Suffolk MA: - 6.11 %

Middlesex MA: + 7.71 %

Exposure Effects on Income in the Boston CSA

For Children with Parents at 75th Percentile of Income Distribution



Causal Exposure Effects:

Suffolk MA: - 3.64 %

Middlesex MA: + 0.54 %

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

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

Top 10 Counties			Bottom 10 Counties		
Rank	County	Impact from Birth (%)	Rank	County	Impact from Birth (%)
1	Dupage, IL	16.00	91	Wayne, MI	-11.39
2	Fairfax, VA	14.98	92	Orange, FL	-12.10
3	Snohomish, WA	14.02	93	Cook, IL	-12.79
4	Bergen, NJ	13.77	94	Palm Beach, FL	-13.01
5	Bucks, PA	12.39	95	Marion, IN	-13.09
6	Norfolk, MA	11.47	96	Shelby, TN	-13.15
7	Montgomery, PA	9.74	97	Fresno, CA	-13.50
8	Montgomery, MD	9.47	98	Hillsborough, FL	-13.82
9	King, WA	9.33	99	Baltimore City, MD	-13.98
10	Middlesex, NJ	9.13	100	Mecklenburg, NC	-14.46

Exposure effects represent % change in adult earnings from growing up from birth (i.e. 20 years of exposure) in county

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

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

Top 10 Counties			Bottom 10 Counties		
Rank	County	Impact from Birth (%)	Rank	County	Impact from Birth (%)
1	Fairfax, VA	10.96	91	Hillsborough, FL	-7.95
2	Westchester, NY	6.88	92	Bronx, NY	-8.33
3	Contra Costa, CA	6.67	93	Broward, FL	-9.20
4	Hamilton, OH	6.32	94	Dist. of Columbia, DC	-9.68
5	Bergen, NJ	6.29	95	Orange, CA	-9.79
6	Gwinnett, GA	6.26	96	San Bernardino, CA	-10.14
7	Norfolk, MA	6.23	97	Riverside, CA	-10.26
8	Worcester, MA	5.38	98	Los Angeles, CA	-10.49
9	Franklin, OH	4.72	99	New York, NY	-11.36
10	Kent, MI	4.61	100	Palm Beach, FL	-13.00

Exposure effects represent % change in adult earnings from growing up from birth (i.e. 20 years of exposure) in county

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

Male Children

Top 10 Counties			Bottom 10 Counties		
Rank	County	Impact from Birth (%)	Rank	County	Impact from Birth (%)
1	Bucks, PA	16.82	91	Milwaukee, WI	-14.80
2	Bergen, NJ	16.62	92	New Haven, CT	-14.96
3	Contra Costa, CA	14.47	93	Bronx, NY	-15.21
4	Snohomish, WA	13.92	94	Hillsborough, FL	-16.30
5	Norfolk, MA	12.45	95	Palm Beach, FL	-16.49
6	Dupage, IL	12.17	96	Fresno, CA	-16.80
7	King, WA	11.15	97	Riverside, CA	-16.97
8	Ventura, CA	10.90	98	Wayne, MI	-17.43
9	Hudson, NJ	10.41	99	Pima, AZ	-23.03
10	Fairfax, VA	9.21	100	Baltimore City, MD	-27.86

Exposure effects represent % change in adult earnings from growing up from birth (i.e. 20 years of exposure) in county

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

Female Children

Top 10 Counties			Bottom 10 Counties		
Rank	County	Impact from Birth (%)	Rank	County	Impact from Birth (%)
1	Dupage, IL	18.18	91	Hillsborough, FL	-10.18
2	Fairfax, VA	15.10	92	Fulton, GA	-11.52
3	Snohomish, WA	14.65	93	Suffolk, MA	-11.54
4	Montgomery, MD	13.64	94	Orange, FL	-12.02
5	Montgomery, PA	11.58	95	Essex, NJ	-12.75
6	King, WA	11.39	96	Cook, IL	-12.83
7	Bergen, NJ	11.20	97	Franklin, OH	-12.88
8	Salt Lake, UT	10.22	98	Mecklenburg, NC	-14.73
9	Contra Costa, CA	9.42	99	New York, NY	-14.94
10	Middlesex, NJ	9.38	100	Marion, IN	-15.50

Exposure effects represent % change in adult earnings from growing up from birth (i.e. 20 years of exposure) in county

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

Gender Average vs. Pooled Specification

Top 10 Counties

Rank	County	Gender Avg (%)	Pooled (%)
1	Dupage, IL	15.12	16.00
2	Snohomish, WA	14.35	14.02
3	Bergen, NJ	14.12	13.77
4	Bucks, PA	13.29	12.39
5	Contra Costa, CA	12.14	8.83
6	Fairfax, VA	12.09	14.98
7	King, WA	11.33	9.33
8	Norfolk, MA	10.81	11.47
9	Montgomery, MD	10.49	9.47
10	Middlesex, NJ	8.61	9.13

Bottom 10 Counties

Rank	County	Gender Avg (%)	Pooled (%)
91	Pima, AZ	-12.16	-8.93
92	Bronx, NY	-12.30	-10.89
93	Milwaukee, WI	-12.32	-9.92
94	Wayne, MI	-12.52	-11.39
95	Fresno, CA	-12.94	-13.50
96	Cook, IL	-13.35	-12.79
97	Orange, FL	-13.46	-12.10
98	Hillsborough, FL	-13.47	-13.82
99	Mecklenburg, NC	-13.81	-14.46
100	Baltimore City, MD	-17.27	-13.98

Exposure effects represent % change in adult earnings from growing up from birth (i.e. 20 years of exposure) in county

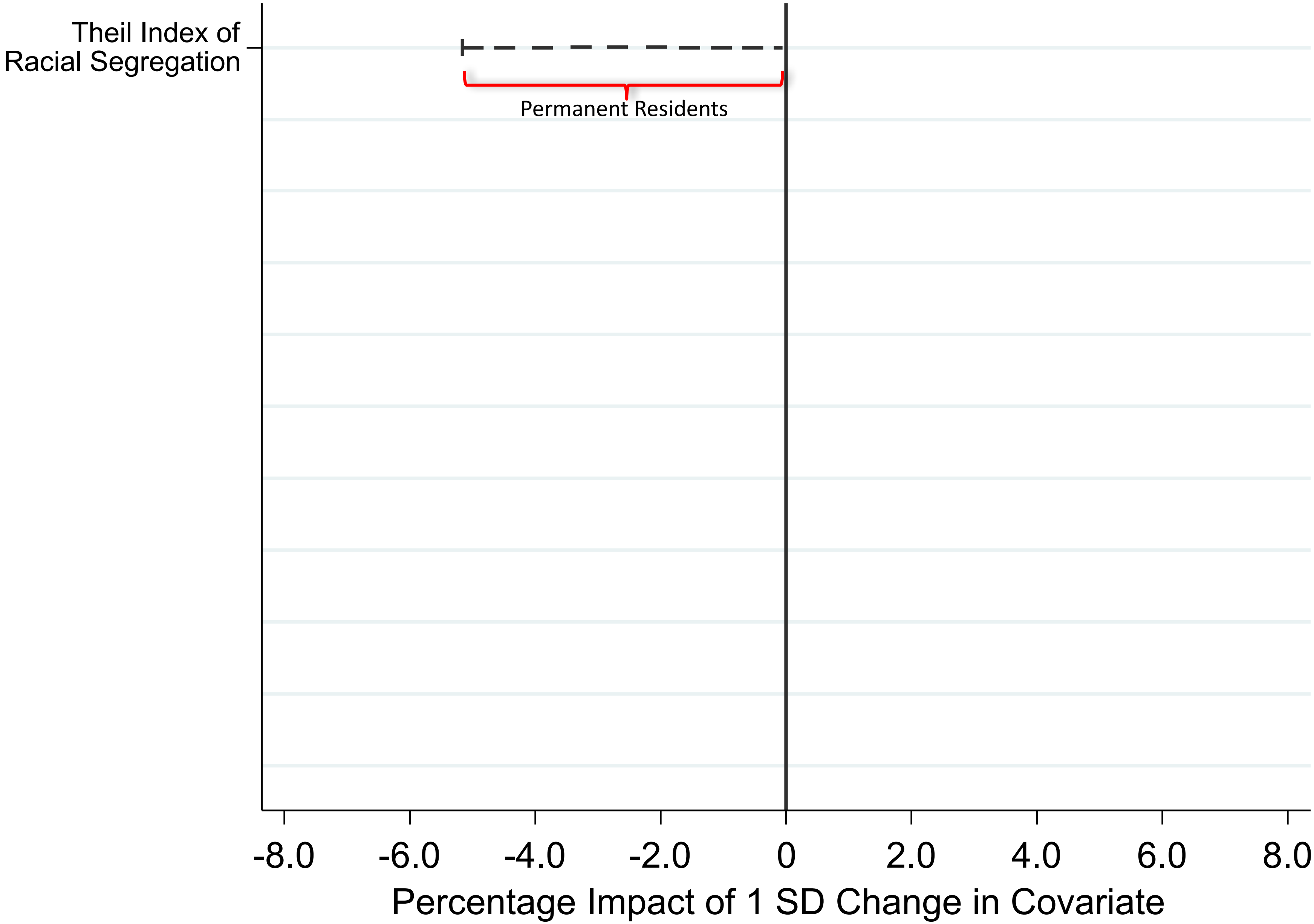
Objective 3: Characteristics of Good Areas

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

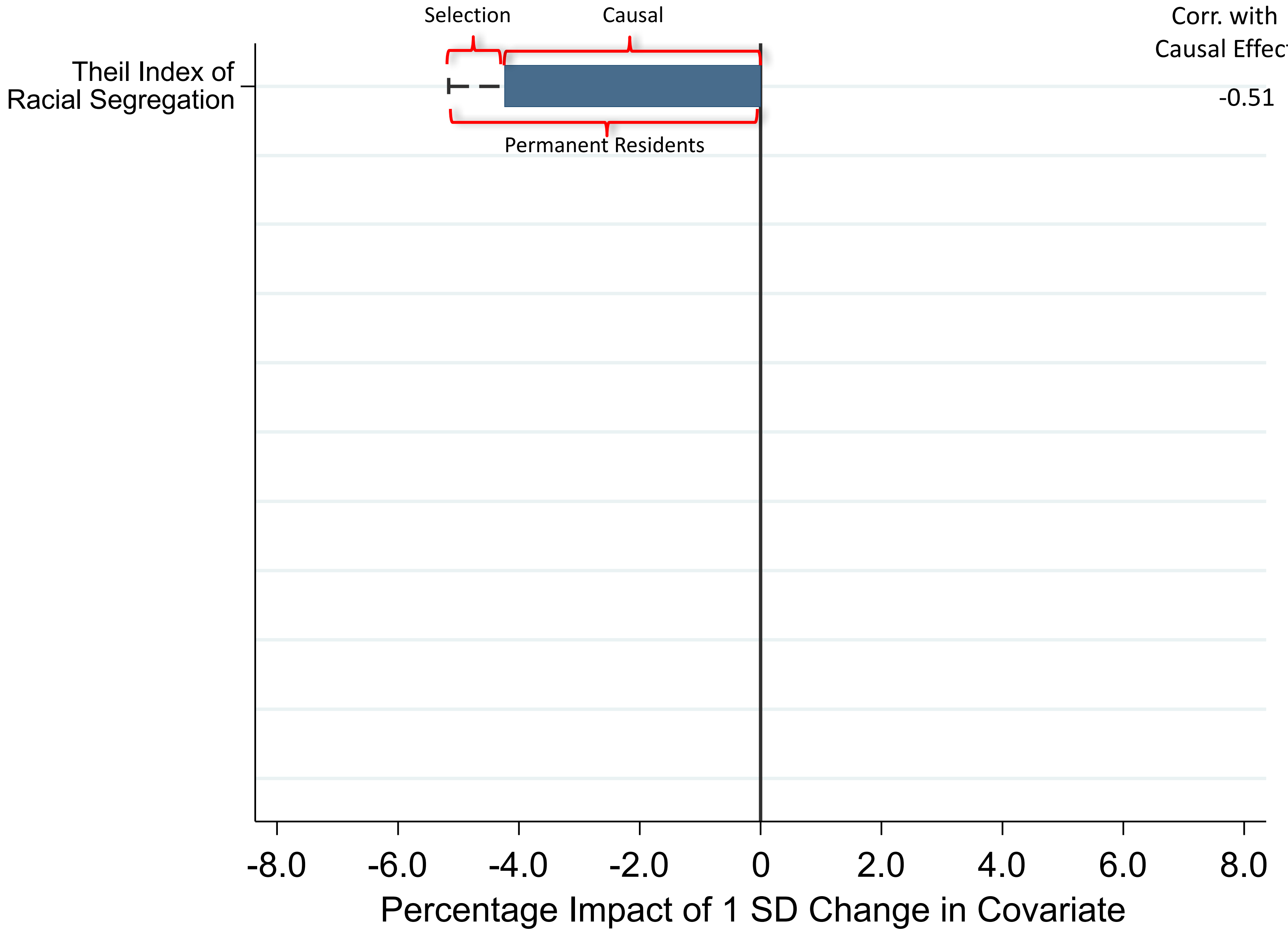
Step 4: Characteristics of Good Areas

- Decompose observed rank for stayers (y_{pc}) into causal and sorting components by multiplying annual exposure effect μ_{pc} by 20:
  - Causal component = $20\mu_{pc}$
  - Sorting component = $y_{pc} - 20\mu_{pc}$
- Re-scale y_{pc}, causal, and sorting components to percentage change in earnings (1 percentile -> 3.1% increase in earnings at p25)
- Regress y_{pc}, causal, and sorting components on covariates
  - Standardize covariates so units represent impact of 1 SD change in covariate on percentage impact on earnings

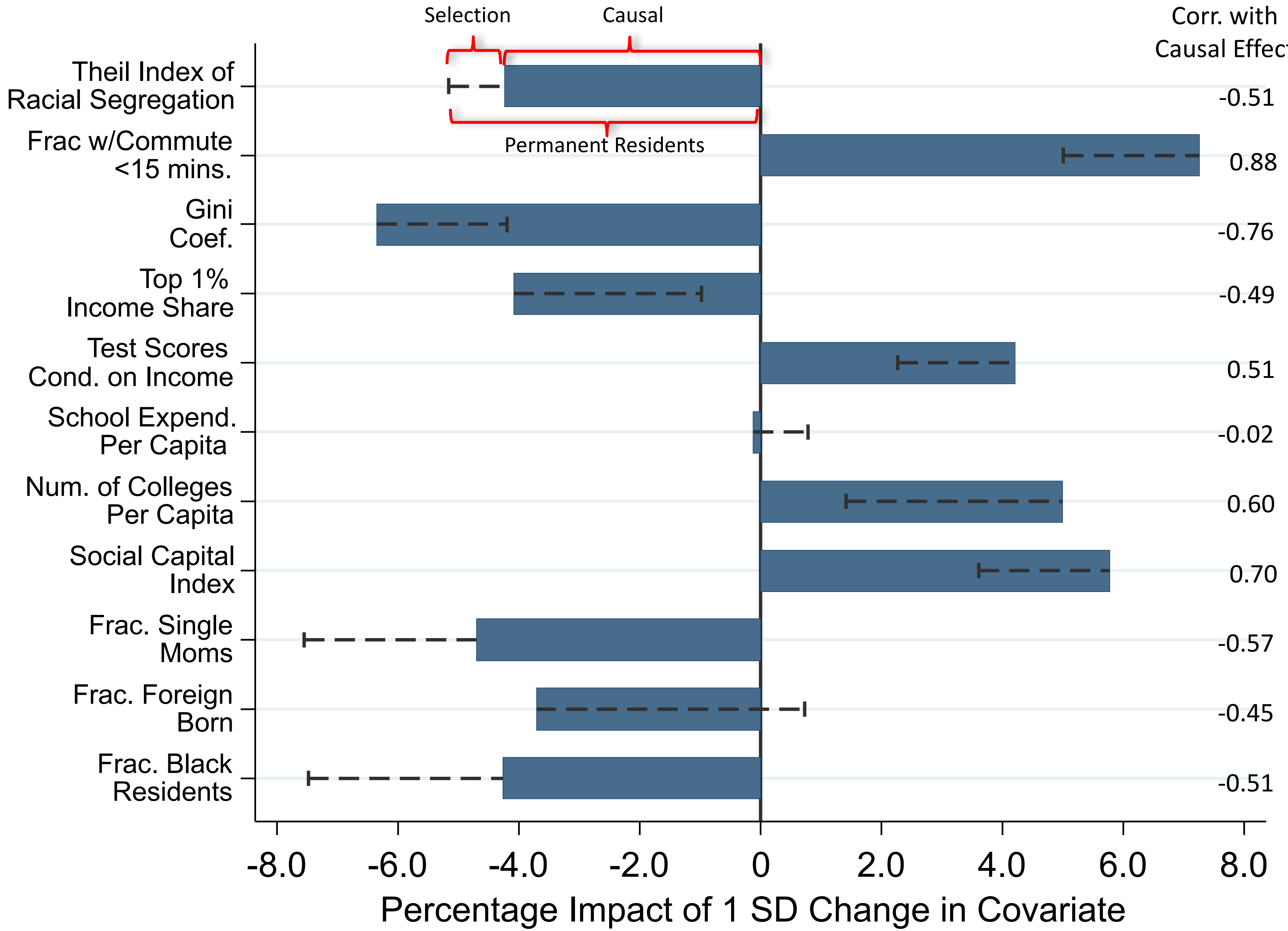
Predictors of Causal Effects For Children at the CZ Level (p25)



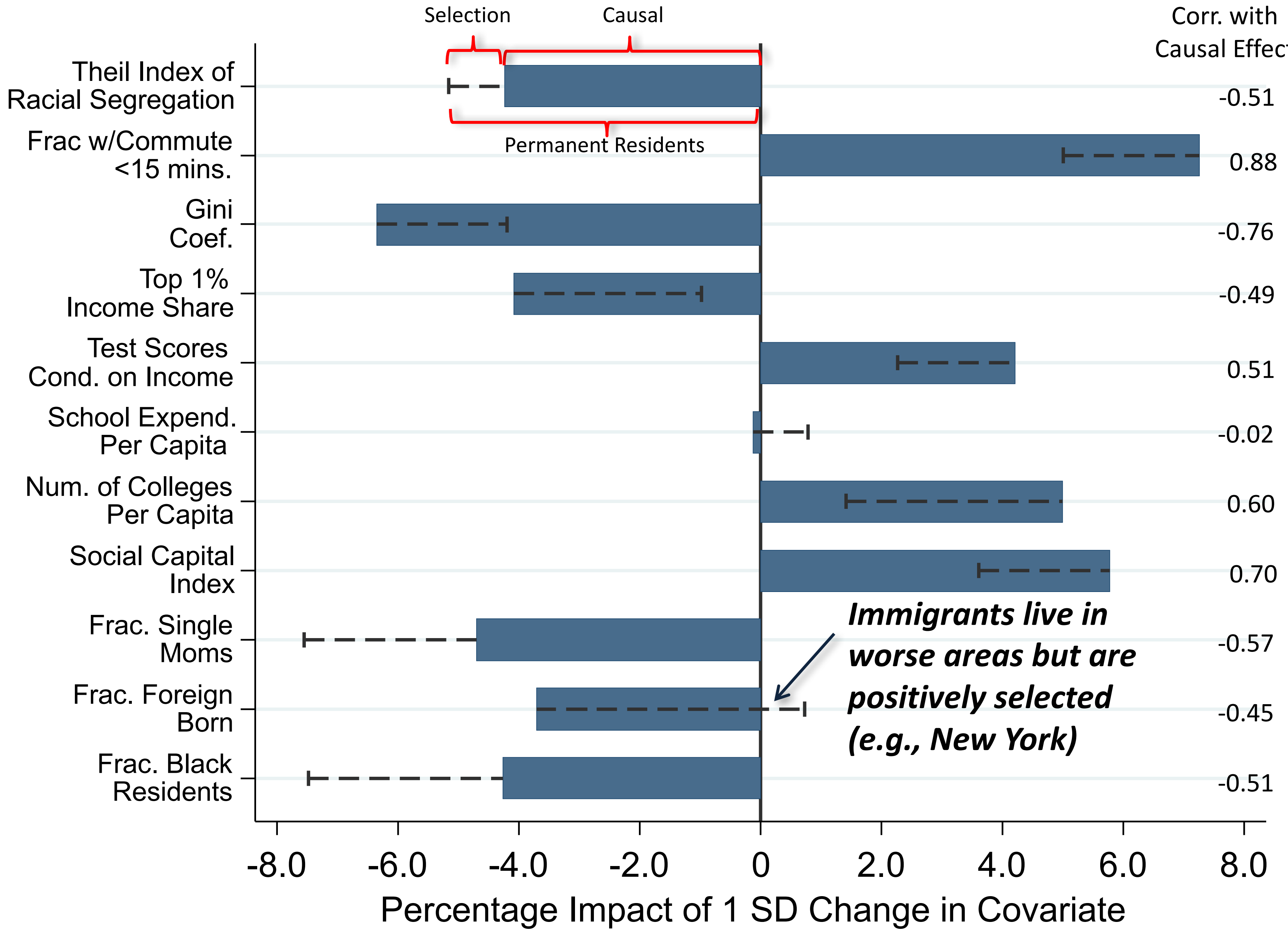
Predictors of Causal Effects For Children at the CZ Level (p25)



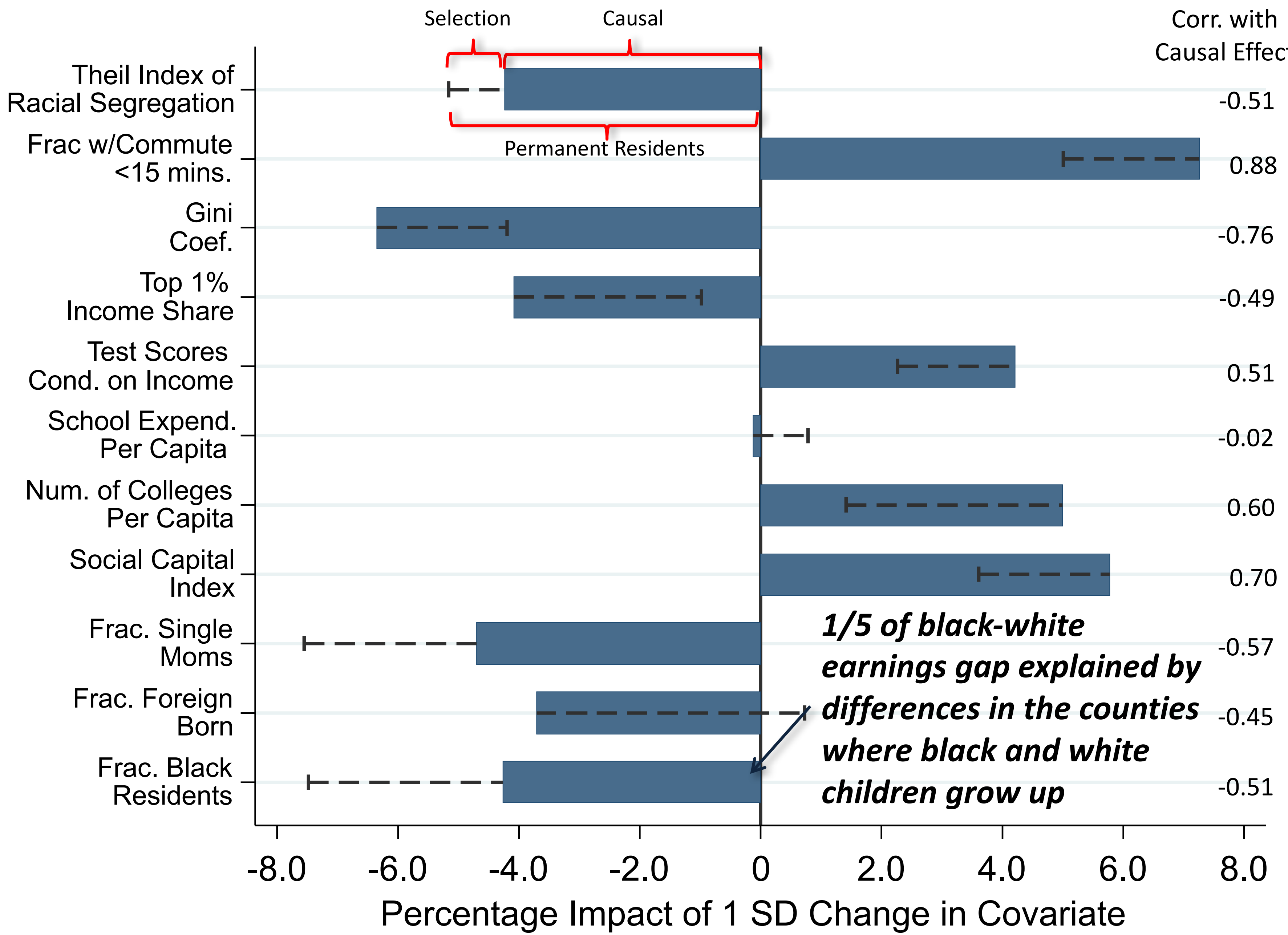
Predictors of Causal Effects For Children at the CZ Level (p25)



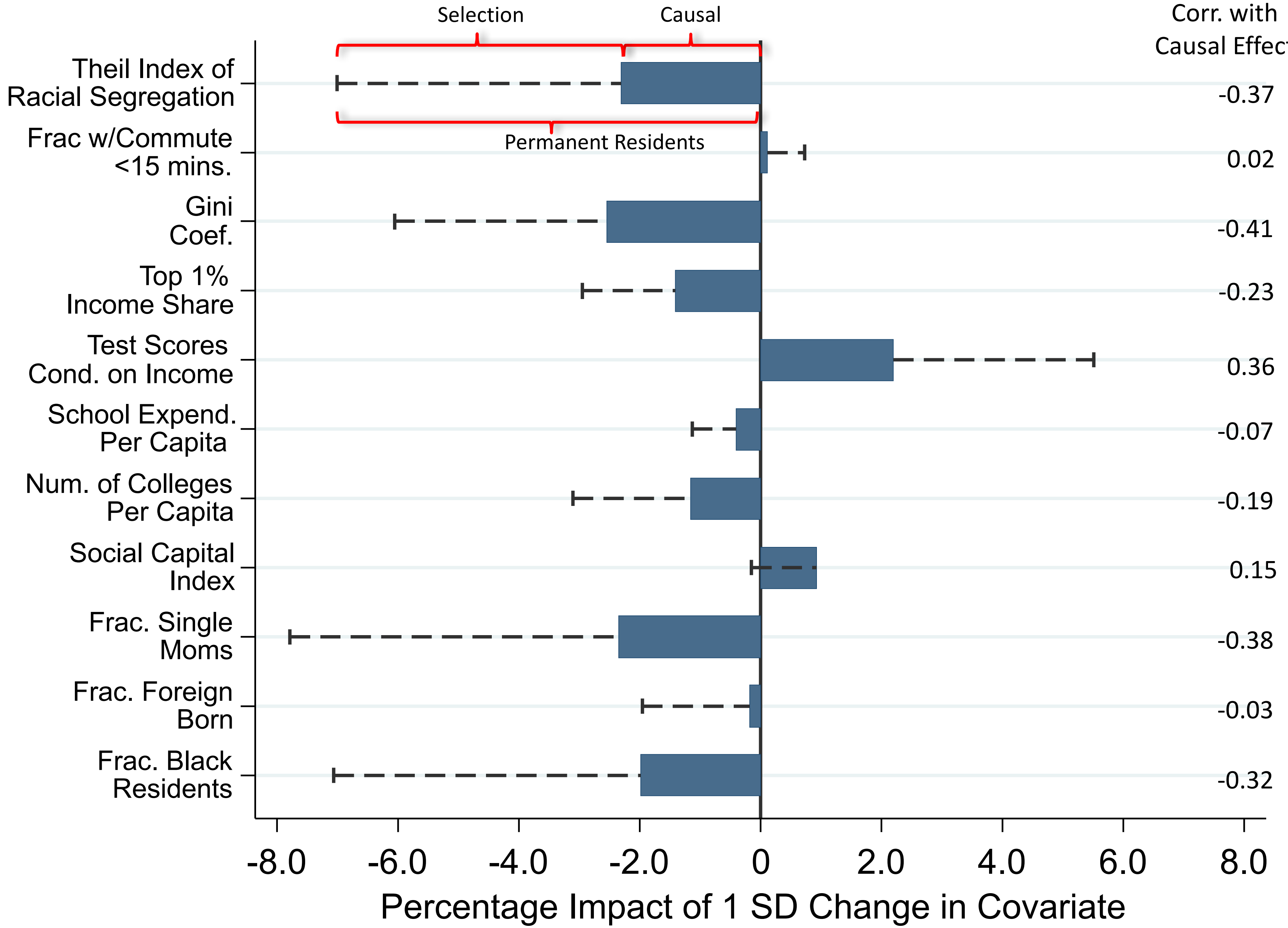
Predictors of Causal Effects For Children at the CZ Level (p25)

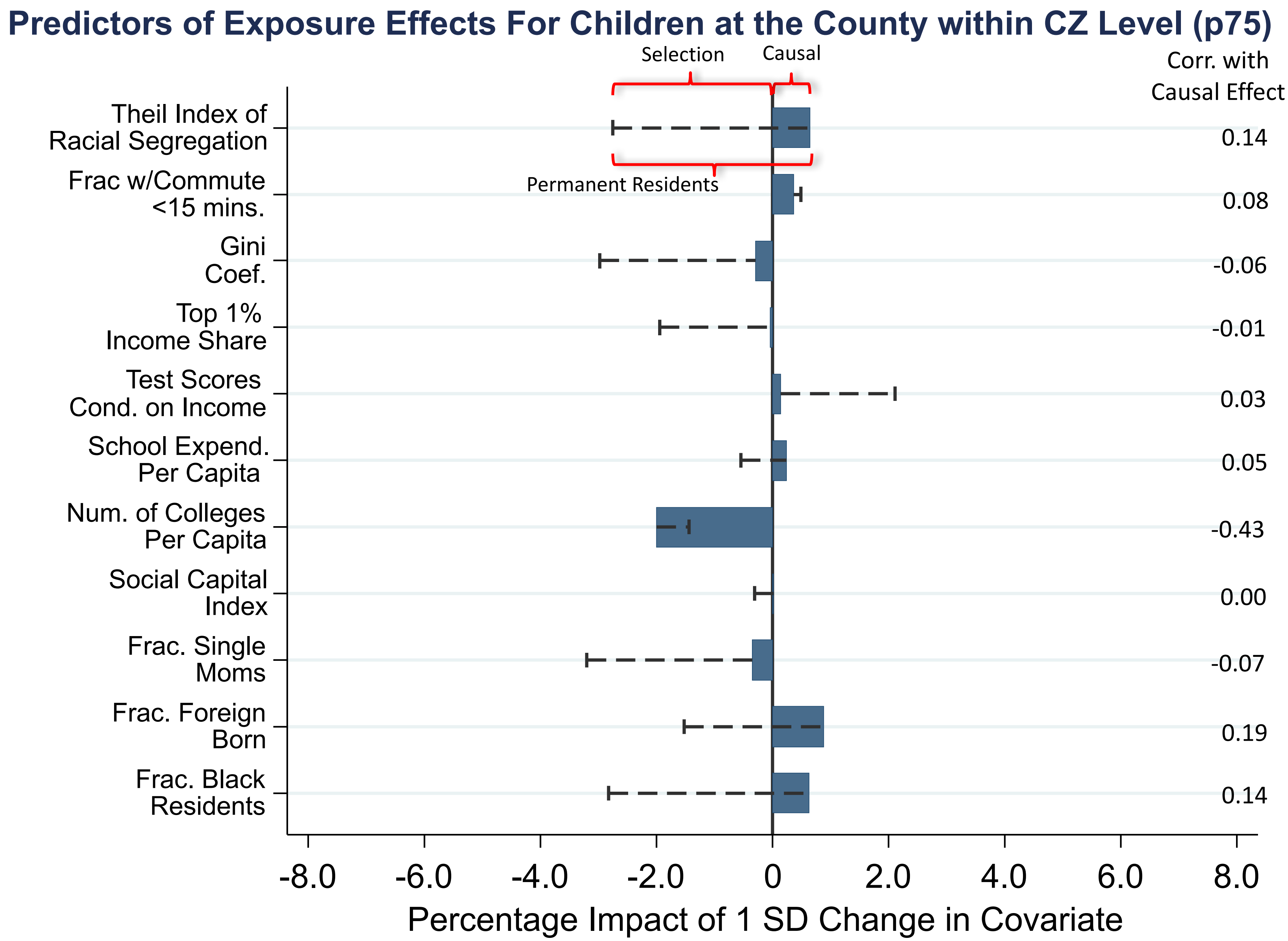


Predictors of Causal Effects For Children at the CZ Level (p25)



Predictors of Exposure Effects For Children at the County within CZ Level (p25)





Predictors of Exposure Effects For Children at the County within CZ Level (p75)
Selection
Causal
Permanent Residents
Corr. with Causal Effect
Theil Index of Racial Segregation
0.14
Frac w/Commute <15 mins.
0.08
Gini Coef.
-0.06
Top 1% Income Share
-0.01
Test Scores Cond. on Income
0.03
School Expend. Per Capita
0.05
Num. of Colleges Per Capita
-0.43
Social Capital Index
0.00
Frac. Single Moms
-0.07
Frac. Foreign Born
0.19
Frac. Black Residents
0.14
-8.0
-6.0
-4.0
-2.0
0
2.0
4.0
6.0
8.0
Percentage Impact of 1 SD Change in Covariate

House Prices

- Does it cost more to live in a county that improves children's outcomes?

- Correlation between causal exposure effect and median rent is *negative* (-0.4) across CZs

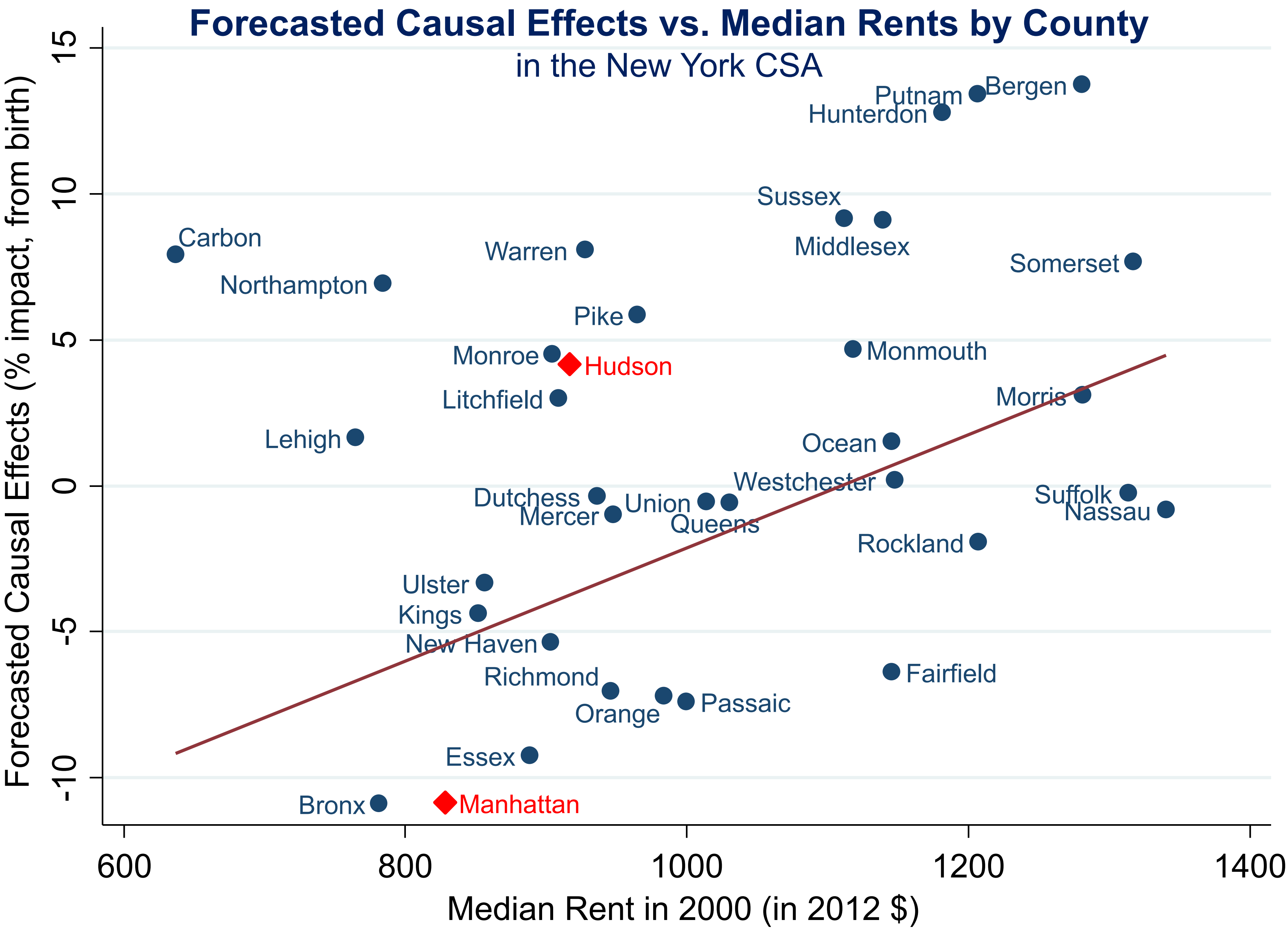
    - Rural areas produce better outcomes

- But, evidence of positive correlation across counties within CZs

    - Moving to a county that causes a 1% increase in child's earnings per year of exposure on average has $176.8 (s.e. 65.50) higher median rent

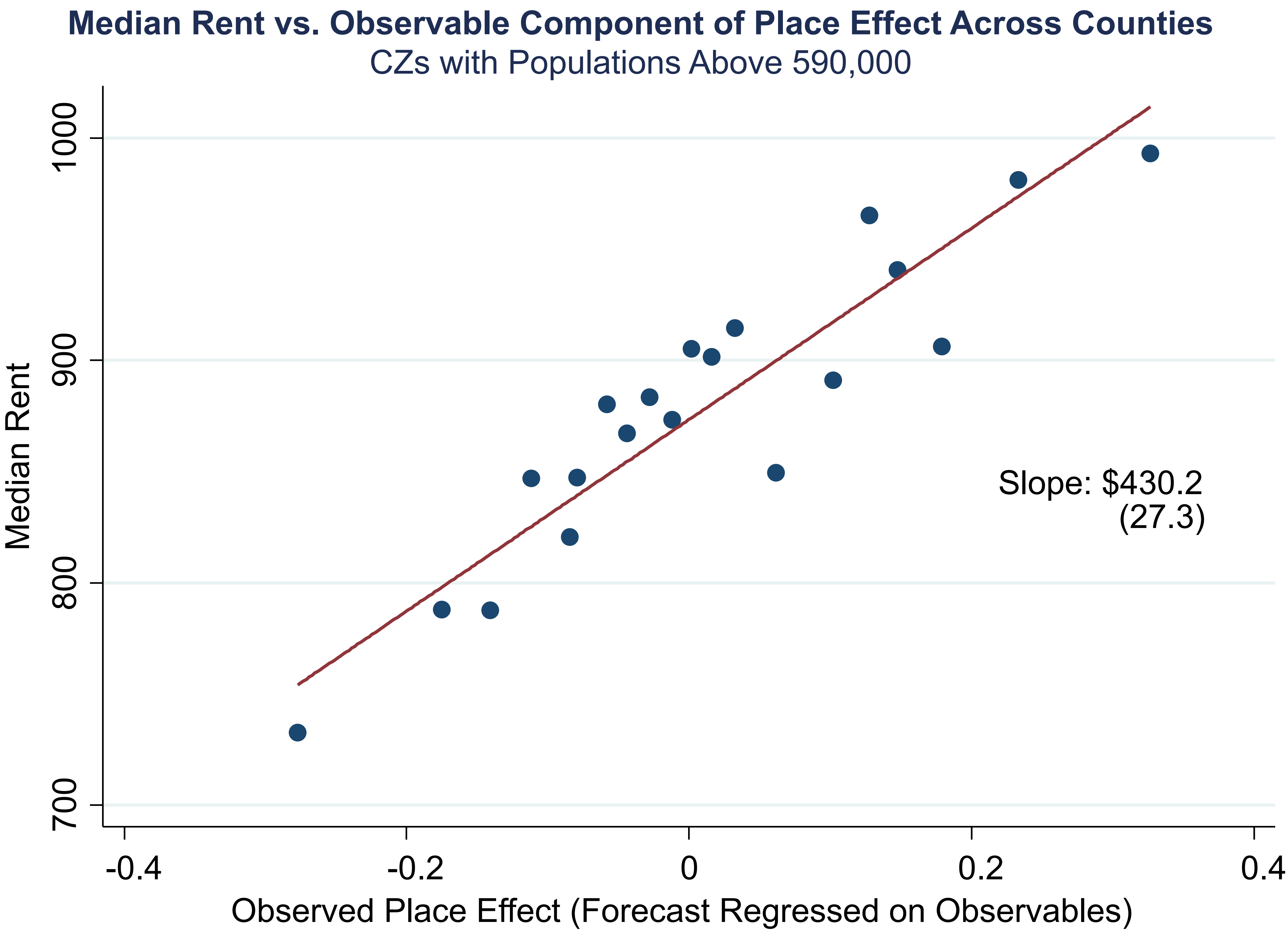
Opportunity vs. House Prices

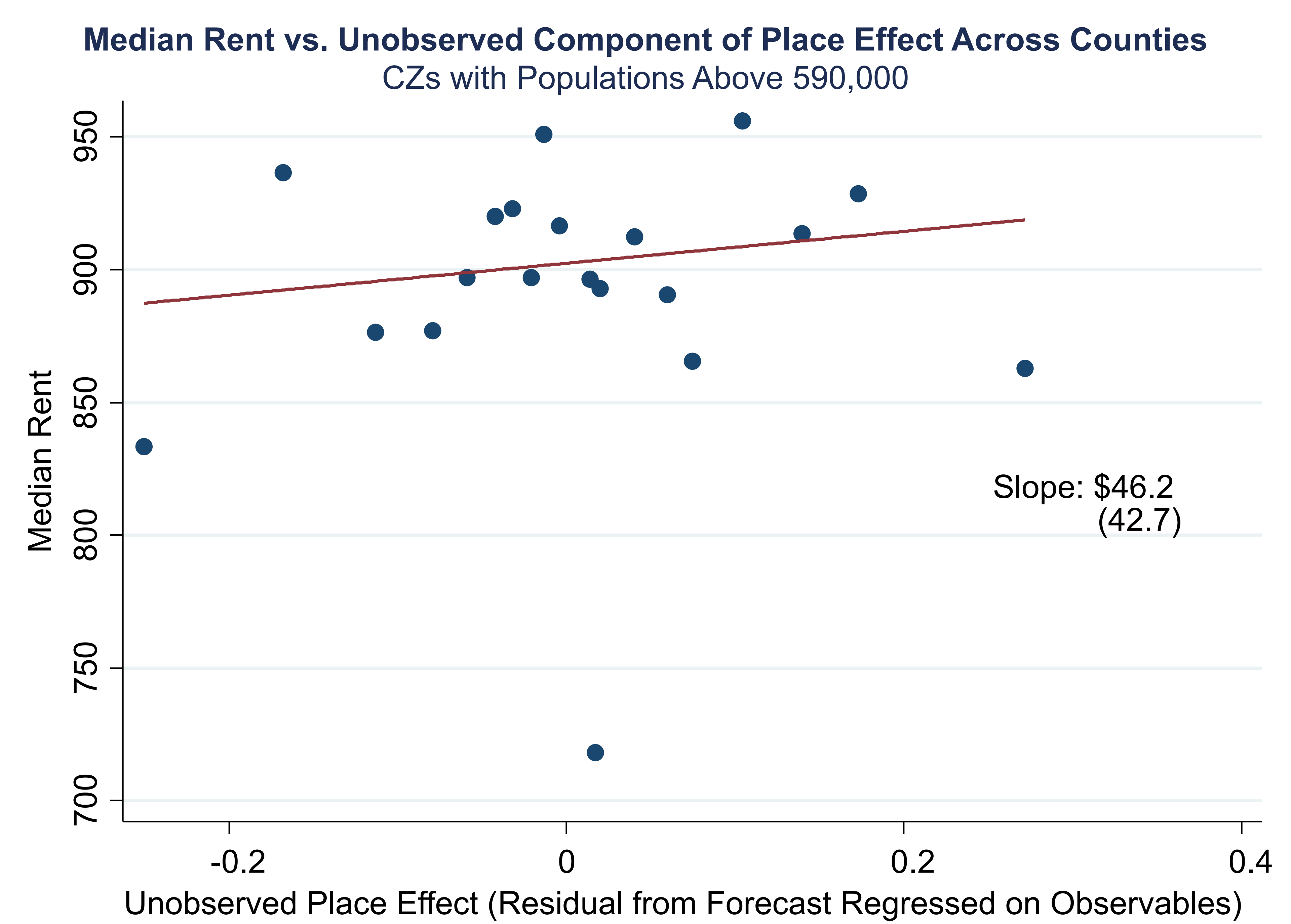
- But, rents explain less than 2% of variation in county causal effects
    - Implies that there are many "opportunity bargains"


Forecasted Causal Effects vs. Median Rents by County
in the New York CSA
Forecasted Causal Effects (% impact, from birth)
Median Rent in 2000 (in 2012 $)
15
10
5
0
-5
-10
600
800
1000
1200
1400
Bergen
Putnam
Hunterdon
Sussex
Middlesex
Carbon
Warren
Somerset
Northampton
Pike
Monroe
Hudson
Monmouth
Litchfield
Morris
Lehigh
Ocean
Westchester
Dutchess
Union
Suffolk
Mercer
Queens
Nassau
Rockland
Ulster
Kings
New Haven
Richmond
Fairfield
Orange
Passaic
Essex
Bronx
Manhattan

House Prices

- Why are causal effects on children not fully capitalized in house prices?
  - Other disamenities (e.g. longer commute)
  - Causal effects not fully observed
- Suggestive evidence of #2: only the observable components of the causal effects are priced
- Define observable component as projection of place effect onto observables: poverty rate, commute time, single parent share, test scores, and Gini
- Define unobservable component as residual from this regression, shrunk to adjust for measurement error
- Regress median rent on observable and unobservable components
  - Roughly one-third of the variance is “observable” and two-thirds is not


Median Rent vs. Observable Component of Place Effect Across Counties
CZs with Populations Above 590,000
Median Rent
1000
900
800
700
-0.4
-0.2
0
0.2
0.4
Observed Place Effect (Forecast Regressed on Observables)
Slope: $430.2
(27.3)



Median Rent vs. Unobserved Component of Place Effect Across Counties
CZs with Populations Above 590,000
Median Rent
950
900
850
800
750
700
-0.2
0
0.2
0.4
Unobserved Place Effect (Residual from Forecast Regressed on Observables)
Slope: $46.2
(42.7)

House Prices

- Main lesson: substantial scope to move to areas that generate greater upward mobility for children without paying much more
    - Especially true in cities with low levels of segregation
- In segregated cities, places that generate good outcomes without having typical characteristics (better schools, lower poverty rates) provide bargains
    - Ex: Hudson County, NJ vs. Bronx in New York metro area
- Encouraging for housing-voucher policies that seek to help low-income families move to better areas

Conclusion

- Findings provide support for place-focused approaches to improving economic opportunity

  1. Substantial scope to help low-income families move to better area without paying higher rents

     - Outcome-based forecasting approach developed here provides a practical method to identify such areas

  2. Places that have high upward mobility have a common set of characteristics, such as less segregation and better schools

     - Suggests that their successes may be replicable in areas that currently offer lower levels of opportunity

Download County-Level Data on Social Mobility in the U.S.

www.equality-of-opportunity.org/data

THE EQUALITY OF OPPORTUNITY PROJECT

HOME | EXECUTIVE SUMMARIES | PAPERS | SLIDES & VIDEOS | CITY RANKINGS | DOWNLOAD DATA | FAQ'S | RESEARCH TEAM | PREVIOUS RESEARCH | PRESS | CONTACT US

Downloadable Data

Data from Chetty and Hendren (2015): Causal Effects, Mobility Estimates and Covariates by County, CZ and Birth Cohort

Data Description			
Online Data Table 1: Preferred Estimates of Causal Place Effects by Commuting Zone	Stata file	Excel file	ReadMe
Online Data Table 2: Preferred Estimates of Causal Place Effects by County	Stata file	Excel file	ReadMe
Online Data Table 3: Complete CZ-Level Dataset: Causal Effects and Covariates	Stata file	Excel file	ReadMe
Online Data Table 4: Complete County-Level Dataset: Causal Effects and Covariates	Stata file	Excel file	ReadMe
Online Data Table 5: Pairwise Place Effects by Origin-Destination Pairs of Commuting Zones	Stata file	Excel file	ReadMe
Online Data Table 6: Parent Income Distribution by Child's Birth Cohort	Stata file	Excel file	ReadMe