Using Big Data to Solve Economic and Social Problems

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HARVARD UNIVERSITY

OPPORTUNITY INSIGHTS

Two Approaches to Increasing Upward Mobility

- **Moving to Opportunity**: Provide Affordable Housing in High-Opportunity Areas

- **Place-Based Investments**: Increase Upward Mobility in Low-Opportunity Areas

Moving to Opportunity Experiment

- Implemented from 1994-1998 at 5 sites: Baltimore, Boston, Chicago, LA, New York

- 4,600 families were randomly assigned to one of three groups:

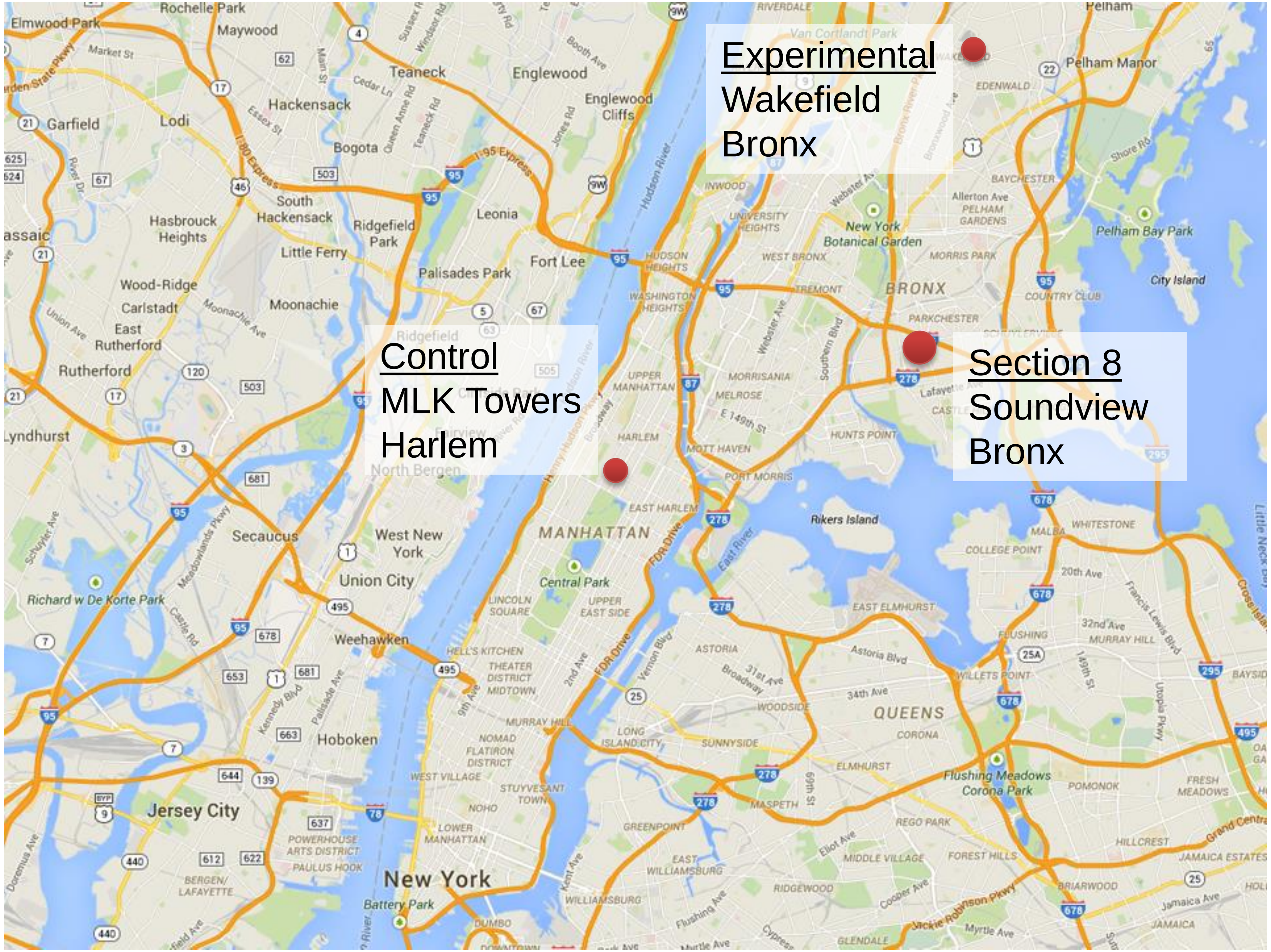
  1. Experimental: offered housing vouchers restricted to low-poverty (<10%) Census tracts

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

  3. Control: not offered a voucher, stayed in public housing

- Compliance rates: 48% of experimental group used voucher, 66% of Section 8 group used voucher

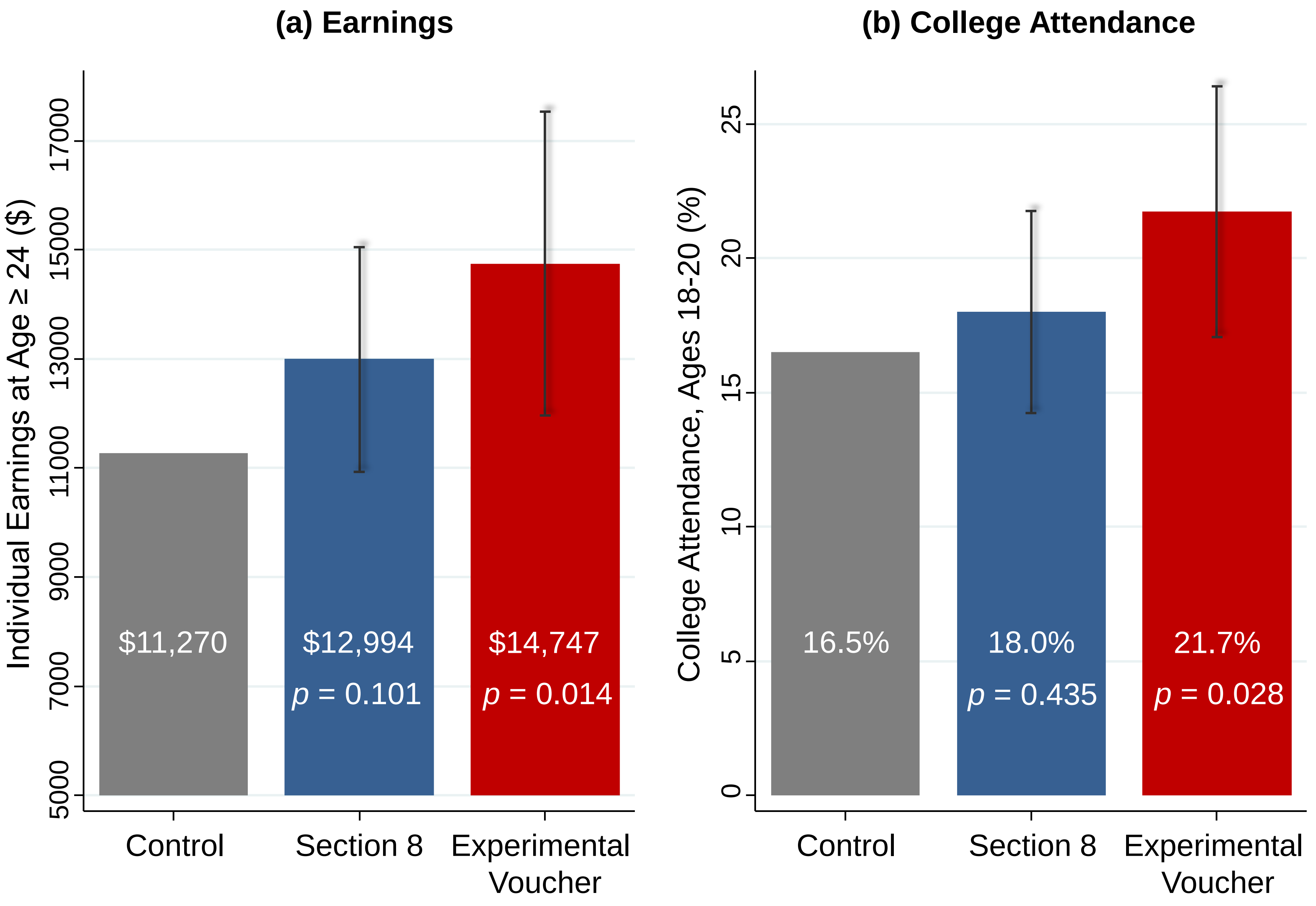
Common MTO Residential Locations in New York



Analysis of MTO Experimental Impacts

- Early research on MTO found little impact of moving to a better area on economic outcomes such as earnings
  - But it focused primarily on adults and older youth at point of move [e.g., Kling, Liebman, and Katz 2007]
- Motivated by our quasi-experimental study (Chetty and Hendren 2018), we test for *exposure effects* among children
  - Does MTO improve outcomes for children who moved when young?
  - Link MTO to tax data to study children's outcomes in mid 20's
  - Compare earnings across groups, adjusting for compliance rates

Impacts of MTO on Children Below Age 13 at Random Assignment



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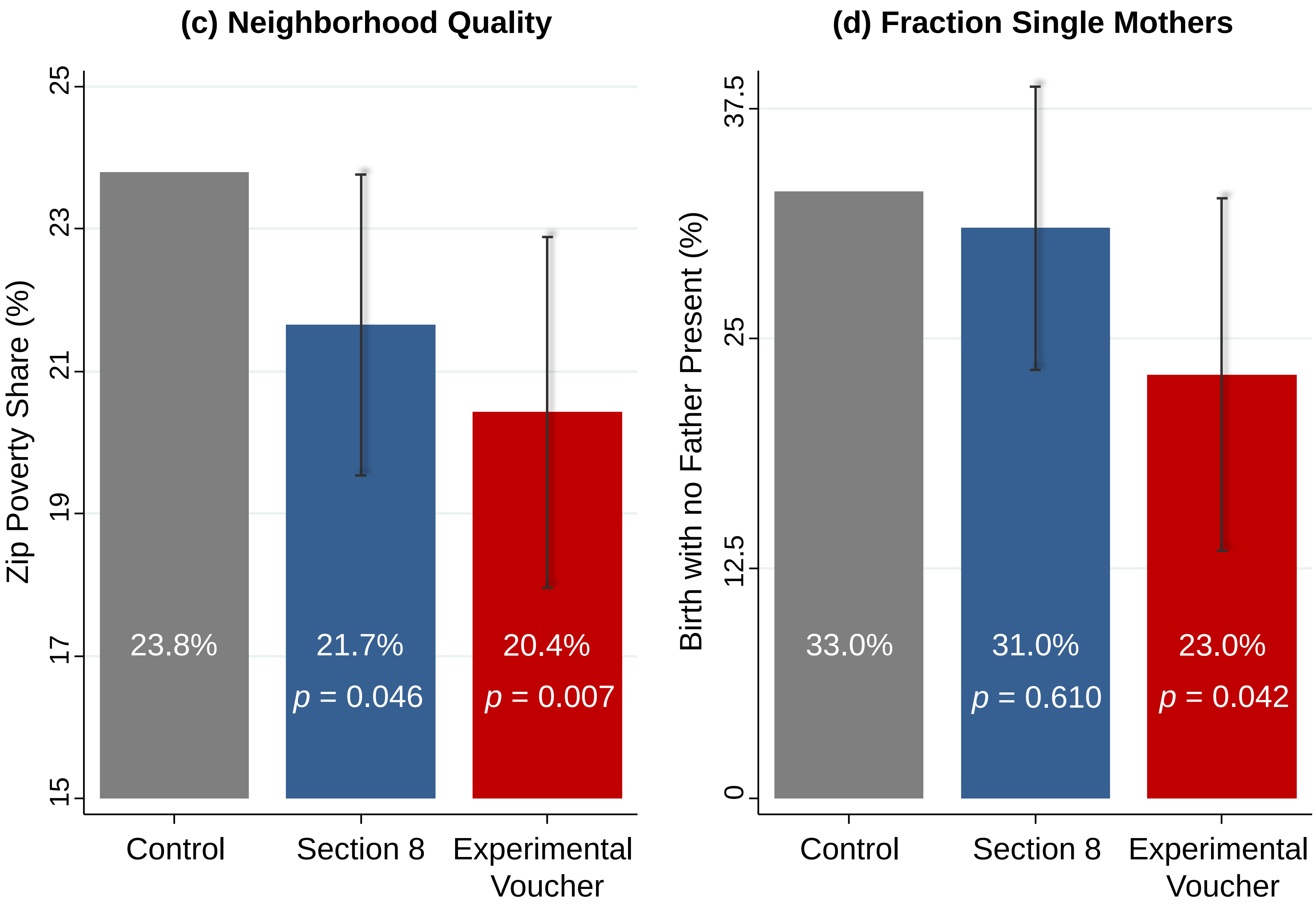
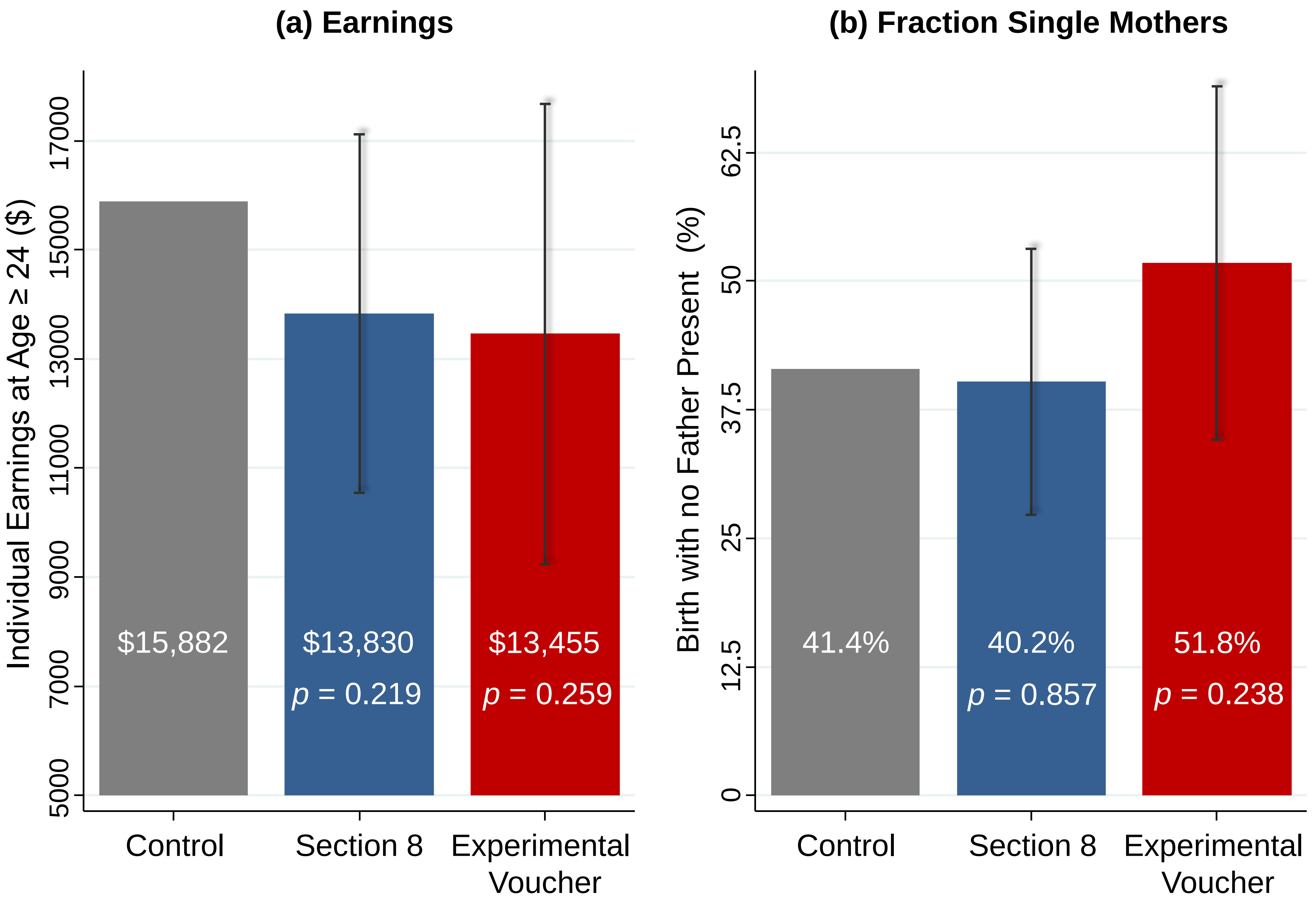
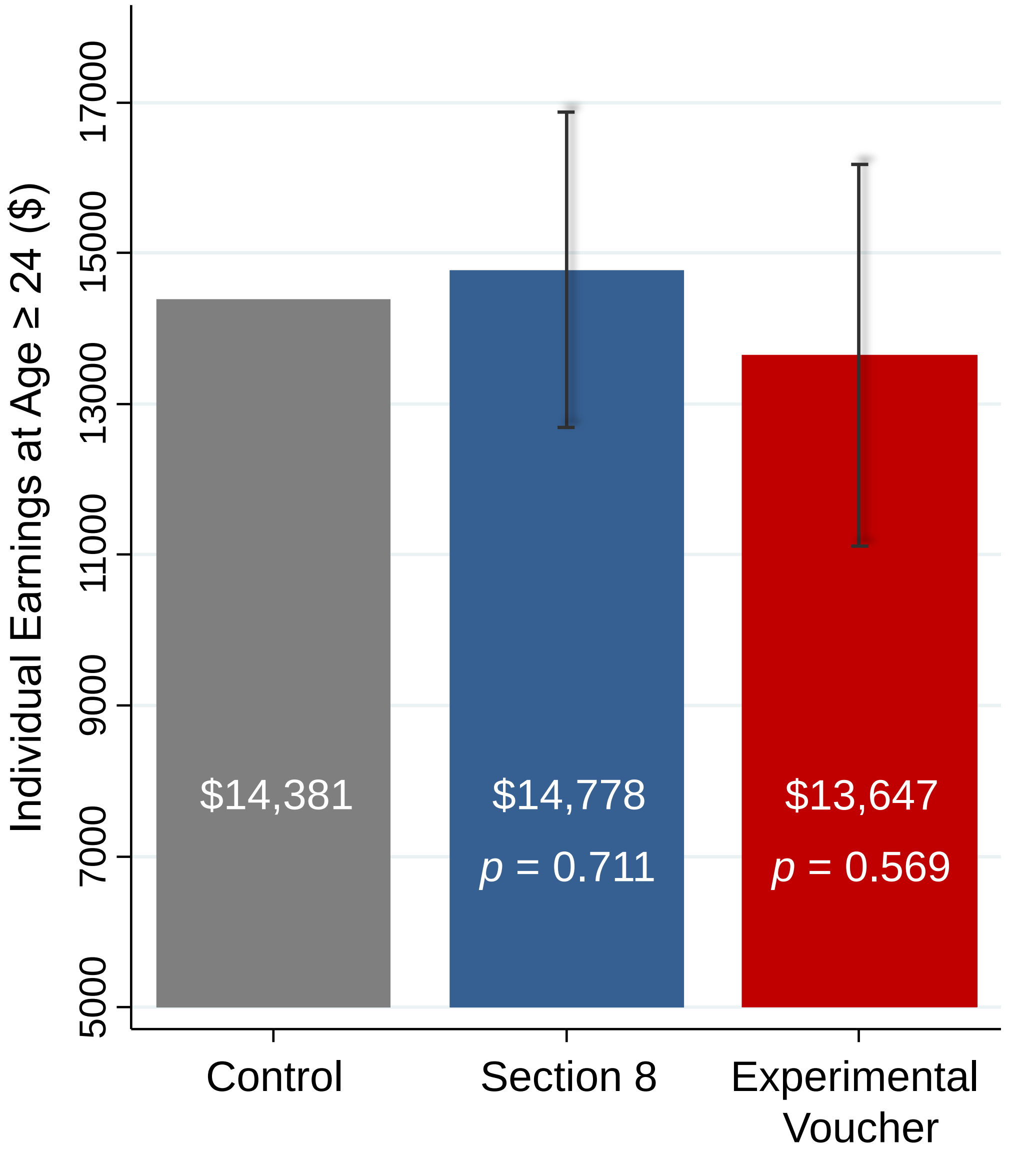


Impacts of MTO on Children Age 13-18 at Random Assignment



Impacts of Moving to Opportunity on Adults' Earnings



Limitations of Randomized Experiments

- Why not use randomized experiments to answer all policy questions?

- Beyond feasibility, there are three common limitations:

1. Attrition: lose track of participants over time → long-term impact evaluation unreliable

   – Especially a problem when attrition rate differs across treatment groups because we lose comparability

   – This problem is largely fixed by the big data revolution: in MTO, we are able to track 99% of participants by linking to tax records

Limitations of Randomized Experiments

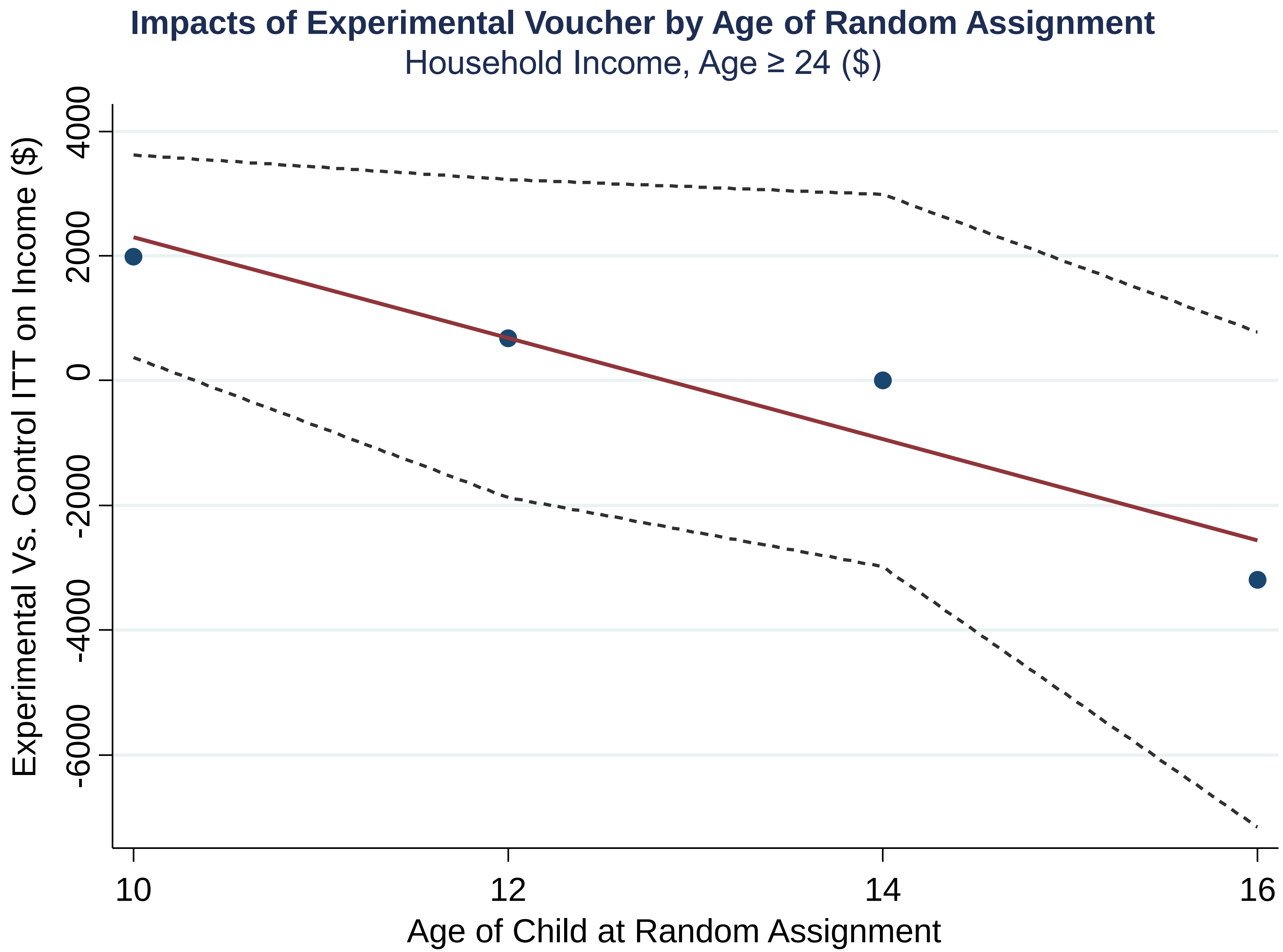
- Why not use randomized experiments to answer all policy questions?

- Beyond feasibility, there are three common limitations:

1. Attrition: lose track of participants over time → long-term impact evaluation unreliable

2. Sample size: small samples make estimates imprecise, especially for long-term impacts

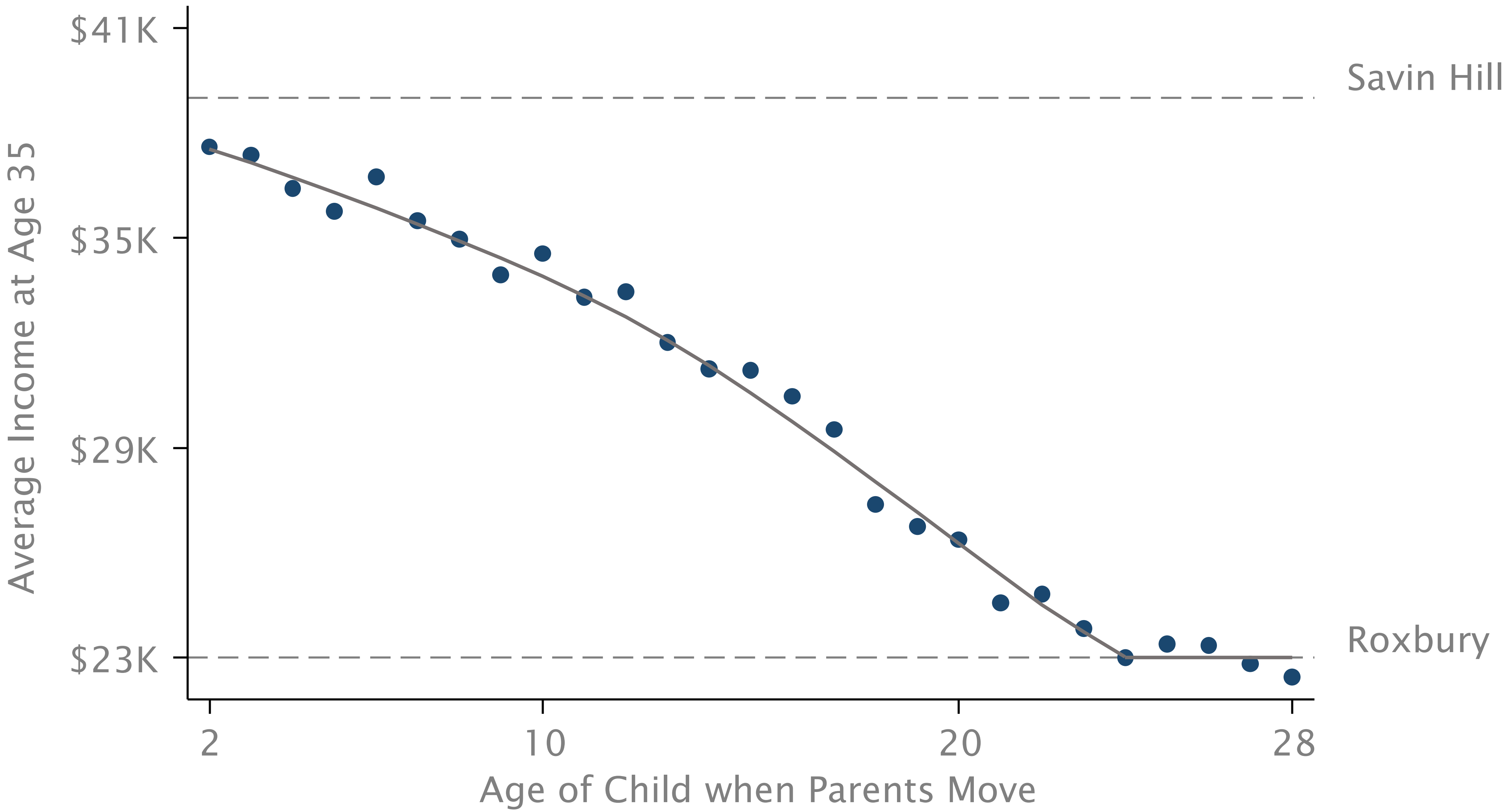
   – This problem is *not* fixed by big data: cost of data has fallen, but cost of experimentation (in social science) has not



Impacts of Experimental Voucher by Age of Random Assignment
Household Income, Age ≥ 24 ($)
Experimental Vs. Control ITT on Income ($)
4000
2000
0
-2000
-4000
-6000
10
12
14
16
Age of Child at Random Assignment

Income Gain from Moving to a Better Neighborhood

By Child's Age at Move



Limitations of Randomized Experiments

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1. Attrition: lose track of participants over time → long-term impact evaluation unreliable

2. Sample size: small samples make estimates imprecise, especially for long-term impacts

3. Generalizability: results of an experiment may not generalize to other subgroups or areas

   – Difficult to run experiments in all subgroups and areas → “scaling up” can be challenging

Quasi-Experimental Methods

- Quasi-experimental methods using big data can address these issues
- Consider study of 3 million families that moved across areas discussed earlier
- How did we achieve comparability across groups in this study?
  - People who move to different areas are not comparable to each other
  - But people who move when children are younger vs. older are more likely to be comparable

→ Approximate experimental conditions by comparing children who move to a new area at different ages

Quasi-Experimental Methods

- Quasi-experimental approach addresses limitations of MTO experiment:

  1. Sample size: much larger samples yield precise estimates of childhood exposure effects (4% convergence per year)

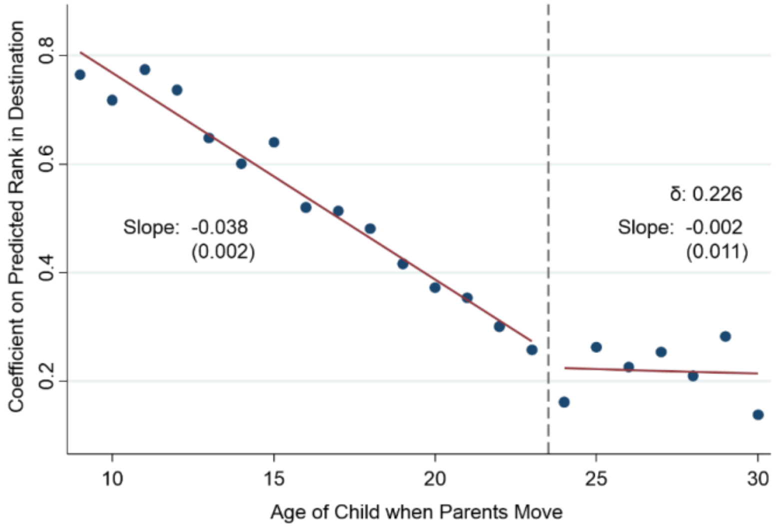
  2. Generalizability: results generalize to all areas of the U.S.

- Limitation of quasi-experimental approach: reliance on stronger assumptions

- Bottom line: reassuring to have evidence from both approaches that is consistent → clear consensus that moving to opportunity works

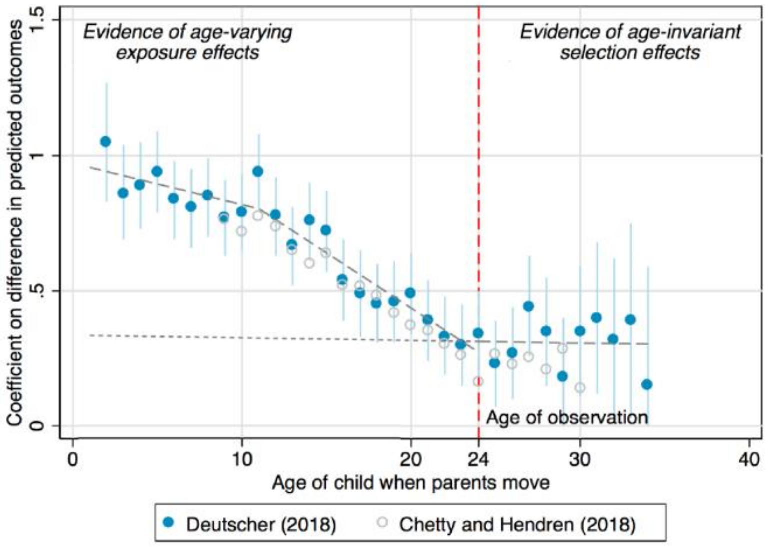
Childhood Exposure Effects Around the World

United States



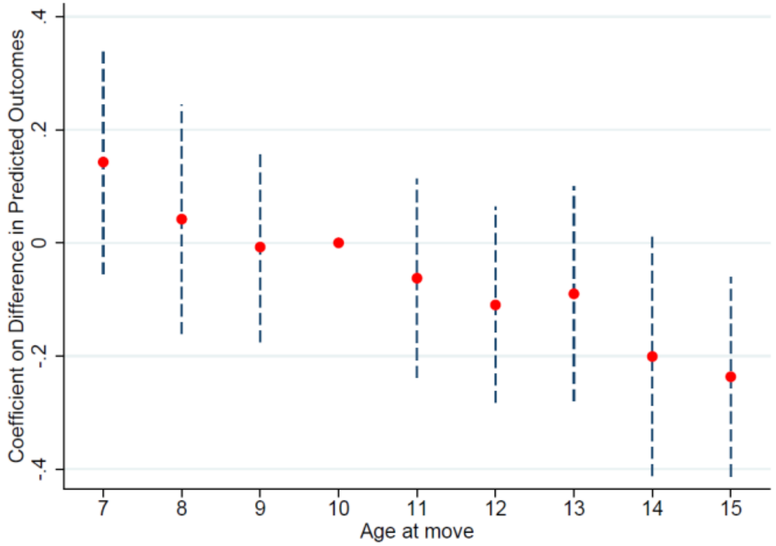
Source: Chetty and Hendren (QJE 2018)

Australia



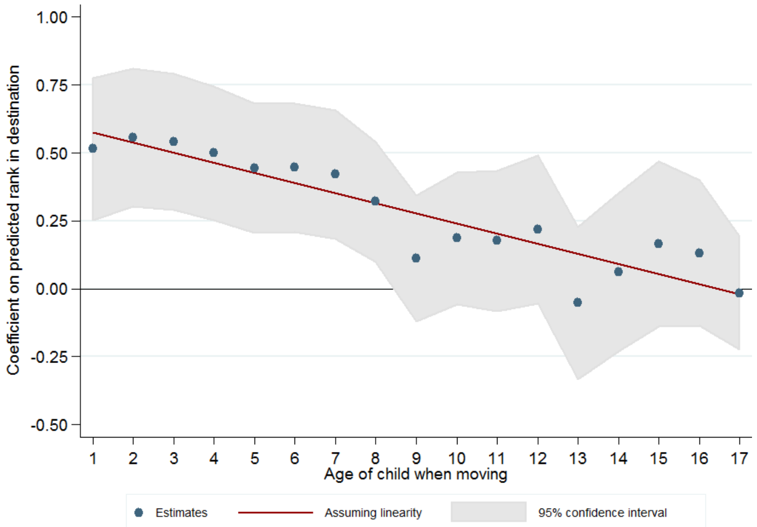
Source: Deutscher (2018)

Montreal, Canada



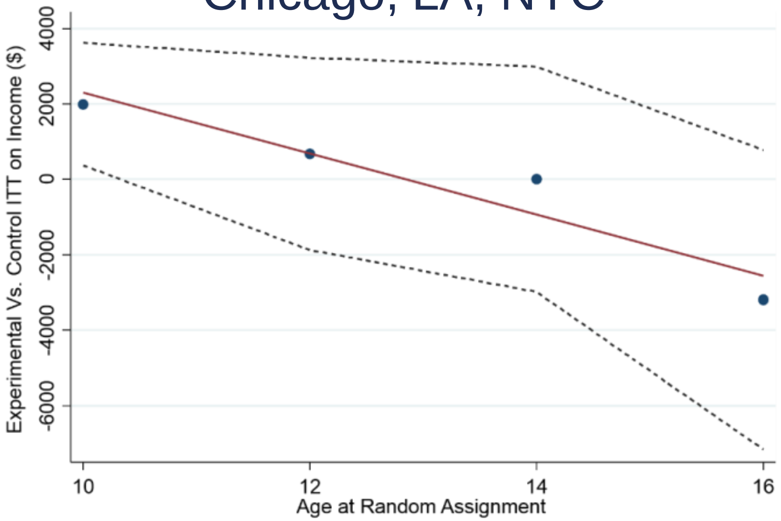
Source: Laliberté (2018)

Denmark



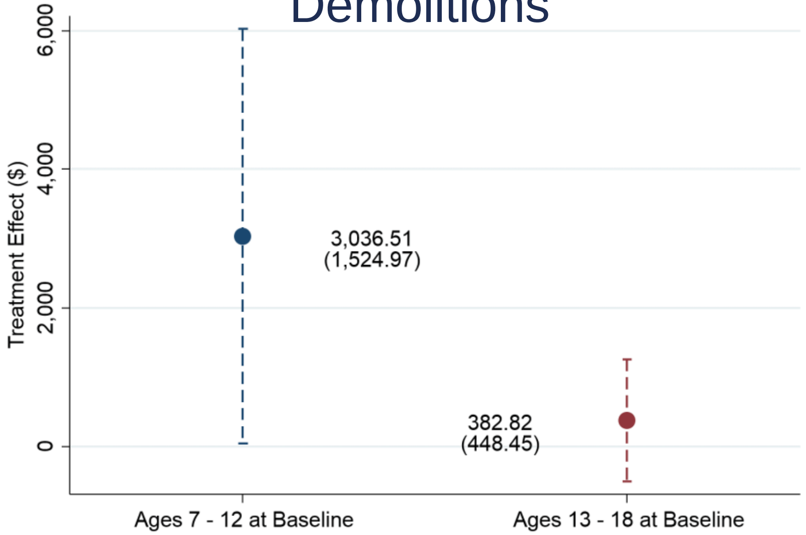
Source: Faurschou (2018)

MTO: Baltimore, Boston, Chicago, LA, NYC



Source: Chetty, Hendren, Katz (AER 2016)

Chicago Public Housing Demolitions



Source: Chyn (AER 2018)

Implications for Housing Voucher Policy

- Housing vouchers can be very effective but must be targeted carefully

1. Vouchers should be targeted at families with young children

    – Current U.S. policy of putting families on waitlists is especially inefficient

Implications for Housing Voucher Policy

- Housing vouchers can be very effective but must be targeted carefully

1. Vouchers should be targeted at families with young children

2. Vouchers should be explicitly designed to help families move to affordable, high-opportunity areas

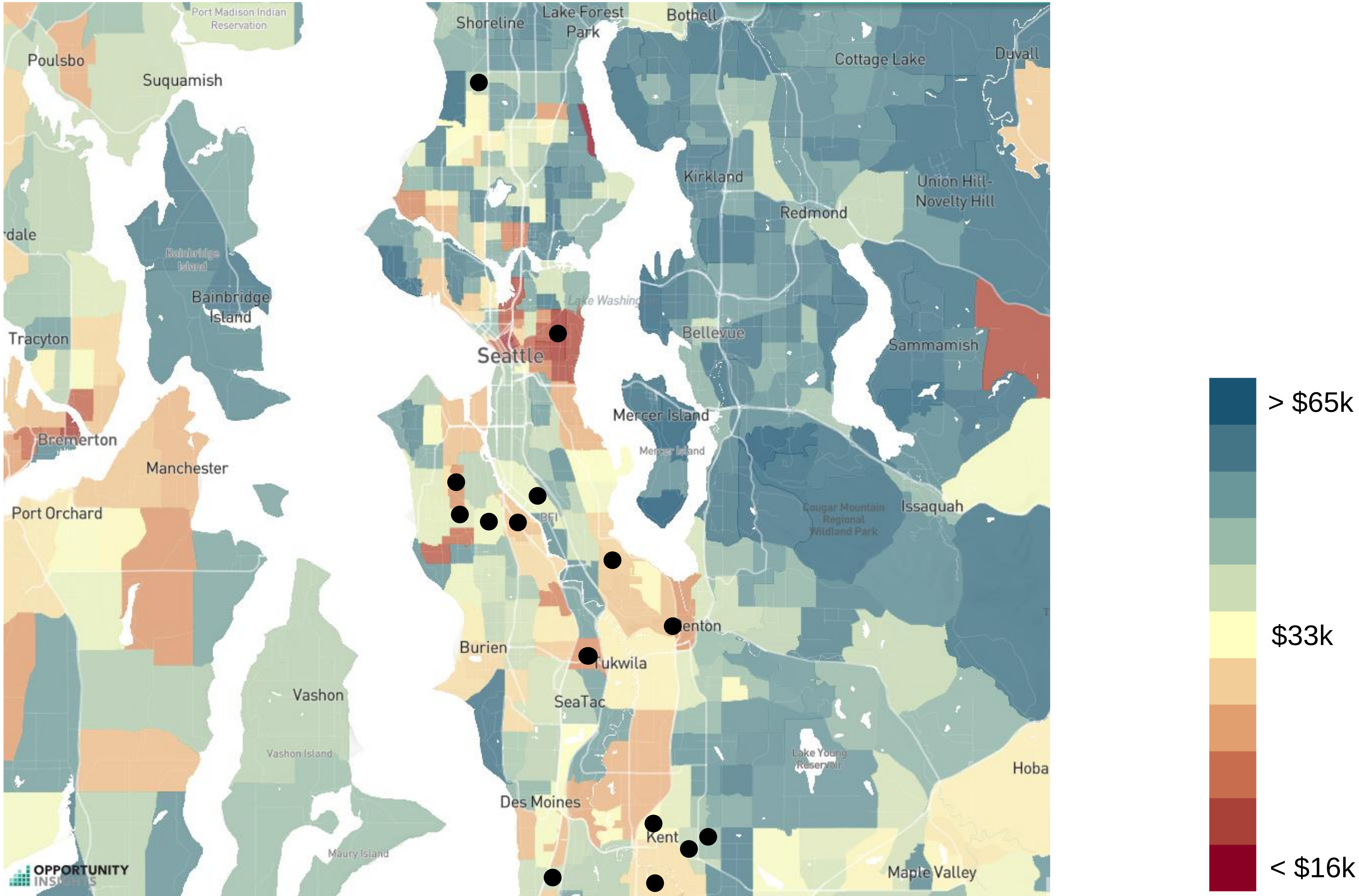
   – In MTO experiment, unrestricted “Section 8” vouchers produced *smaller* gains even though families could have made same moves

   – More generally, low-income families rarely use cash transfers to move to better neighborhoods [Jacob et al. 2015]

   – 80% of the 2.1 million Section 8 vouchers are currently used in high-poverty, low-opportunity neighborhoods

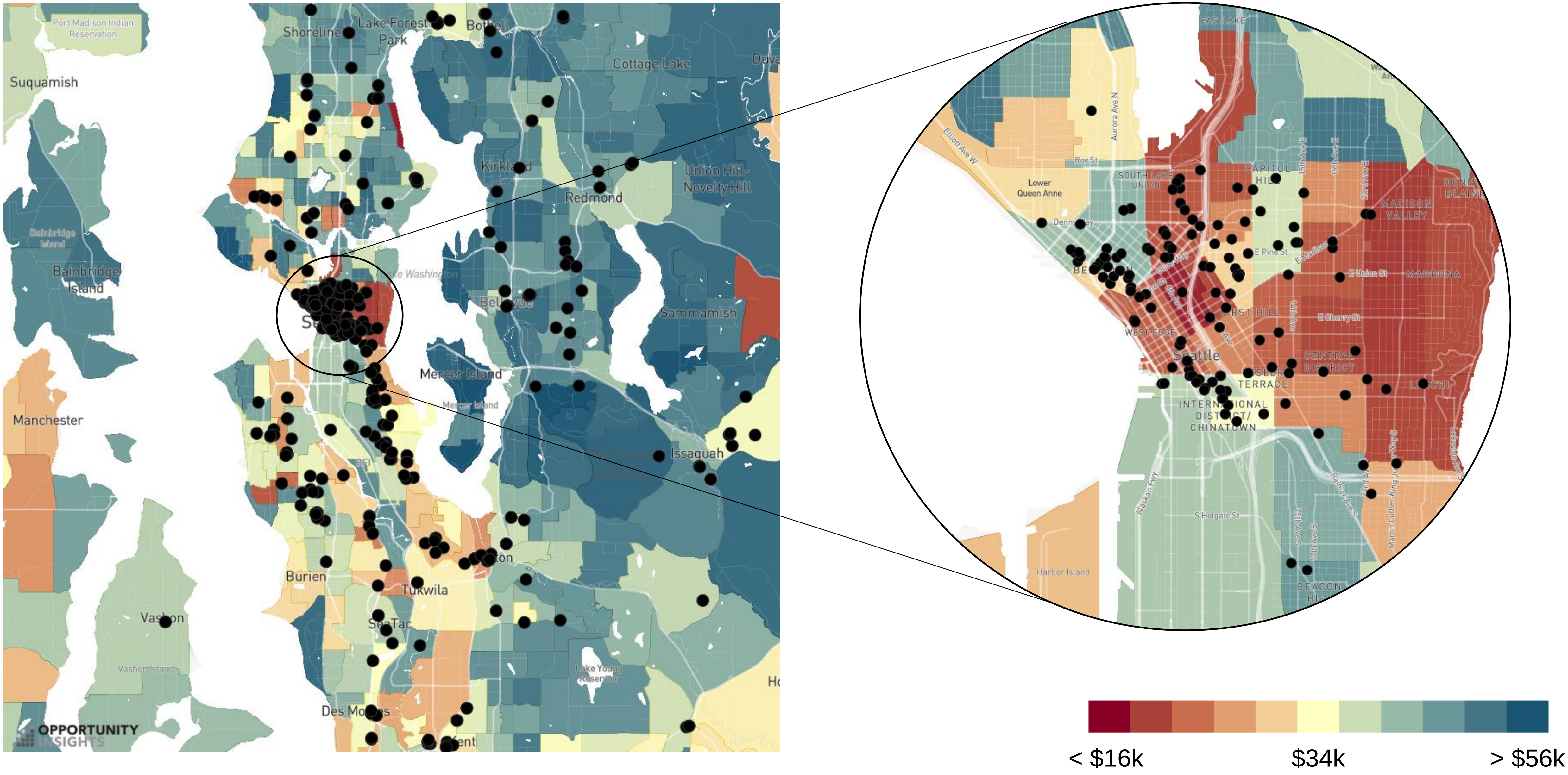
Is Affordable Housing in Seattle Maximizing Opportunities for Upward Mobility?

Most Common Current Locations of Families Receiving Housing Vouchers



Is the Low Income Housing Tax Credit Reducing Mobility out of Poverty?

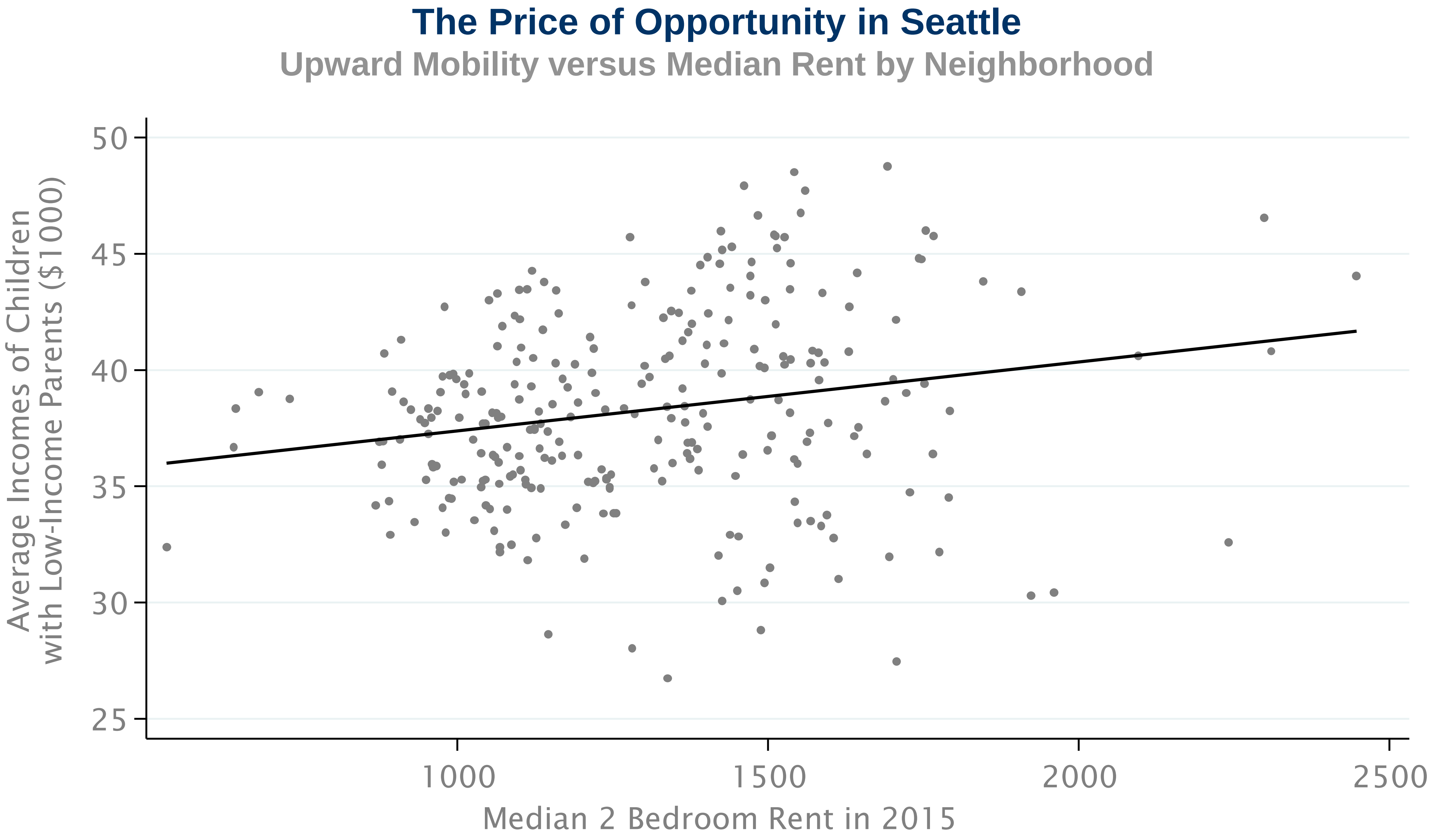
Location of LIHTC projects in Seattle



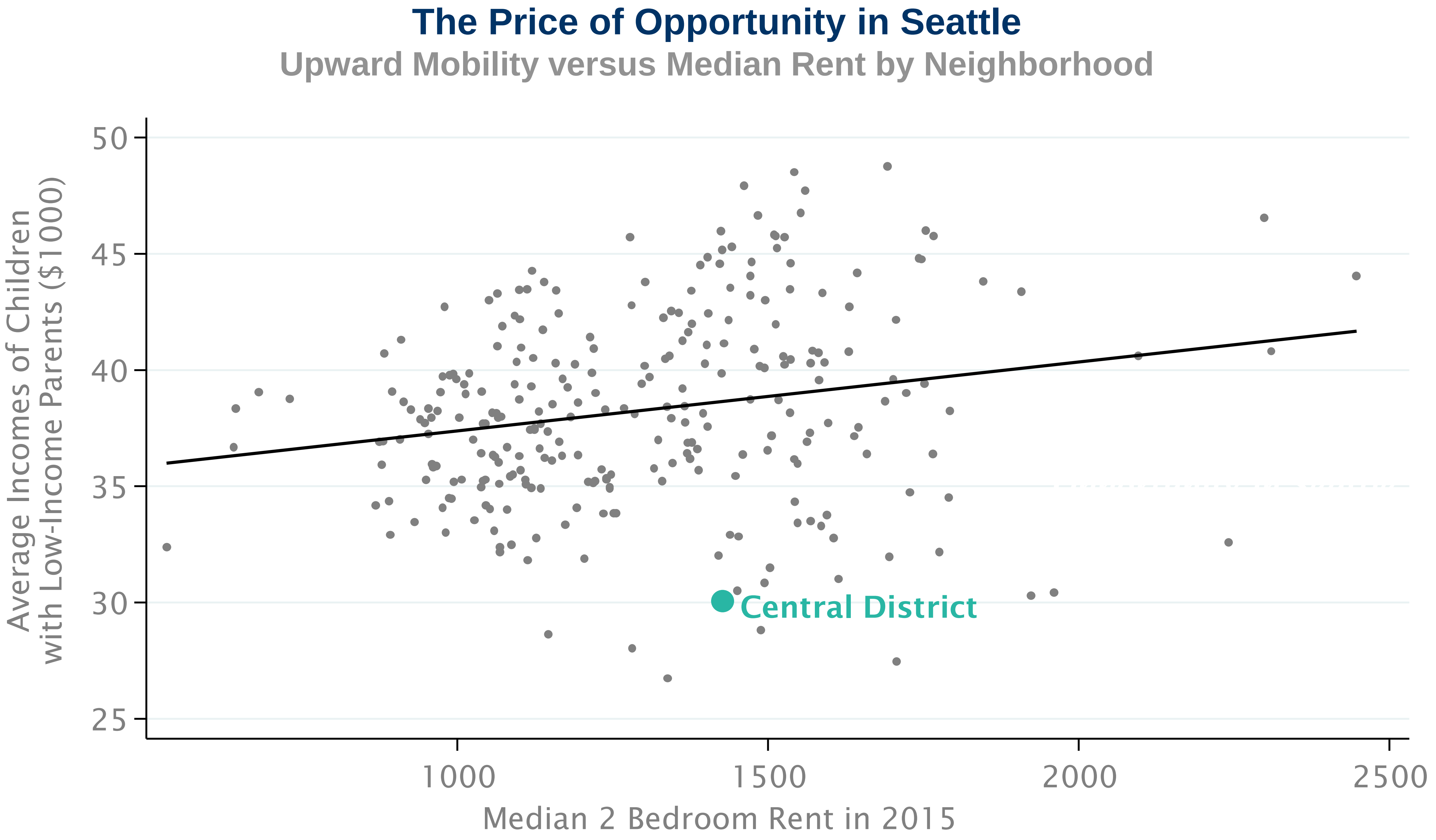
Why Don’t More Low-Income Families Move to Opportunity?

- One simple explanation: areas that offer better opportunity may be unaffordable

- To test whether this is the case, examine relationship between measures of upward mobility and rents



The Price of Opportunity in Seattle
Upward Mobility versus Median Rent by Neighborhood
Average Incomes of Children
with Low-Income Parents ($1000)
50
45
40
35
30
25
1000
1500
2000
2500
Median 2 Bedroom Rent in 2015


The Price of Opportunity in Seattle
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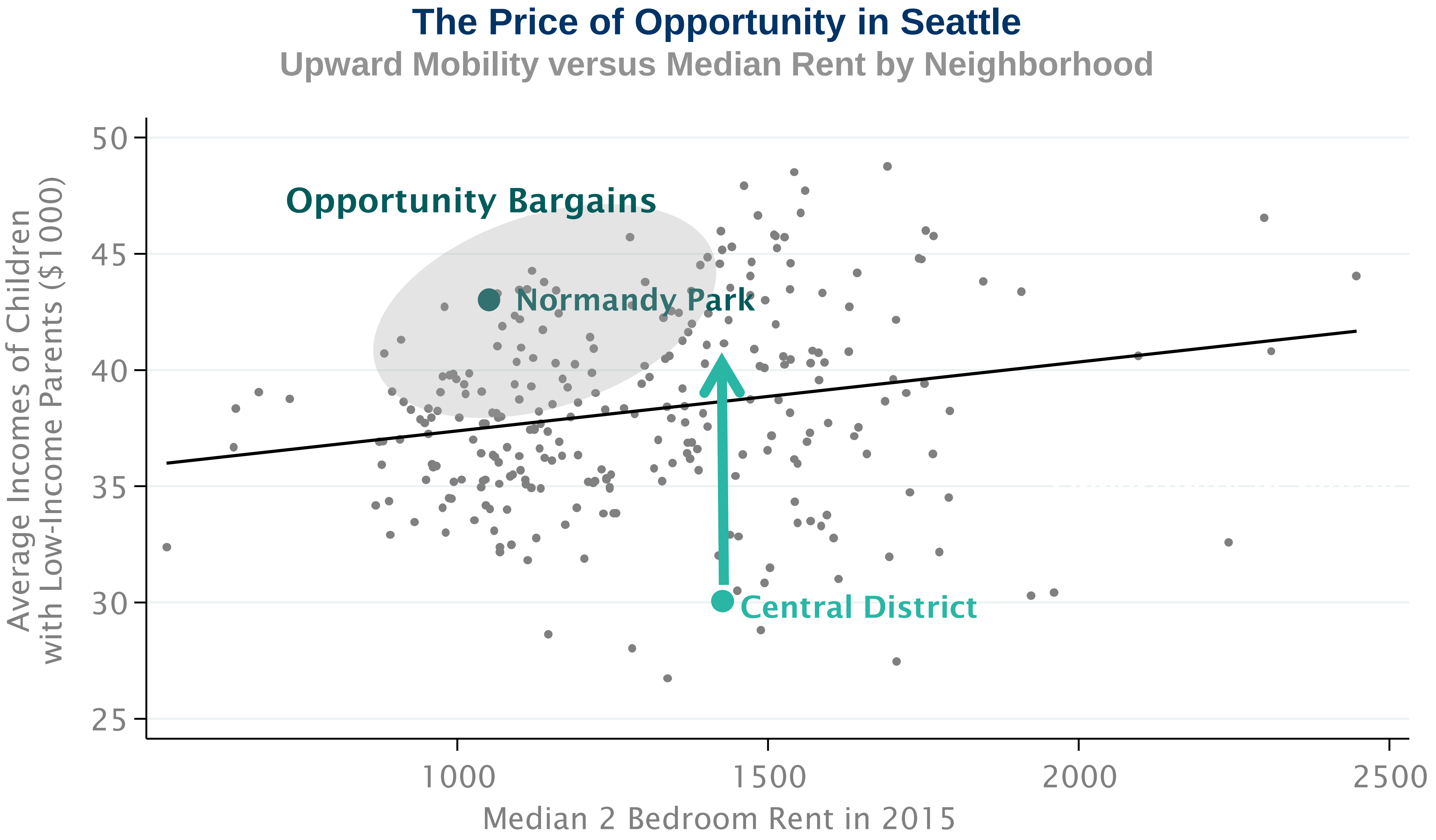
50
45
40
35
30
25
1000
1500
2000
2500
Median 2 Bedroom Rent in 2015
Central District


The Price of Opportunity in Seattle
Upward Mobility versus Median Rent by Neighborhood
Opportunity Bargains
Normandy Park
Central District
Average Incomes of Children
with Low-Income Parents ($1000)
50
45
40
35
30
25
1000
1500
2000
2500
Median 2 Bedroom Rent in 2015

Stability of Historical Measures of Opportunity

- Tract-level data on children's outcomes provide new information that could be helpful in helping families move to opportunity

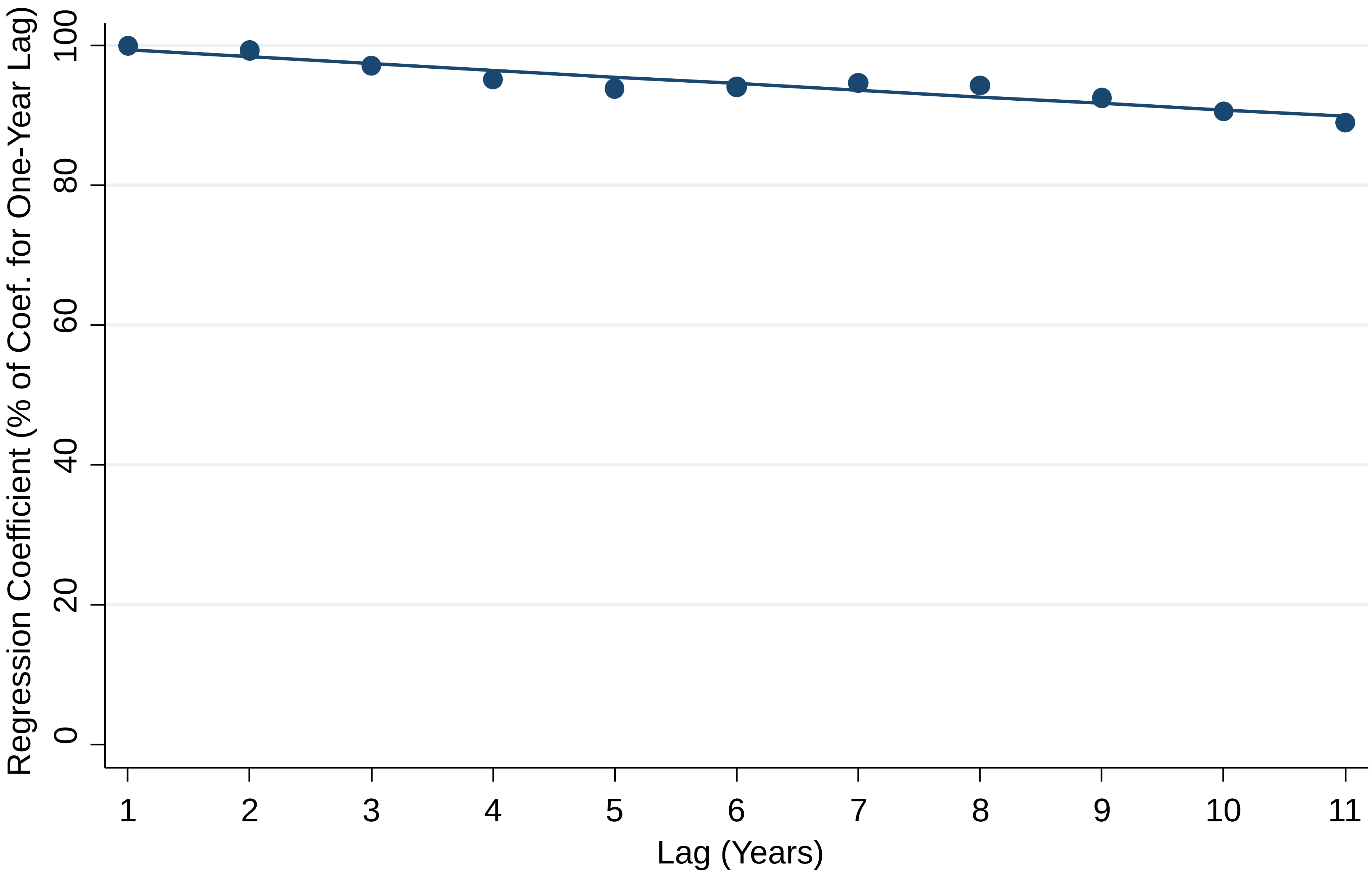
- Practical concern: data on upward mobility necessarily are historical, since one must wait until children grow up to observe their earnings

  - Opportunity Atlas estimates are based on children born in the early 1980s, who grew up in the 1990s and 2000s

- Are historical estimates useful predictors of opportunity for children who are growing up in these neighborhoods now?

Stability of Tract-Level Estimates of Upward Mobility

Regression Estimates Using Estimates by Birth Cohort



Creating Moves to Opportunity

Pilot study to help families with housing vouchers move to high-opportunity areas in Seattle using three approaches:

- Providing information to tenants
- Recruiting landlords
- Offering housing search assistance

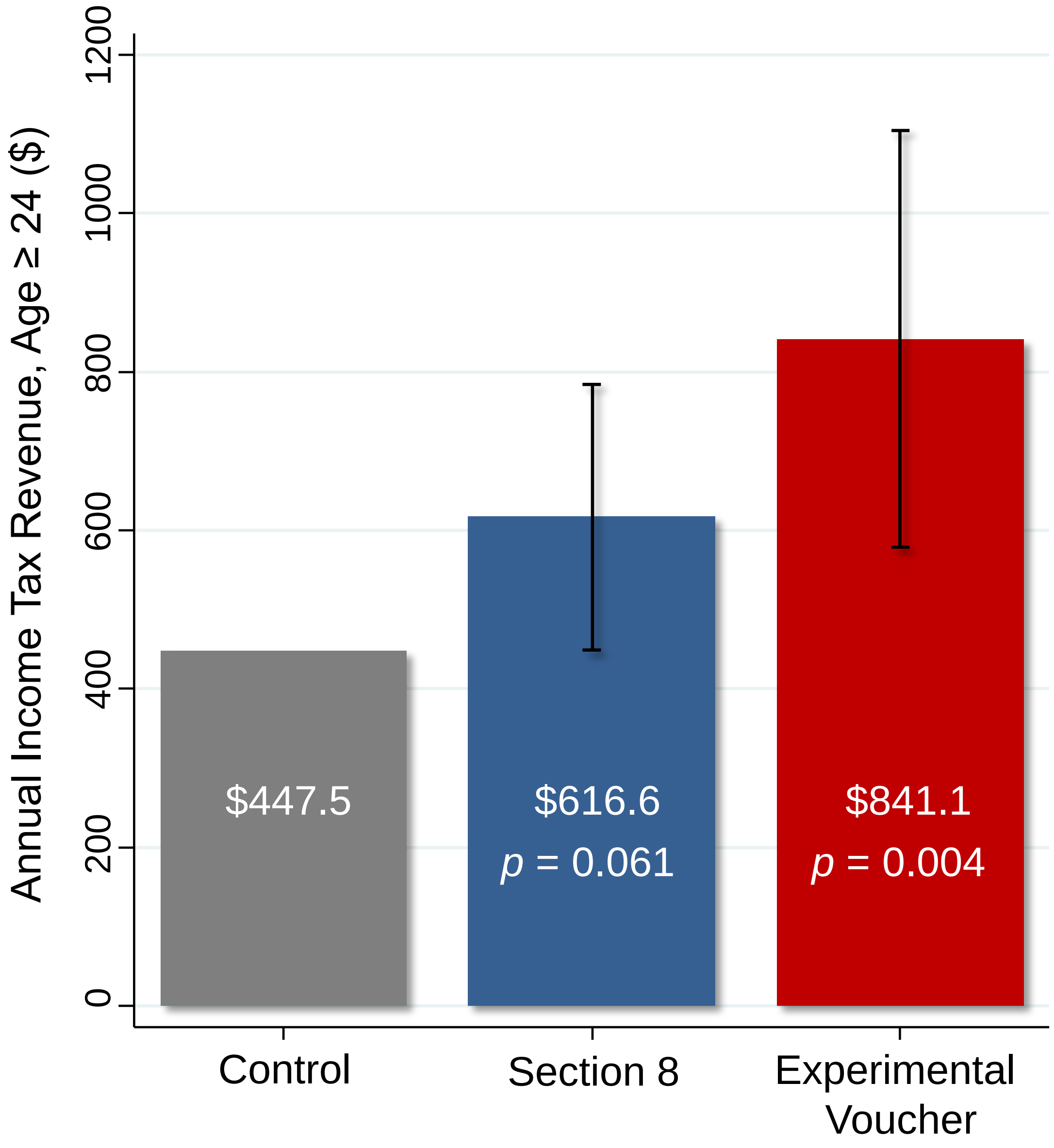
Bergman, Chetty, DeLuca, Hendren, Katz, Palmer 2019

Moving to Opportunity: Potential Concerns

1. Costs: is the voucher program too expensive to scale up?

   - Vouchers can *save* taxpayers money relative to public housing projects in long run

Impacts of MTO Experiment on Annual Income Tax Revenue in Adulthood for Children Below Age 13 at Random Assignment



Moving to Opportunity: Potential Concerns

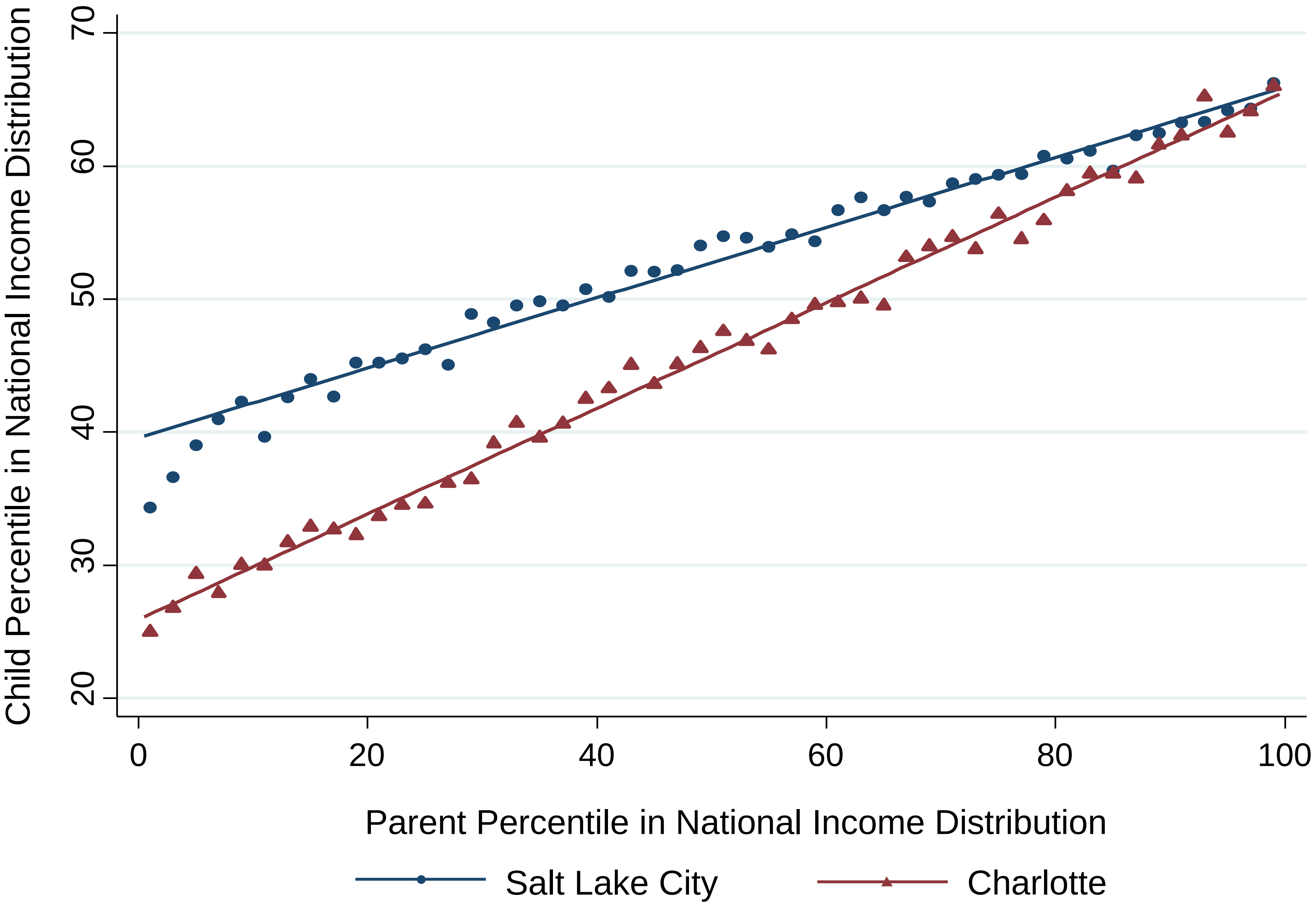
1. Costs: is the voucher program too expensive to scale up?

2. Negative spillovers: does integration hurt the rich?

    - Evaluate this by examining how outcomes of the rich vary across areas in relation to outcomes of the poor

    - Empirically, more integrated areas do not have worse outcomes for the rich on average…

Children's Outcomes vs. Parents Incomes in Salt Lake City vs. Charlotte



Moving to Opportunity: Potential Concerns

1. Costs: is the voucher program too expensive to scale up?

2. Negative spillovers: does integration hurt the rich?

3. Limits to scalability

   - Moving **everyone** from one neighborhood to another is unlikely to have significant effects

   - Ultimately need to turn to policies that improve low-mobility neighborhoods rather than moving low-income families

Two Approaches to Increasing Upward Mobility

- **Moving to Opportunity**: Provide Affordable Housing in High-Opportunity Areas

- **Place-Based Investments**: Increase Upward Mobility in Low-Opportunity Areas

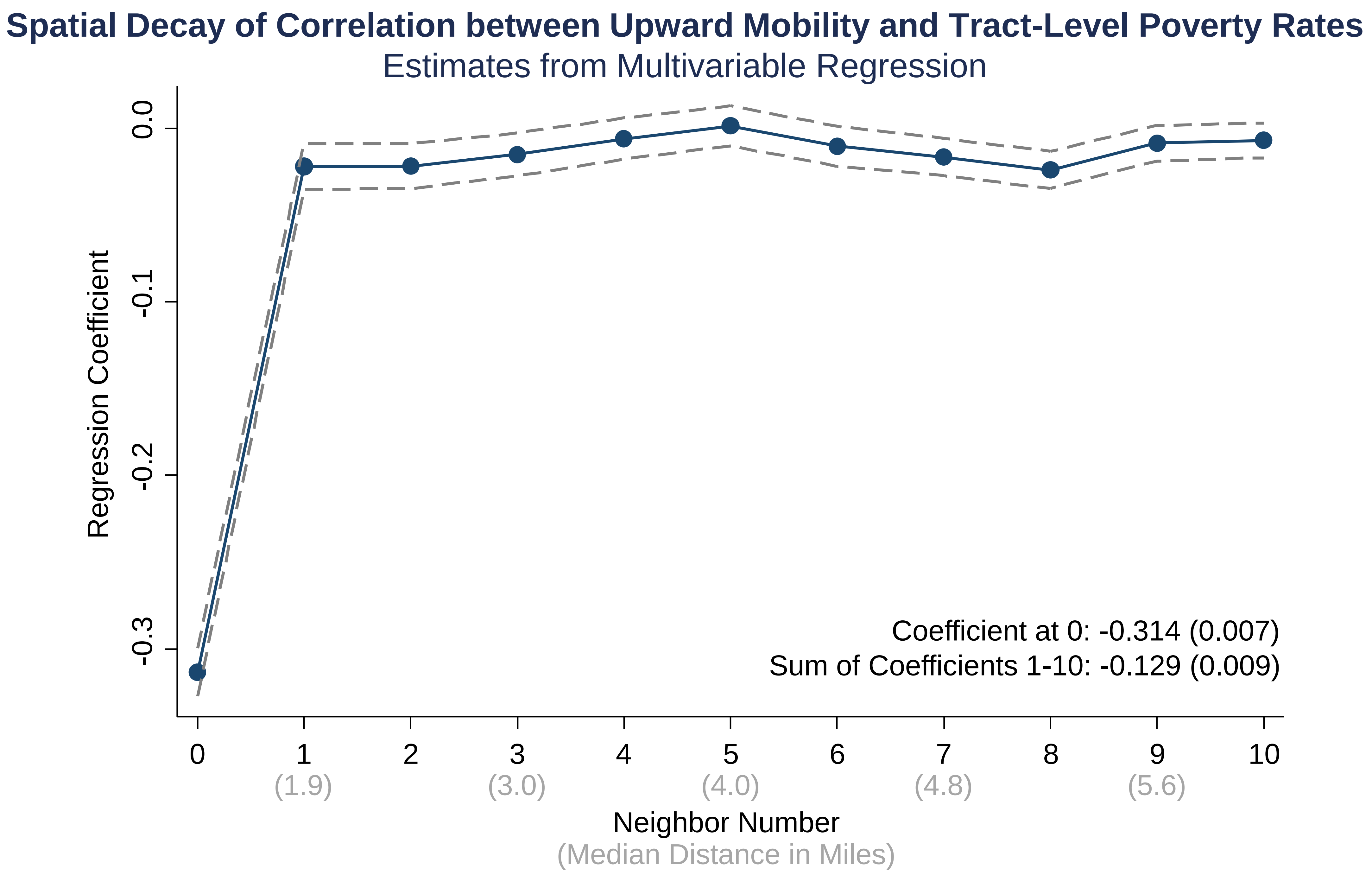
Place-Based Investments: Characteristics of High-Mobility Neighborhoods

Lower poverty rates

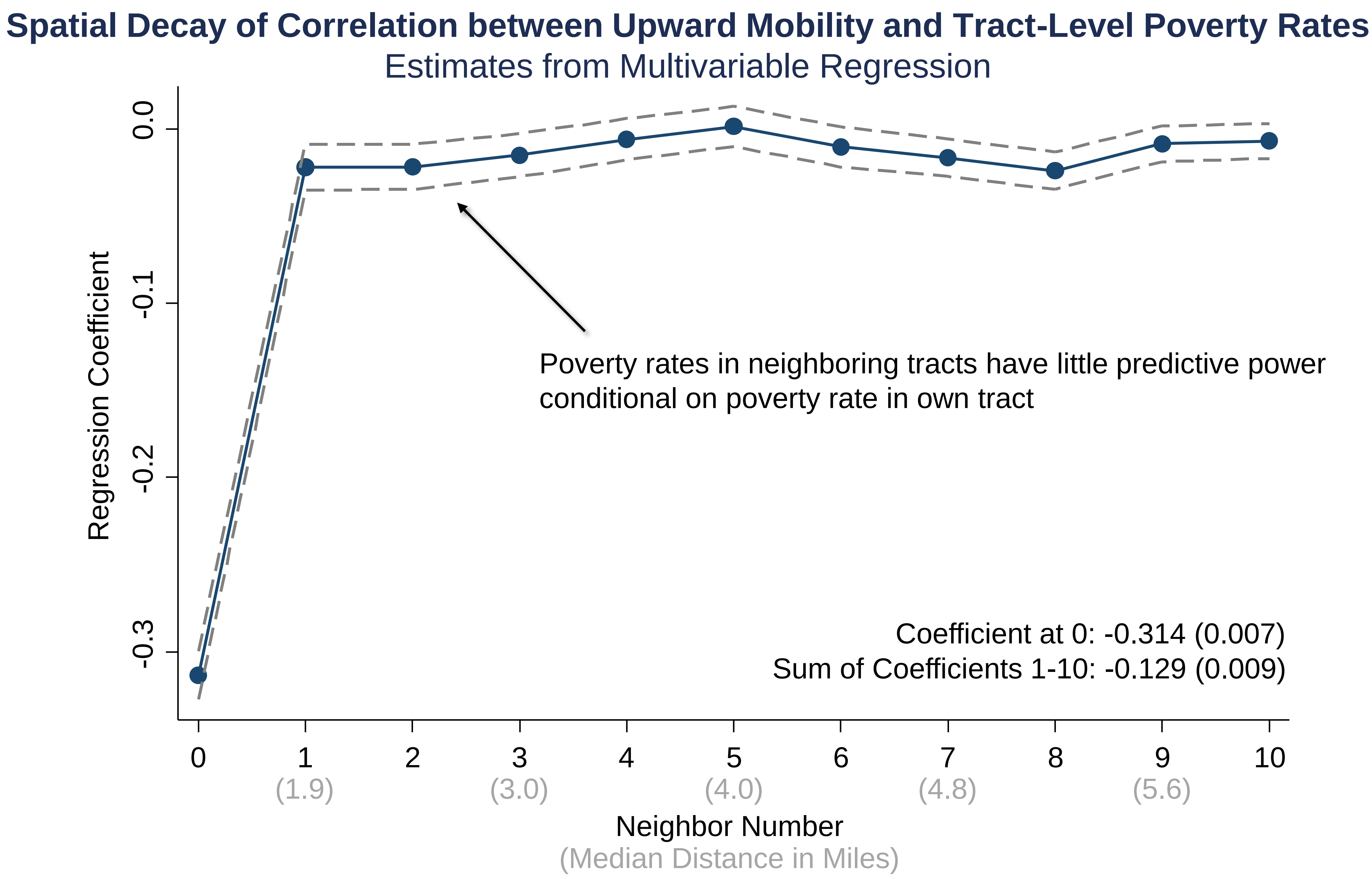
More stable family structure

Greater social capital

Better school quality



Spatial Decay of Correlation between Upward Mobility and Tract-Level Poverty Rates
Estimates from Multivariable Regression
Regression Coefficient
0.0
-0.1
-0.2
-0.3
Coefficient at 0: -0.314 (0.007)
Sum of Coefficients 1-10: -0.129 (0.009)
0
1
2
3
4
5
6
7
8
9
10
(1.9)
(3.0)
(4.0)
(4.8)
(5.6)
Neighbor Number
(Median Distance in Miles)


Spatial Decay of Correlation between Upward Mobility and Tract-Level Poverty Rates
Estimates from Multivariable Regression
Regression Coefficient
0.0
-0.1
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Poverty rates in neighboring tracts have little predictive power
conditional on poverty rate in own tract
Coefficient at 0: -0.314 (0.007)
Sum of Coefficients 1-10: -0.129 (0.009)
0
1
(1.9)
2
3
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5
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6
7
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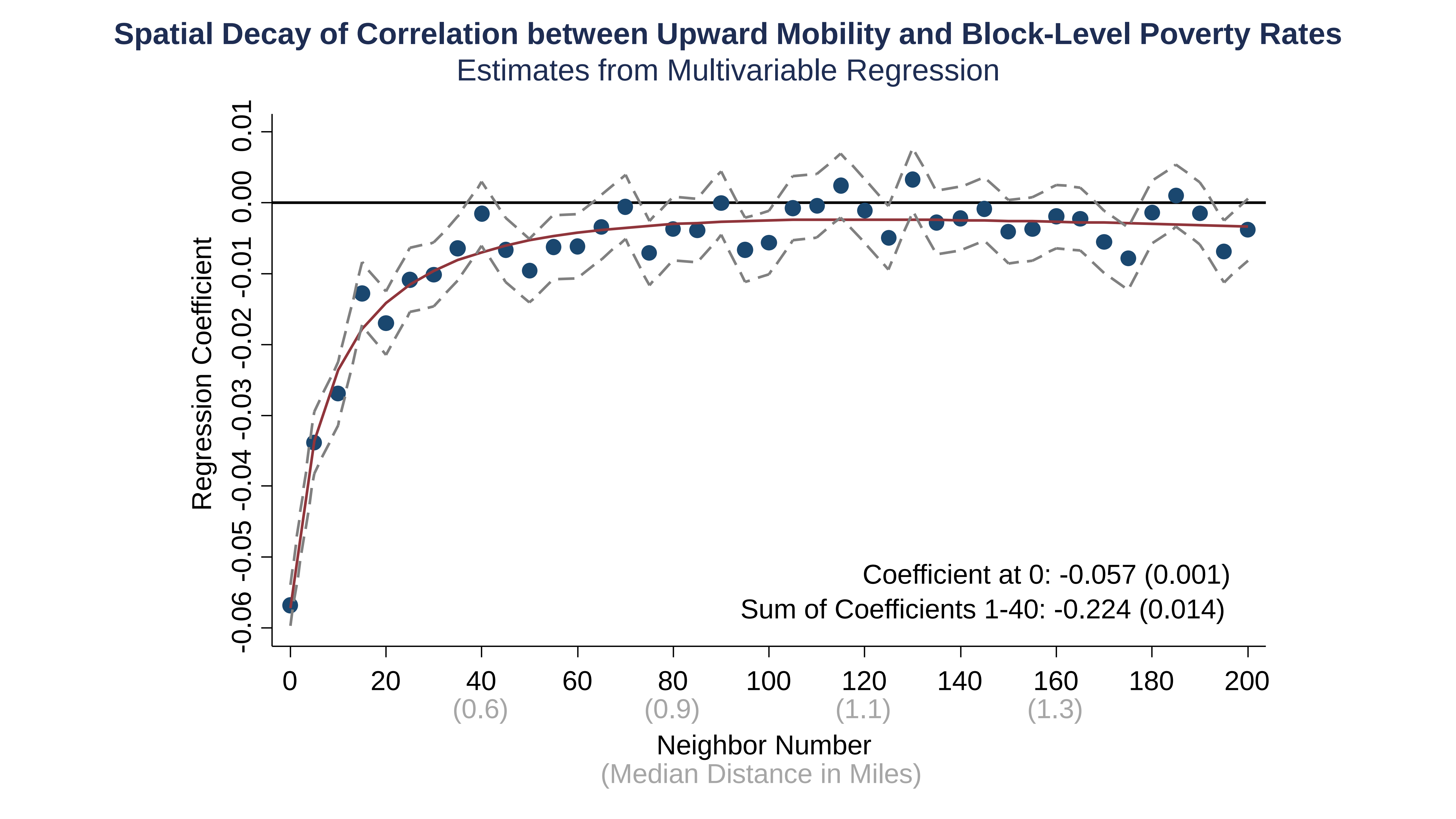
8
9
(5.6)
10
Neighbor Number
(Median Distance in Miles)


Spatial Decay of Correlation between Upward Mobility and Block-Level Poverty Rates
Estimates from Multivariable Regression
Regression Coefficient
0.01
0.00
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
Coefficient at 0: -0.057 (0.001)
Sum of Coefficients 1-40: -0.224 (0.014)
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)

What Place-Based Policies are Most Effective in Increasing Upward Mobility?

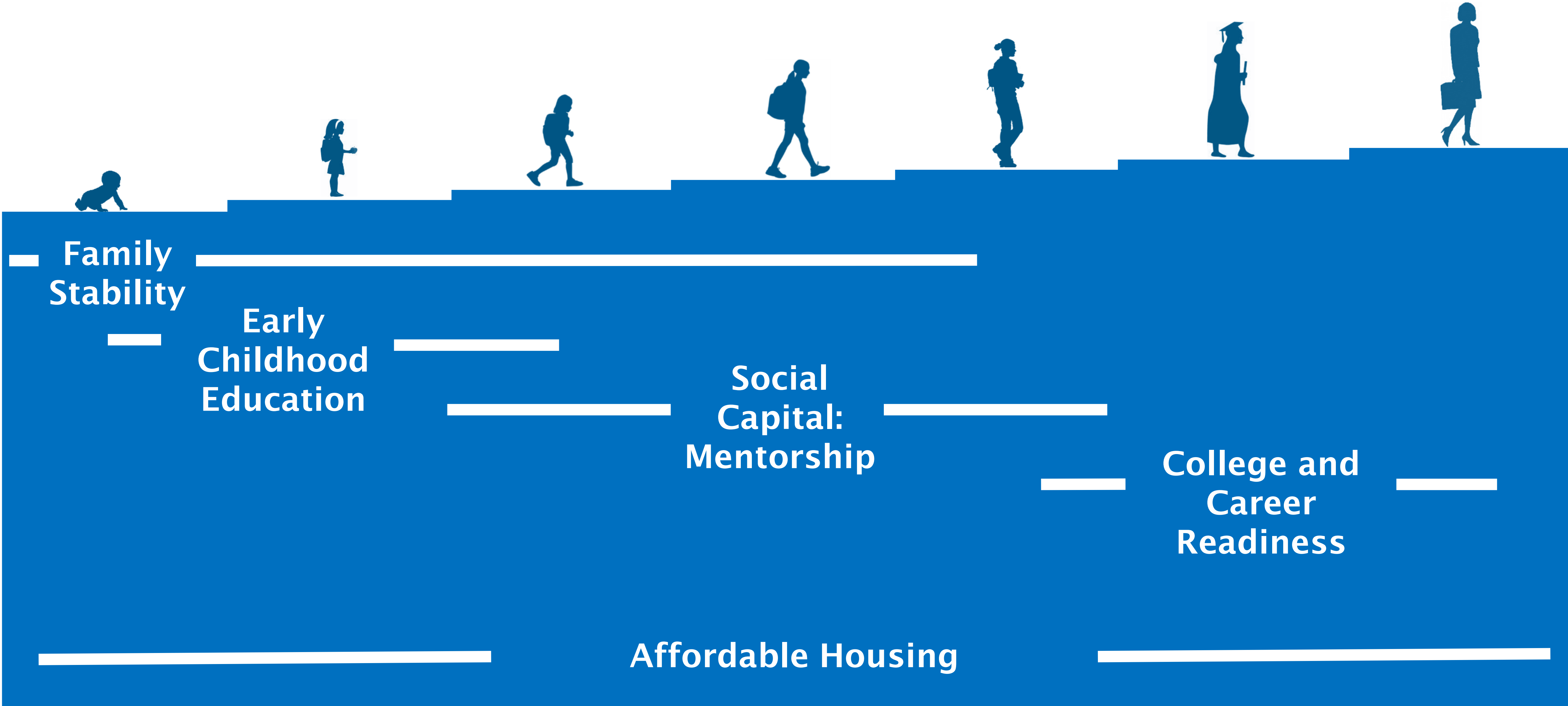
- Current research frontier: understanding what types of interventions can improve children’s outcomes in lower-mobility places
  - Many efforts by local governments and non-profits to revitalize neighborhoods, but little evidence to date on what works
  - Key challenge: traditionally, very difficult to track the outcomes of **prior residents** rather than current neighborhood conditions

What Place-Based Policies are Most Effective in Increasing Upward Mobility?

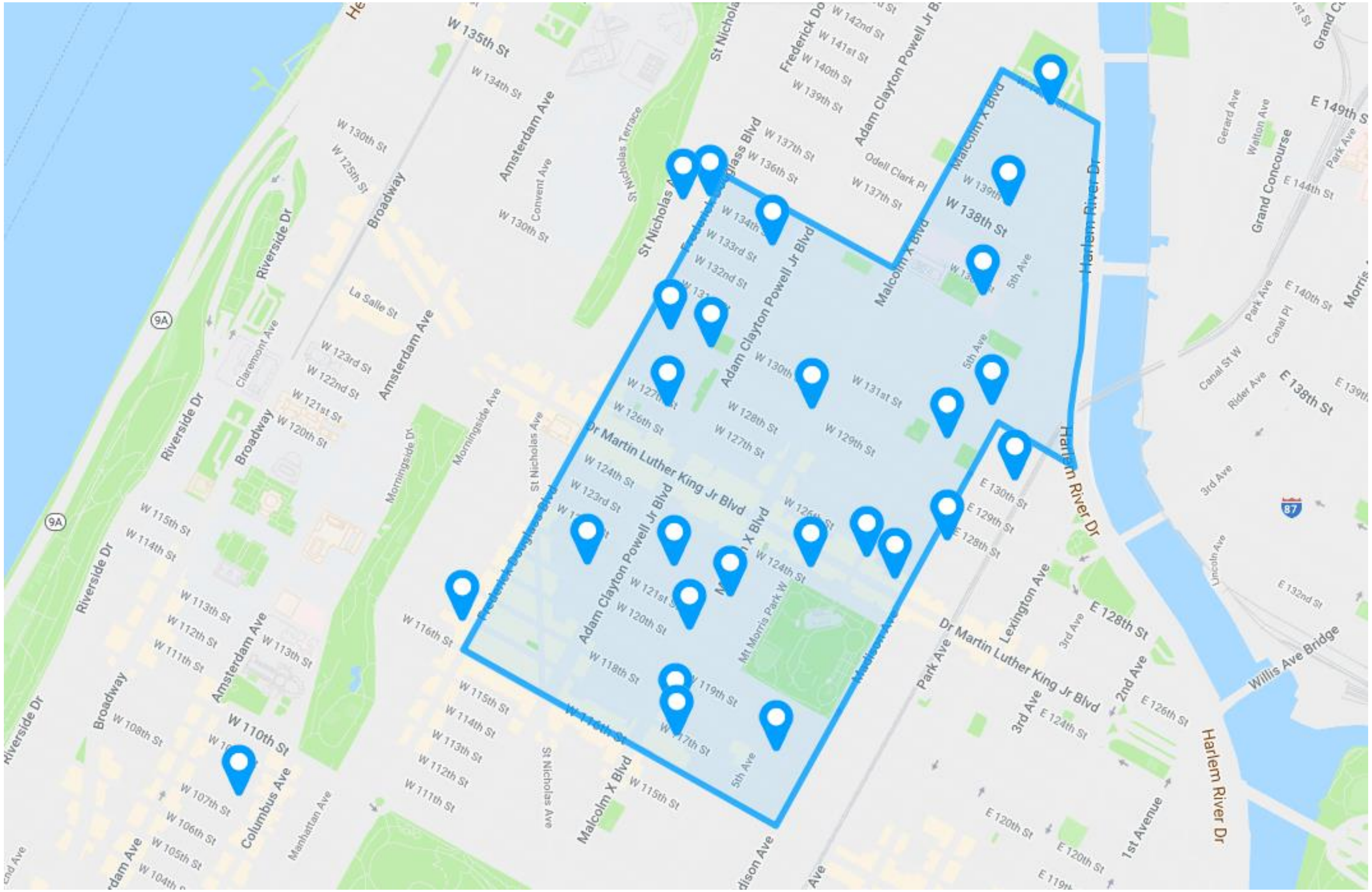
- Ongoing work at Opportunity Insights: tackle this problem using new data and interventions that build on what we know so far

  - Organizing framework: building a “pipeline” of opportunity from childhood to adulthood

Building a Pipeline for Economic Opportunity



The Harlem Children's Zone



Harlem Children's
ZONE


HARLEM CHILDREN'S ZONE PROMISE ACADEMY
Google
NYC
Goldman Sachs Gives
CIVIC BUILDERS

Building Social Capital: Promising Interventions

- BAM and Credible Messengers: mentoring programs focused on reducing violence and incarceration
- Peer forward: older students provide younger students with college application guidance and support
- Harmony Project: mentoring young children through music

New ‘Atlas’ of mobility shows how kids from different Charlotte neighborhoods have done

October 1, 2018

Mobility ‘Atlas’ shows city kids’ progress

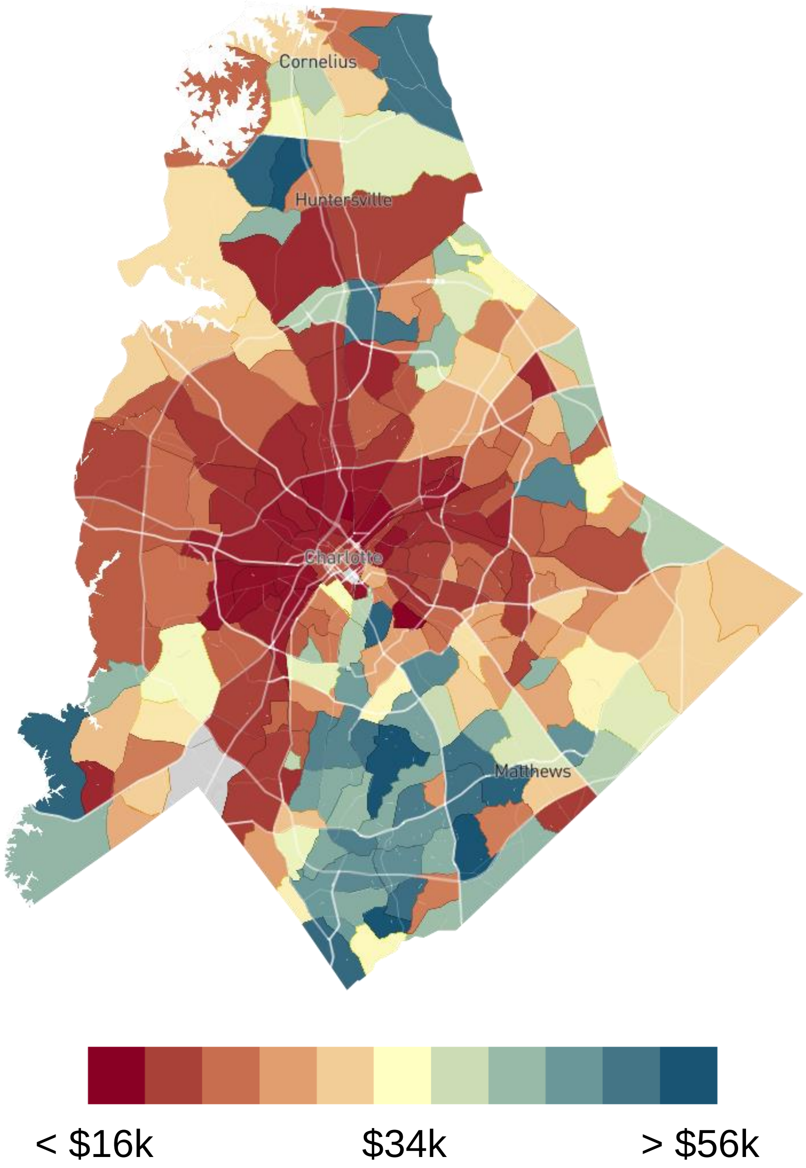
The Charlotte Observer

It’s hard to imagine a bigger gulf than the one between academic researchers crunching data at Harvard and families trapped by poverty and hopelessness in Charlotte.

The two came together in the public imagination four years ago, when professors labeled Charlotte the worst of the country’s 50 biggest commuting areas at giving children of poverty a chance to move into affluence. The sting of that label has driven sweeping change in the way local leaders talk about public policy, social justice and daily life.

Now the research team that shamed Charlotte into action has signed on to work with the city’s public and private officials to see whether data can help policy and philanthropy bring real-life change. They bring a massive database compiled by academics — with information on income, family status, rent, race, immigration and more — and are sharing it with the public as well as the experts.

The Geography of Opportunity in Charlotte



Using Historical Data to Evaluate Place-Based Policies

- In parallel to testing new interventions, we are using historical data and quasi-experimental methods to analyze previous place-based policies

- First step: digitize data from tapes at the Census Bureau to build a longitudinal dataset that will allow us to follow Americans starting with those born in 1954

- Use these data to study the impacts of place-based interventions (Harlem Children's Zone, Hope VI demolitions, Enterprise Zones, …) on prior residents

- What types of interventions improve prior residents' outcomes rather than simply displacing them?