

# Using Big Data To Solve Economic and Social Problems

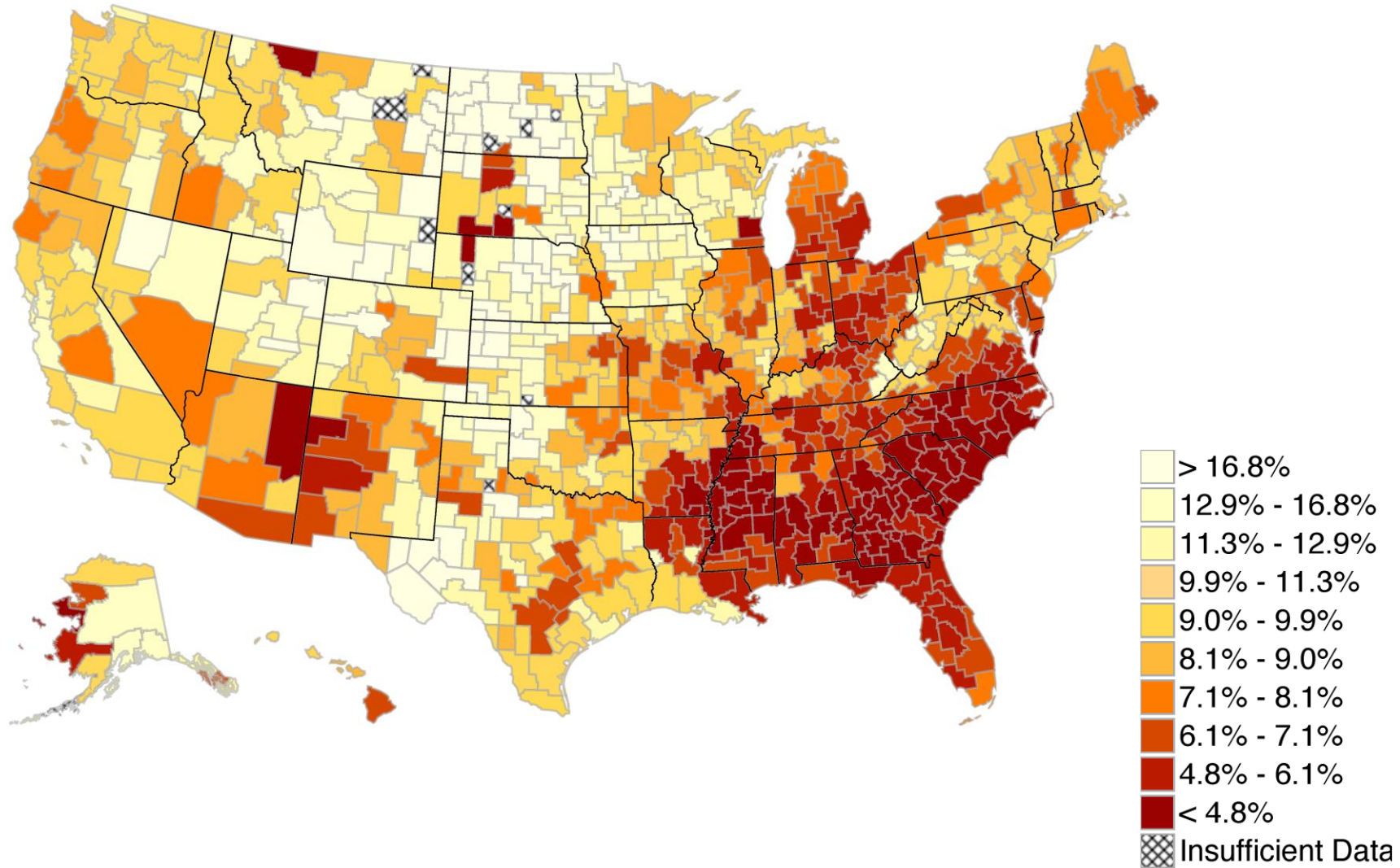
Professor Raj Chetty  
Head Section Leader Rebecca Toseland

Photo Credit: Florida Atlantic University



# The Geography of Upward Mobility in the United States

Probability of Reaching the Top Fifth Starting from the Bottom Fifth



*Note: Lighter Color = More Upward Mobility*

*Download Statistics for Your Area at [www.equality-of-opportunity.org](http://www.equality-of-opportunity.org)*

# Policies to Increase Upward Mobility

- How can we increase upward mobility in areas with low rates of mobility?
- One approach: *place-based* policies that try to address problems in low-opportunity areas
- Five correlations identified in last lecture provide some clues about factors that might matter
- But little hard evidence to date on what place-based policies actually work

# Policies to Increase Upward Mobility

- Alternative approach: help families move to higher-opportunity areas using affordable housing policies
- Even if we don't know *why* these areas produce better outcomes, this could increase upward mobility
- This lecture: discuss this “moving to opportunity” approach to increase mobility
  - Methodological focus: randomized experiments

Reference: Chetty, Hendren, Katz. “The Long-Term Effects of Exposure to Better Neighborhoods: New Evidence from the Moving to Opportunity Experiment” *AER* 2016.

# Affordable Housing Policies

- Many potential policies to help low-income families move to better neighborhoods:
  - Subsidized housing vouchers to rent better apartments
  - Mixed-income affordable housing developments
  - Changes in zoning regulations and building restrictions
- Are such housing policies effective in increasing social mobility?
  - Useful benchmark: cash grants of an equivalent dollar amount to families with children

# Affordable Housing Policies

- Economic theory predicts that **cash grants** of an equivalent dollar amount are better than expenditures on housing
- Yet the U.S. spends \$45 billion per year on housing vouchers, tax credits for developers, and public housing
- Are these policies effective, and how can they be better designed to improve social mobility?
- Study this question here by focusing specifically on the role of housing vouchers for low-income families

# Studying the Effects of Housing Vouchers

- Question: will a given child  $i$ 's earnings at age 30 ( $Y_i$ ) be higher if his/her family receives a housing voucher?
- Definitions:
  - $Y_i(V=1)$  = child's earnings if family gets voucher
  - $Y_i(V=0)$  = child's earnings if family does not get voucher
- Goal: estimate

$$\mathbf{G} = Y_i(V=1) - Y_i(V=0)$$

# Studying the Effects of Housing Vouchers

- Fundamental problem in empirical science: we do not observe  $Y_i(V=1)$  and  $Y_i(V=0)$  for the same person
  - We only see one of the two potential outcomes for each child
  - Either the family received a voucher or didn't...
- How can we solve this problem?
  - This is the focus of research on causality in statistics



# Randomized Experiments

- Gold standard solution: run a randomized experiment (“A/B testing”)
- Example: take 10,000 children and flip a coin to determine if they get a voucher or not
- Difference in average earnings across the two groups equals the causal effect of getting the voucher (G)
  - Intuition: two groups are identical except for getting voucher  
→ difference in earnings capture causal effect of voucher

# Importance of Randomization

- Suppose we instead compared 10,000 people, half of whom applied for a voucher and half of whom didn't
- Could still compare average earnings in these two groups
- But in this case, there is no guarantee that differences in earnings are only driven by the voucher
- There could be many other differences across the groups:
  - Those who applied may be more educated
  - Or they may live in worse areas to begin with
- Randomization eliminates all other such differences

# Non-Compliance in Randomized Experiments

- Common problem in randomized experiments: non-compliance
  - In medical trials: patients may not take prescribed drugs
  - In voucher experiment: families offered a voucher may not actually use it to rent a new apartment
- We can't force people to comply with treatments; we can only offer them a treatment
  - How can we learn from experiments in the presence of such non-compliance?

## Adjusting for Non-Compliance

- Solution: adjust estimated impact for rate of compliance
- Example: suppose half the people offered a voucher actually used it to rent a new apartment
  - Suppose raw difference in earnings between those offered voucher and not offered voucher is \$1,000
  - Then effect of using voucher to rent a new apartment must be \$2,000 (since there is no effect on those who don't move)
- More generally, divide estimated effect by rate of compliance:

$$\text{True Impact} = \text{Estimated Impact} / \text{Compliance Rate}$$

# Moving to Opportunity Experiment

- Implemented from 1994-1998 at 5 sites: Baltimore, Boston, Chicago, LA, New York
- 4,600 families living in high-poverty public housing projects 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

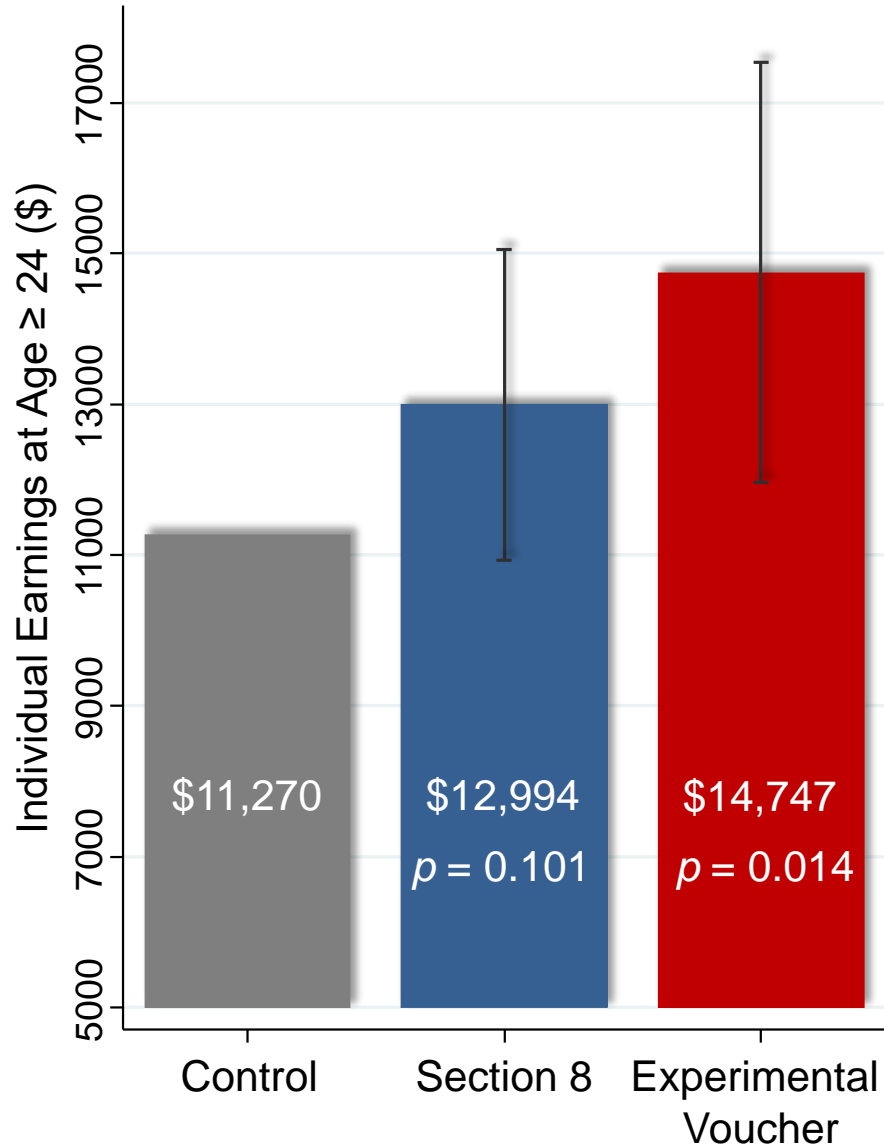


# Analysis of MTO Experimental Impacts

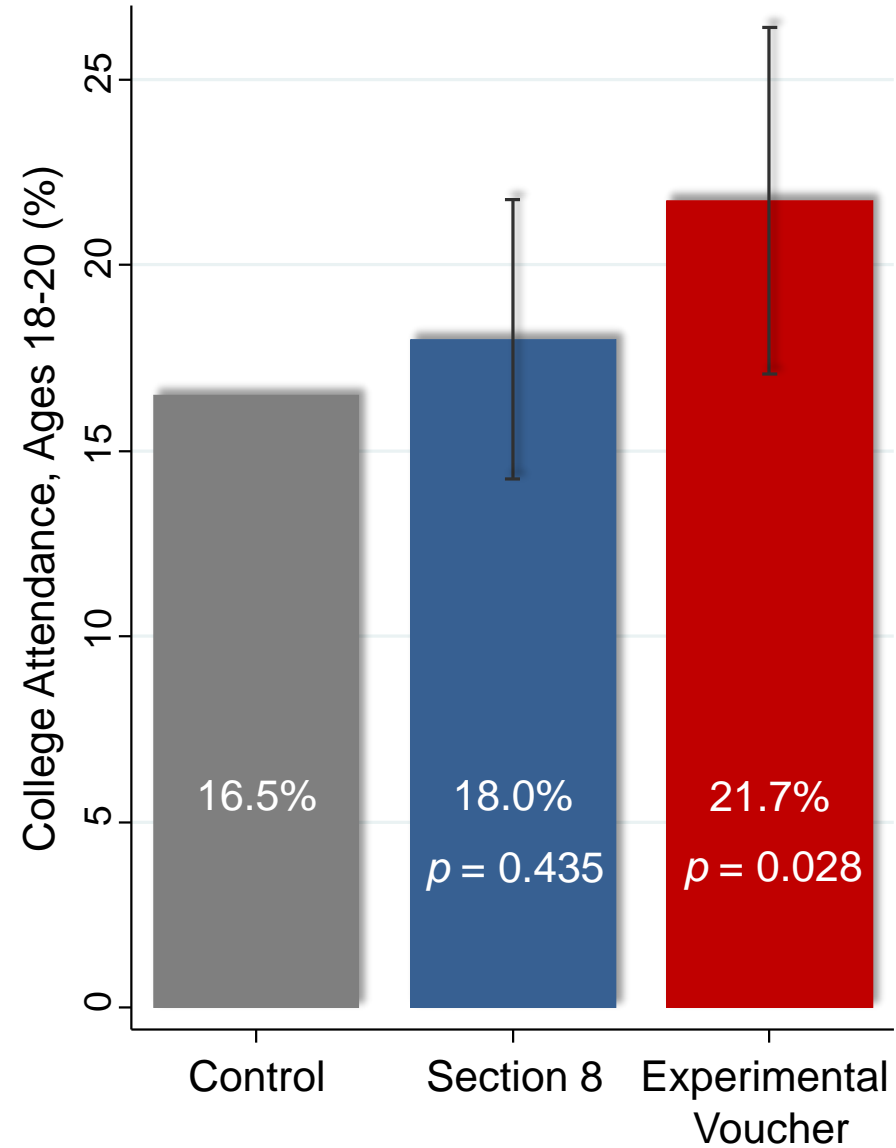
- Prior research on MTO has found little impact of moving to a better area on economic outcomes such as earnings
  - But has focused on adults and older youth at point of move [e.g., Kling, Liebman, and Katz 2007]
- Motivated by quasi-experimental study discussed in last lecture, we test for *exposure 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

## (a) Earnings



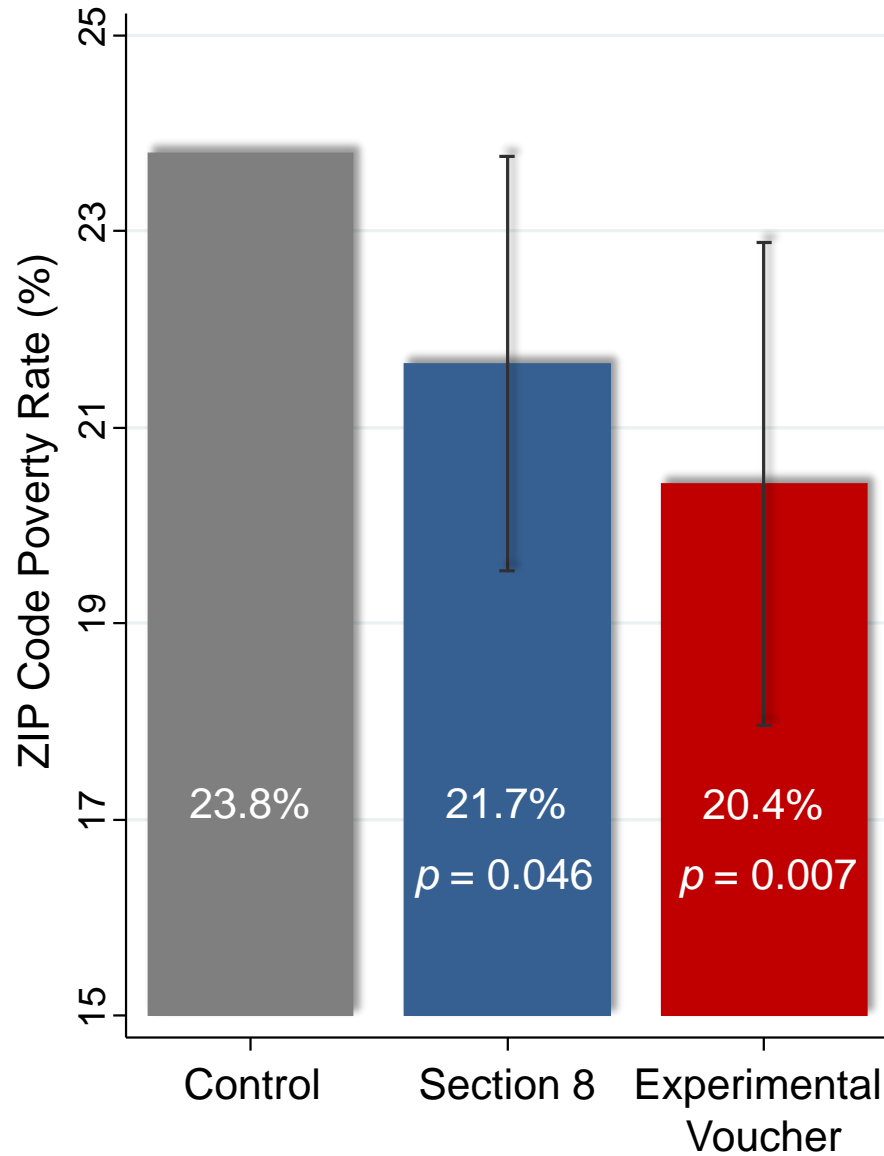
## (b) College Attendance



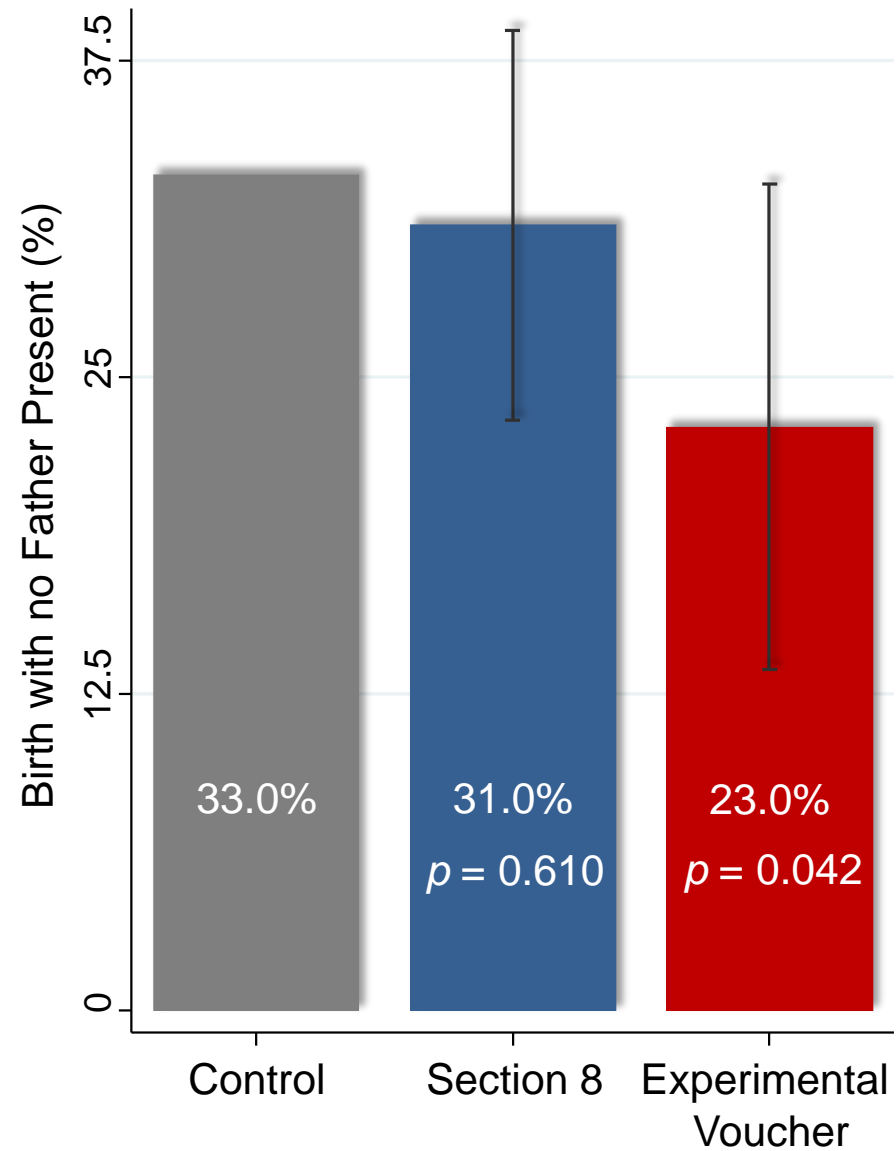


# Impacts of MTO on Children Below Age 13 at Random Assignment

## (c) Neighborhood Quality

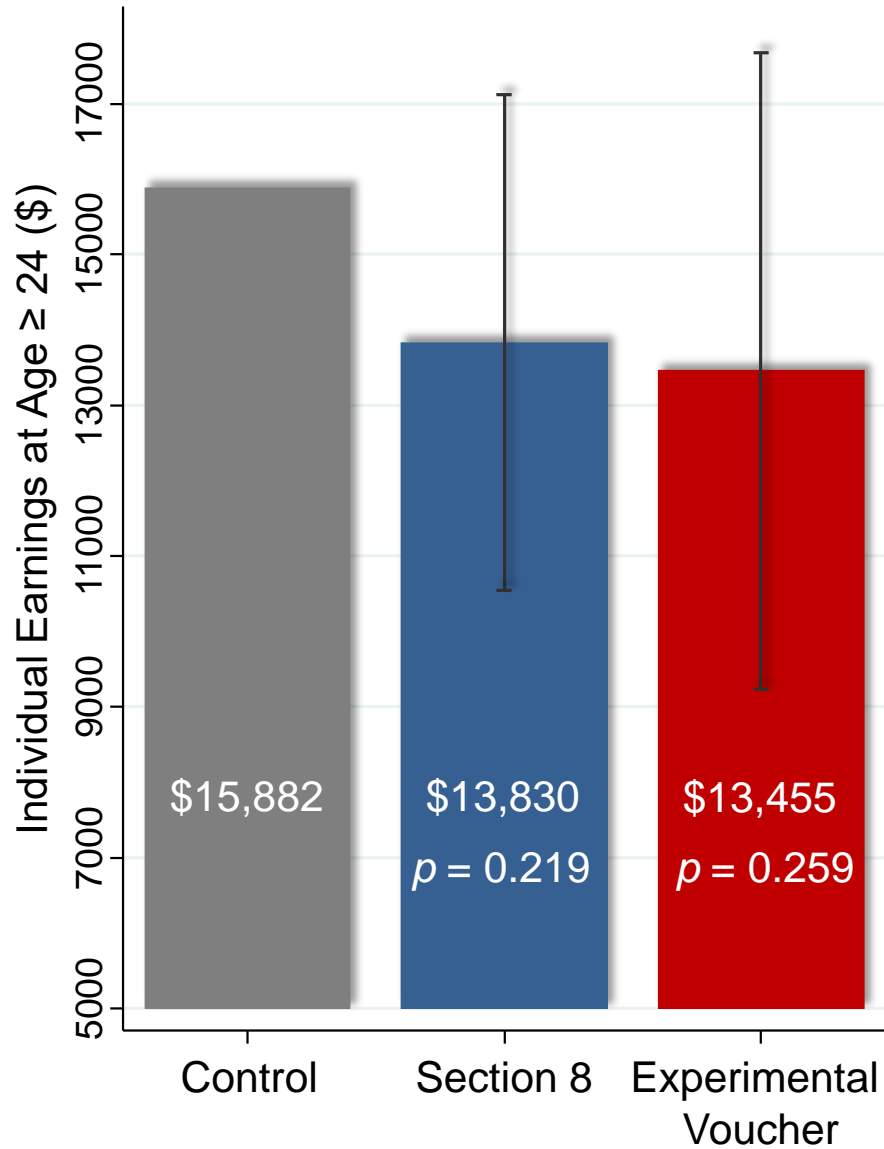


## (d) Fraction Single Mothers

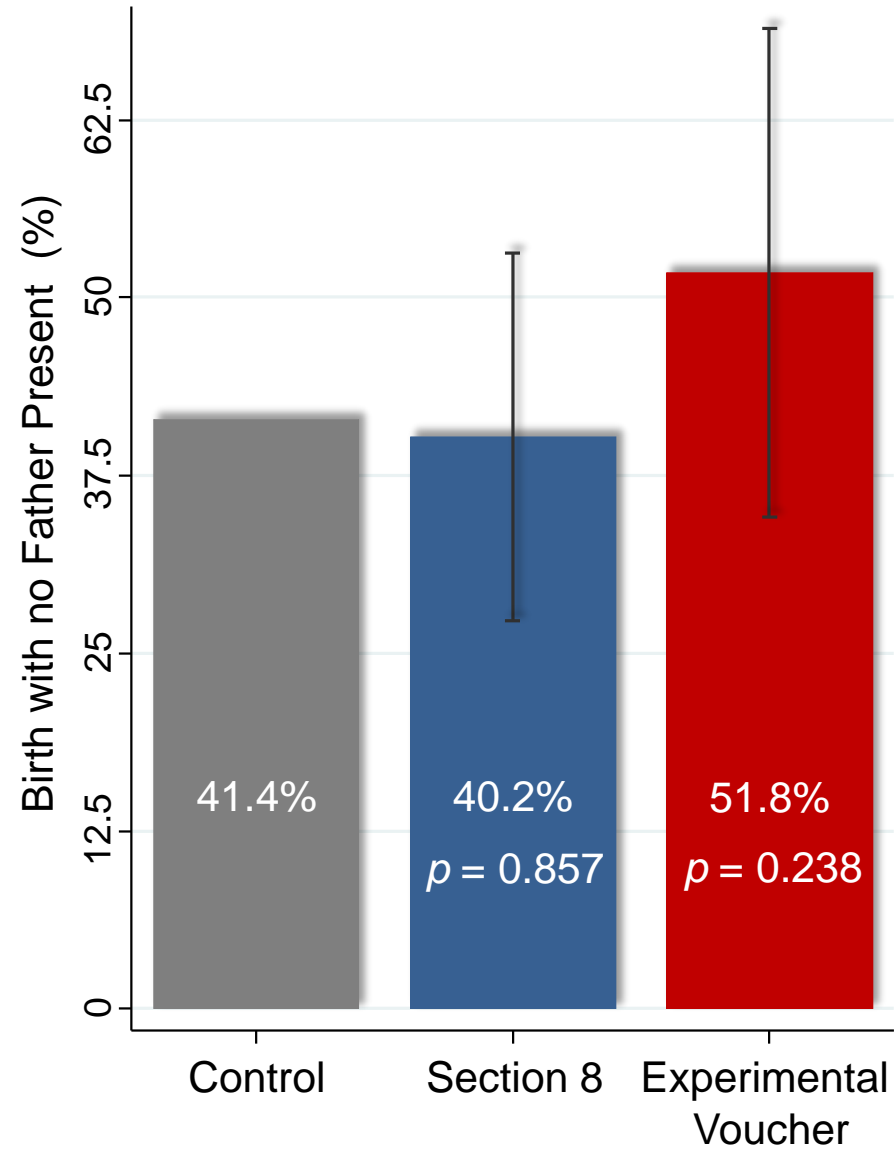


# Impacts of MTO on Children Age 13-18 at Random Assignment

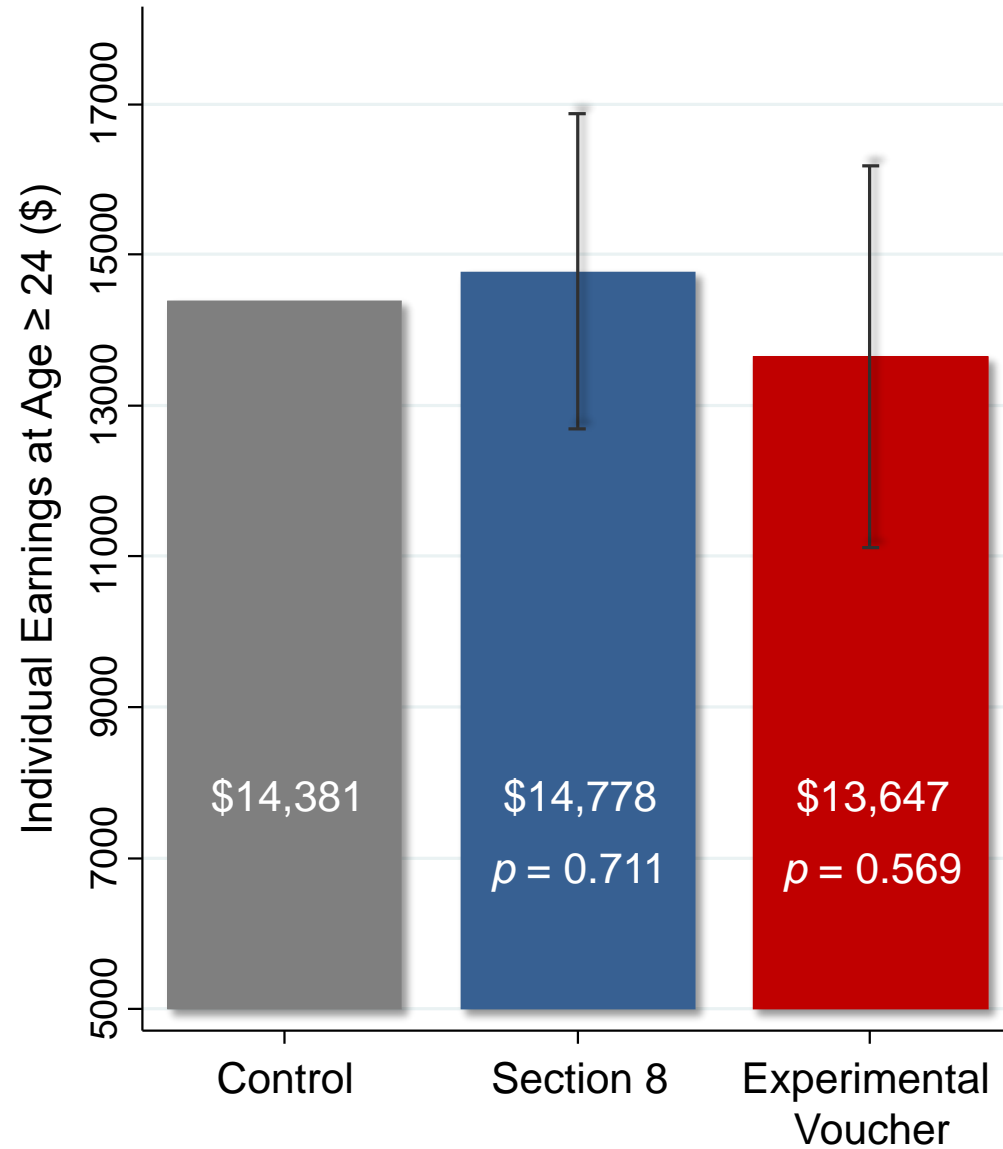
## (a) Earnings



## (b) Fraction Single Mothers



# Impacts of Moving to Opportunity on Adults' Earnings



# Limitations of Randomized Experiments

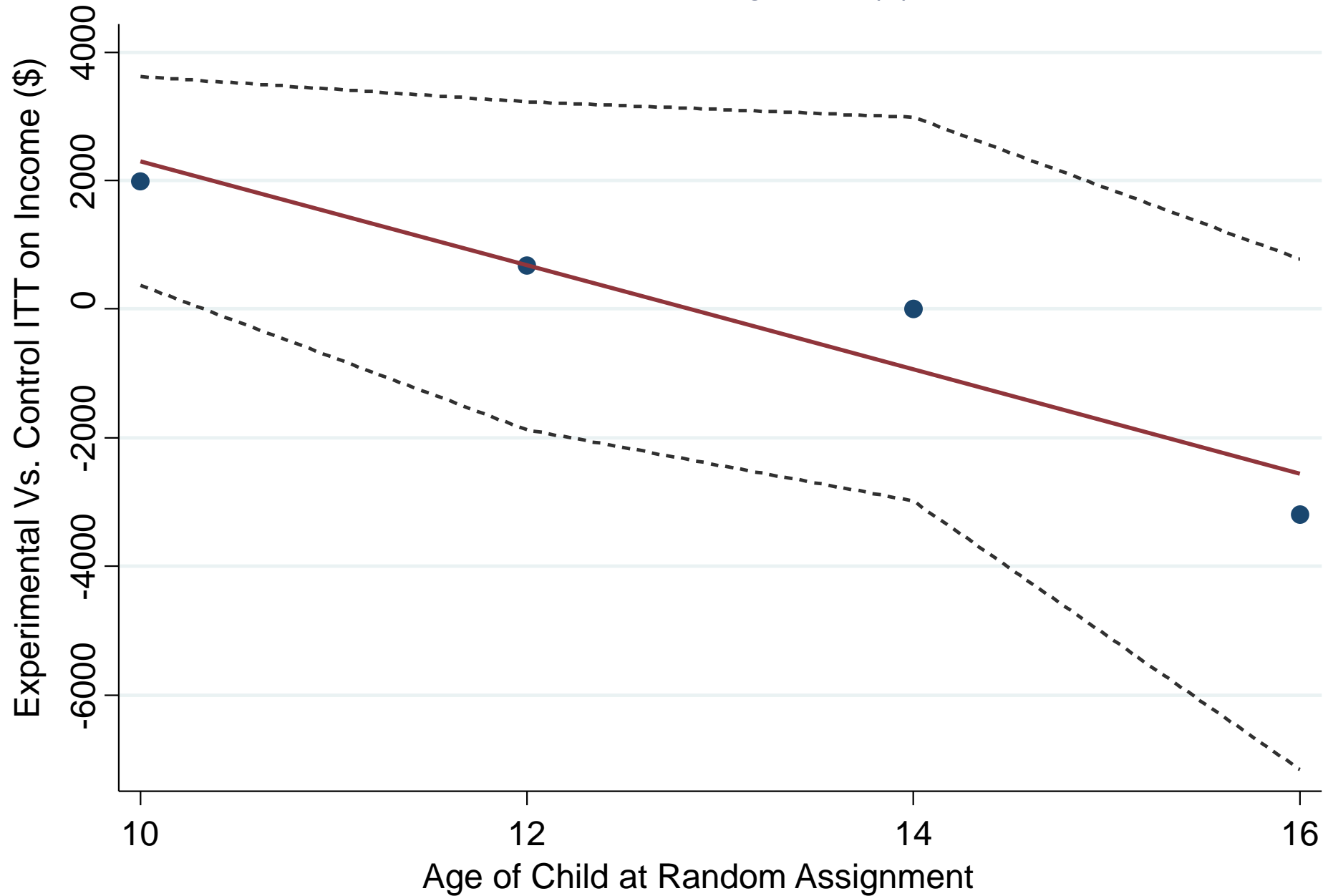
- Why not use randomized experiments to answer all policy questions?
- Beyond feasibility, there are three common limitations:
  1. Attrition: lose track of participants over time → long-term impact evaluation unreliable
    - Especially a problem when attrition rate differs across treatment groups because 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  $\geq 24$  (\$)



# 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
  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 7 million families that moved across areas discussed in last lecture (Chetty and Hendren 2016)
- 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
  - 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 (linear, 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

# 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

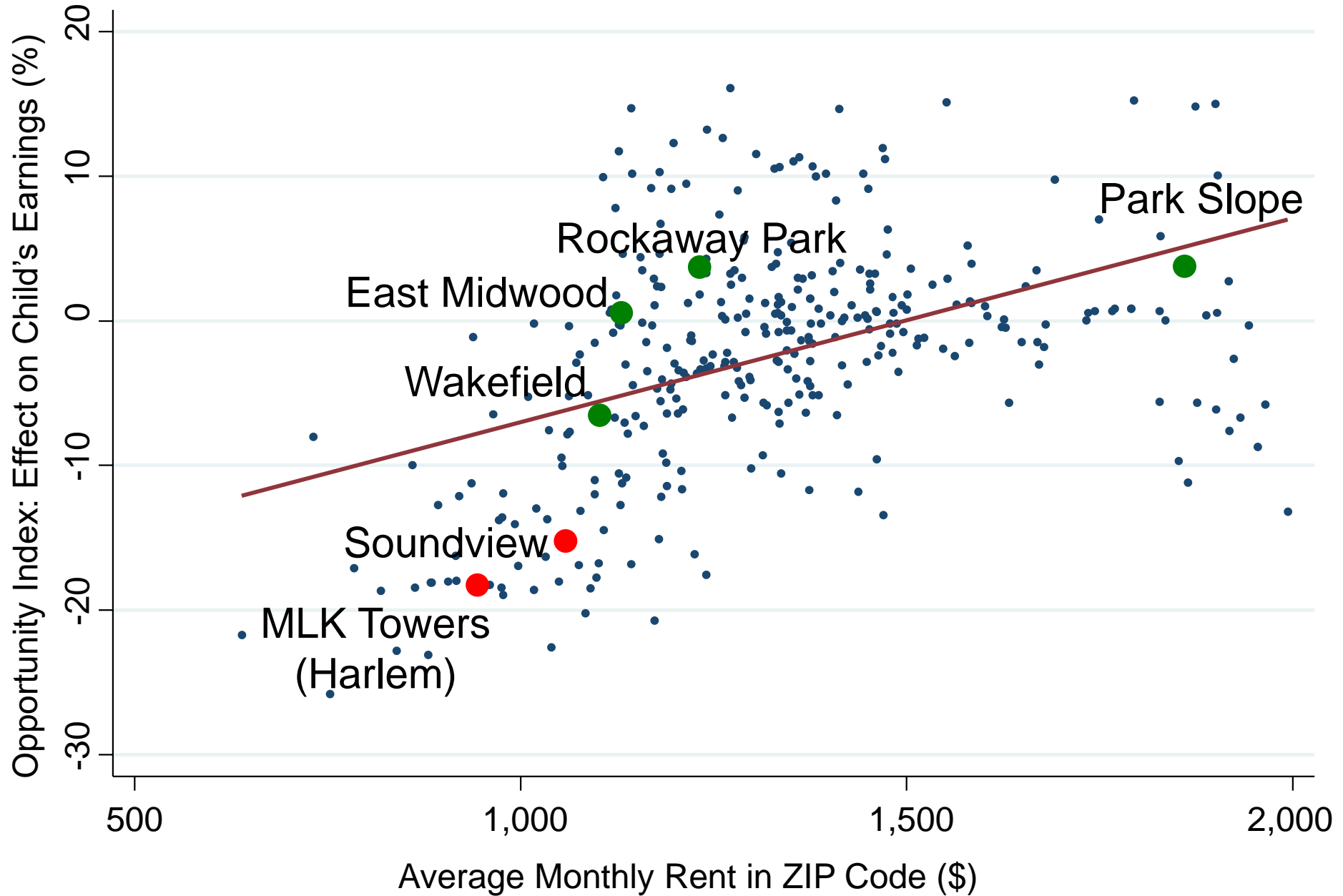
- Housing vouchers can be very effective but must be targeted carefully
  1. Vouchers should be targeted at families with young children
  2. Vouchers should be explicitly designed to help families move to affordable, high-opportunity areas
    - In MTO experiment, unrestricted “Section 8” vouchers produced *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. QJE 2015]
    - 80% of the 2.1 million Section 8 vouchers are currently used in high-poverty, low-opportunity neighborhoods

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

- One simple explanation: areas that offer better opportunity may be unaffordable
- To explore this, we are constructing estimates of opportunity at narrower geographies, by ZIP code and Census tract
- These data reveal that there are many *opportunity bargains*:
  - Areas with relatively low rents that offer good opportunities for kids

# Opportunity Bargains at the ZIP Code Level in the New York Area

Preliminary Estimates



# Creating Moves to Opportunity in Seattle

*Help families with Housing Choice Vouchers in Seattle/King County move to high opportunity areas using three approaches*



**INFORMATION  
& FINANCIAL  
ASSISTANCE**

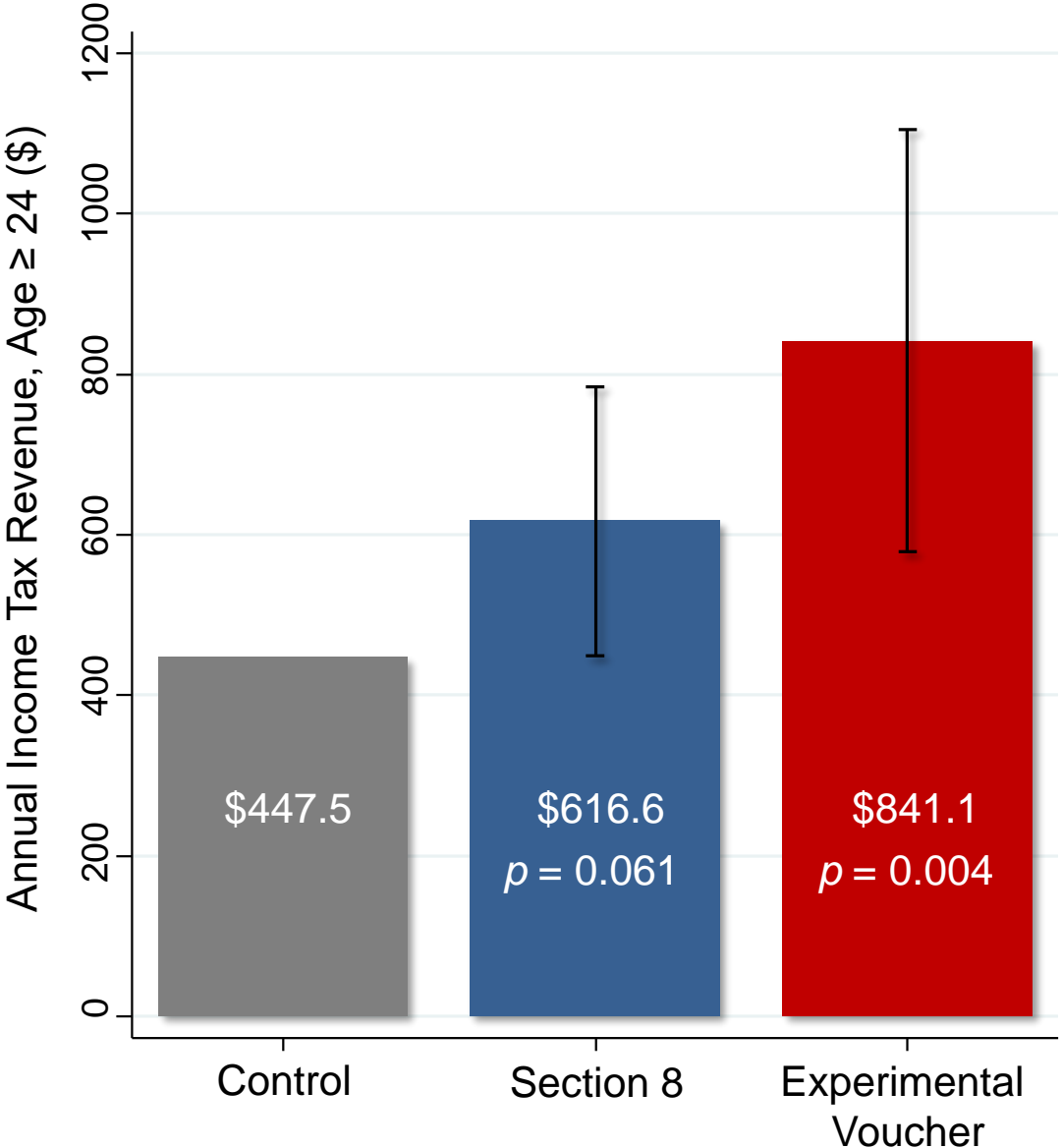
**REDUCED  
LANDLORD  
BARRIERS**

**RENTAL  
BROKER  
ASSISTANCE**

# Integration through Housing Vouchers: 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 on Annual Income Tax Revenue in Adulthood for Children Below Age 13 at Random Assignment

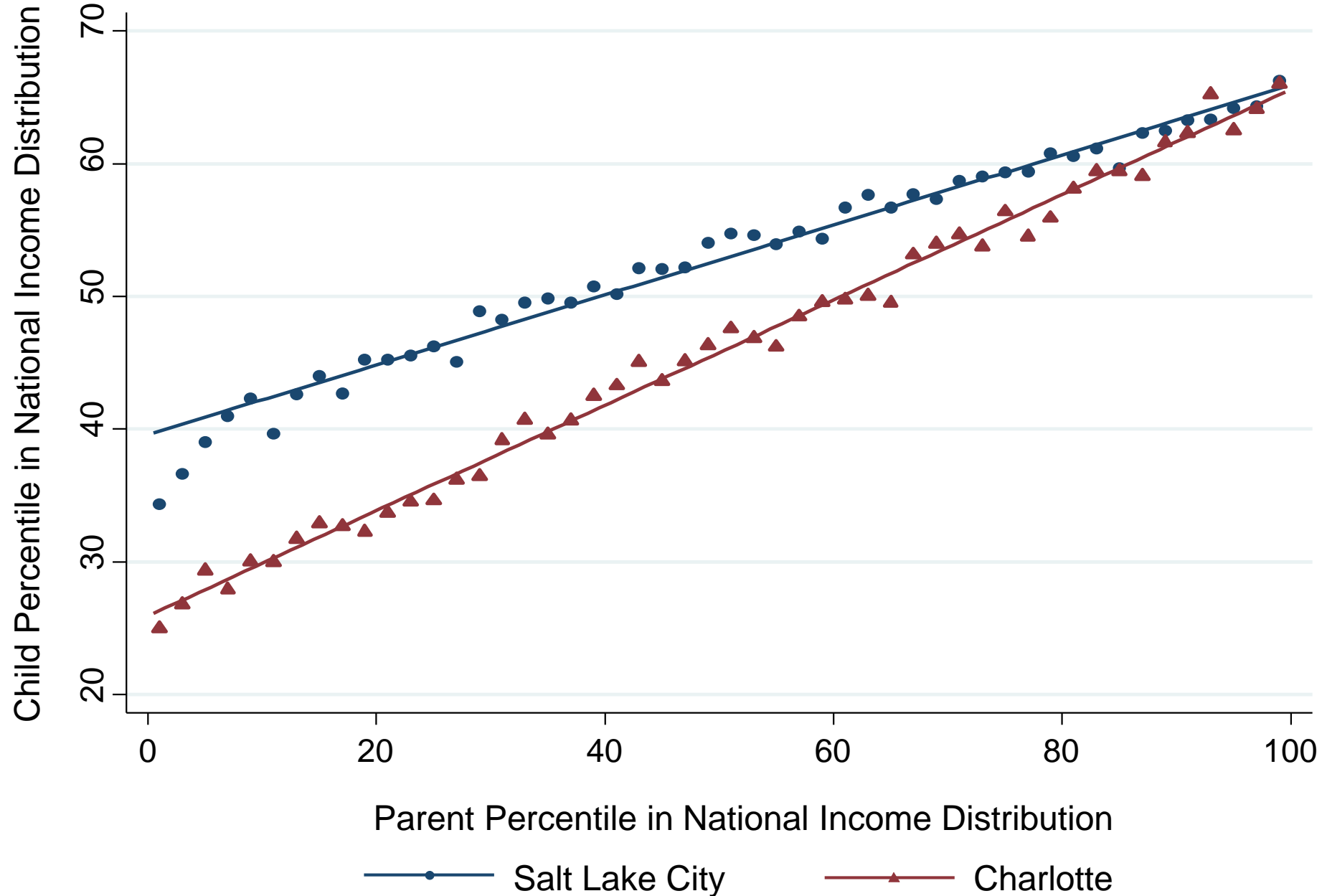




# Integration through Housing Vouchers: Potential Concerns

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 neighborhoods do not have worse outcomes for the rich on average...

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



# Integration through Housing Vouchers: 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* in Harlem to Bronx is unlikely to have significant effects
  - Ultimately need to turn to policies that increase integration in other ways rather than moving low-income families