

Neighborhood Effects: Differences in Opportunity Across Local Areas Urban Economics

Ignacio Sarmiento-Barbieri

Universidad de los Andes

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Residential Location Patterns: US

Table 1
Poverty in cities and suburbs

Row		Center city resident	Suburban resident
1	All	0.1990	0.0753
2	Northeast	0.2089	0.0599
3	Midwest	0.1984	0.0565
4	South	0.1865	0.0744
5	West	0.1895	0.1031

Residential Location Patterns: Atlanta, Phoenix, Los Angeles

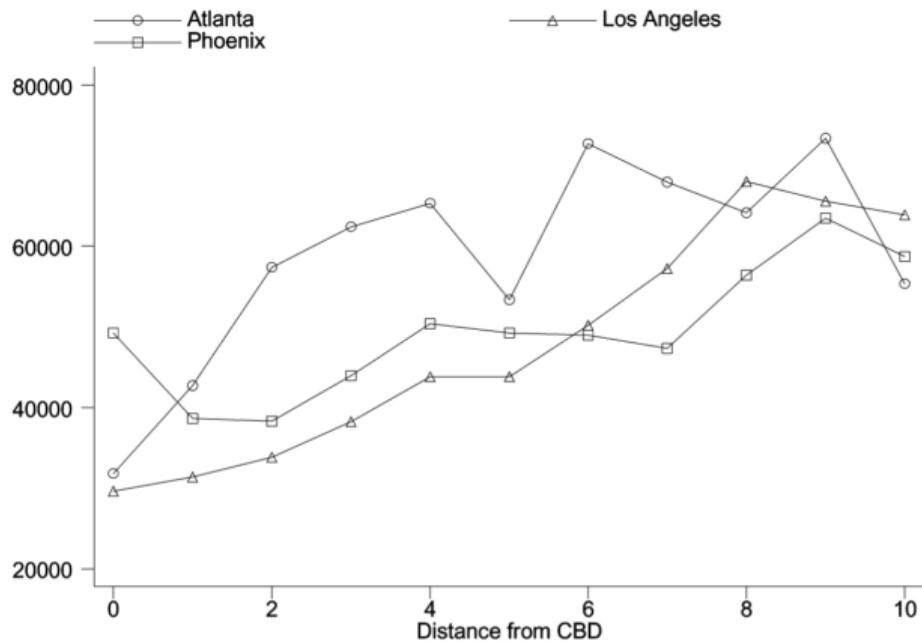


Fig. 2. Income and distance from the CBD in three new cities.

Residential Location Patterns: Europe

Table 1
Central-city vs. suburban incomes in France and the US

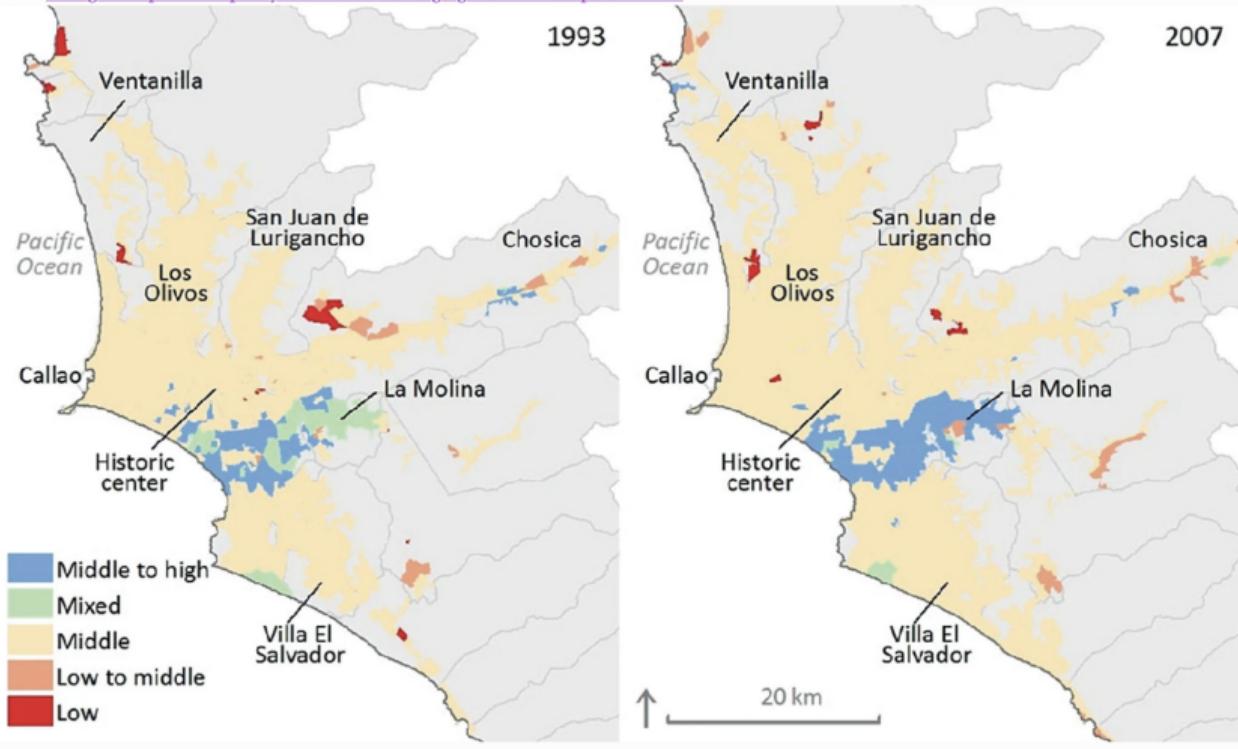
Case	Household income ^a	
	Central-city	Suburbs
Ile de France (Paris metro area)	124 000 Fr. ^b	106 000 Fr.
Province (other metro areas)	76 000 Fr.	84 000 Fr.
France (all metro areas)	84 000 Fr.	82 000 Fr.
Detroit (metro area)	\$20 207	\$40 084
U.S. (all metro areas)	\$26 727	\$26 314

^a Household incomes are the 1990 average value in France and the 1989 median value in the U.S. The French data are from Nicot (1996), and the U.S. data are from the 1990 Census.

^b The current franc-dollar exchange rate is approximately 6 francs per dollar.

Residential Location Patterns: Lima

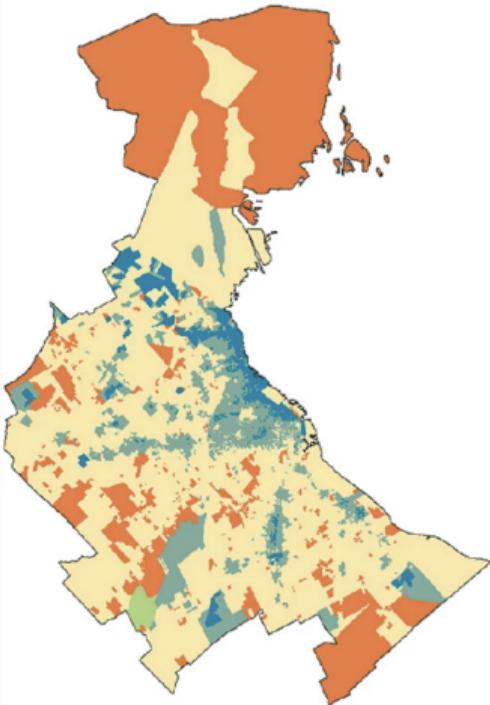
From: [Changes in Spatial Inequality and Residential Segregation in Metropolitan Lima](#)



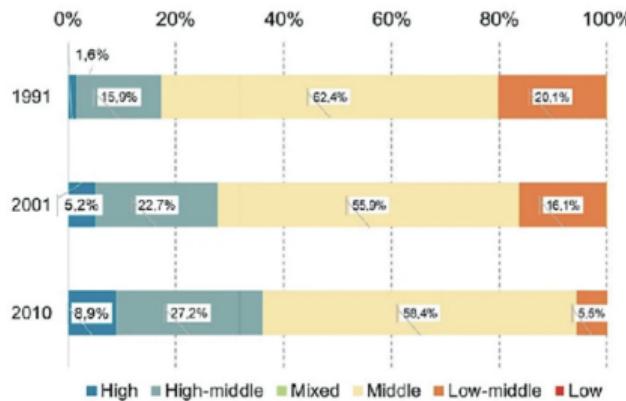
Classification of neighbourhoods by socio-economic composition in Lima.

Residential Location Patterns: Buenos Aires

2010



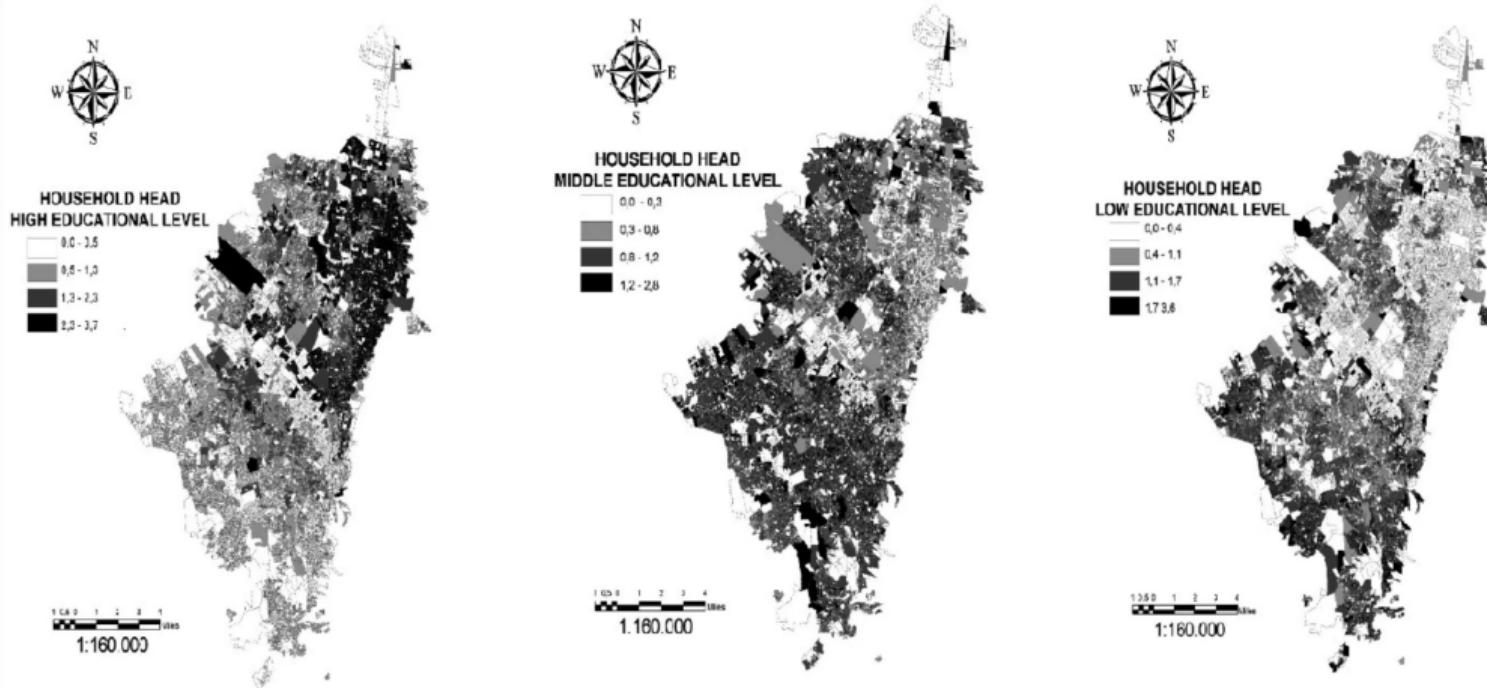
Socioeconomic Status Classification



Source Population and housing censuses 1991, 2001, and 2010, INDEC, author's maps

Residential Location Patterns: Bogotá

From: [Socioeconomic Residential Segregation and Income Inequality in Bogotá: An Analysis Based on Census Data of 2005](#)



Source Elaboration by the authors based on Population Census DANE ([2005](#))

Location quotient for household leader by high, medium, and low education level in Bogotá, 2005.

Residential Location Patterns by Race: NYC



Source: <https://www.washingtonpost.com/graphics/2018/national/segregation-us-cities/>

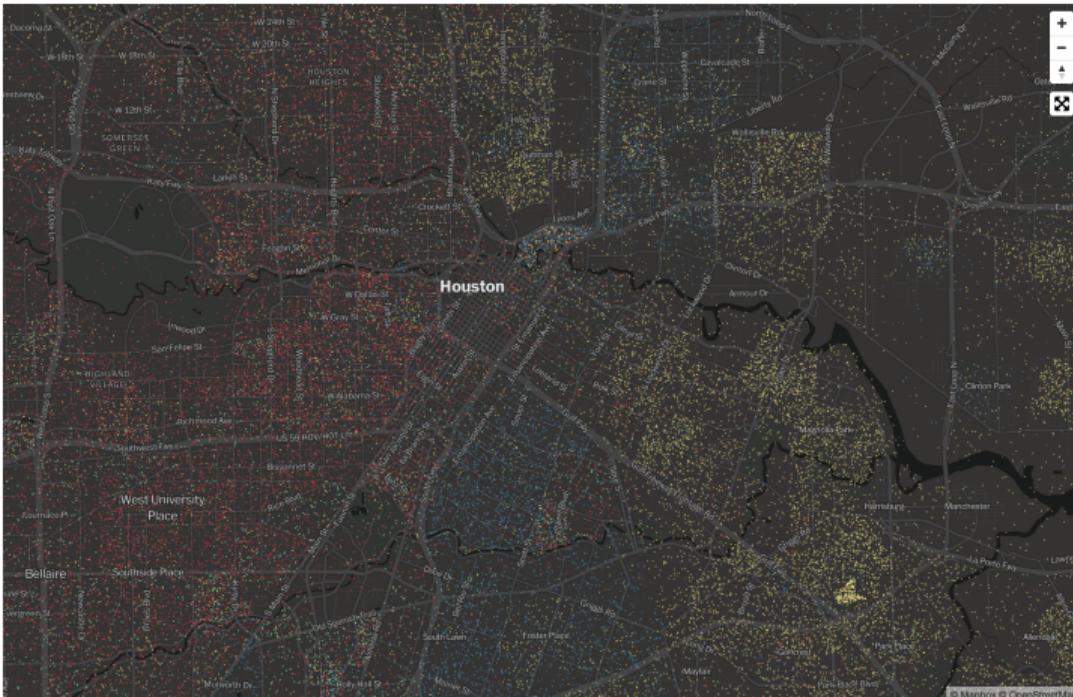
Residential Location Patterns by Race: Chicago



ID Source:

<https://www.washingtonpost.com/graphics/2018/national/segregation-us-cities/>

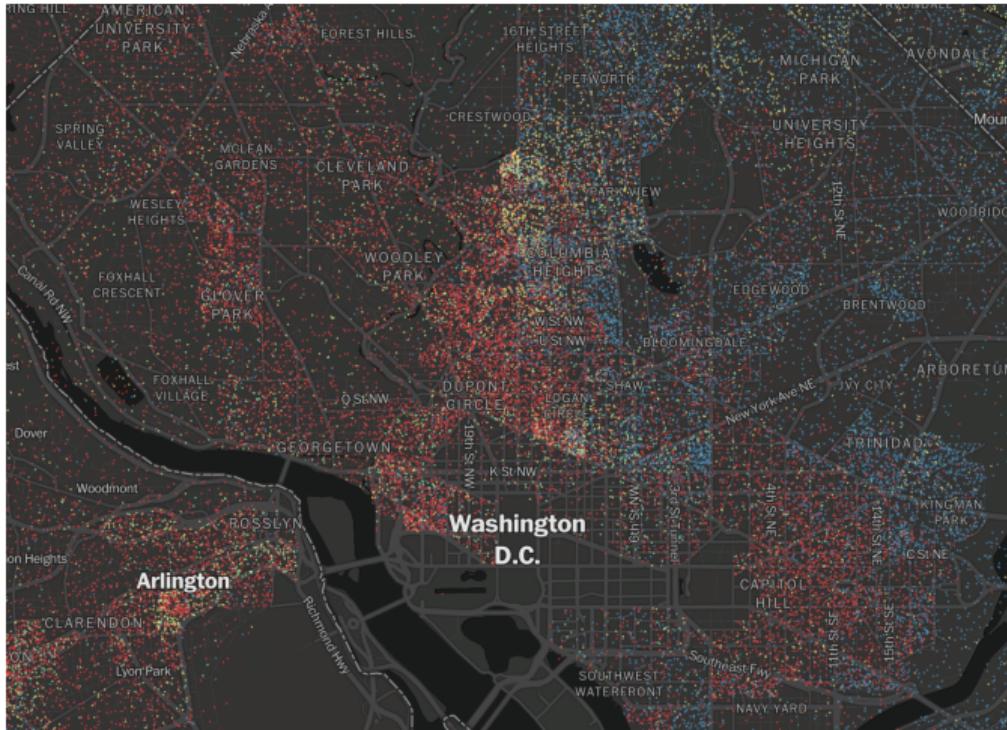
Residential Location Patterns by Race: Houston



Source:

<https://www.washingtonpost.com/graphics/2018/national/segregation-us-cities/>

Residential Location Patterns by Race: Washington, DC



Source:

<https://www.washingtonpost.com/graphics/2018/national/segregation-us-cities/>

Five Strongest Correlates of Upward Mobility

1 Segregation

- ▶ Greater racial and income segregation associated with lower levels of mobility

Neighborhood Effects

- ▶ Recent literature has shown that the neighborhood where people live has important implications for individual outcomes.

THE IMPACTS OF NEIGHBORHOODS ON INTERGENERATIONAL MOBILITY I: CHILDHOOD EXPOSURE EFFECTS*

RAJ CHETTY AND NATHANIEL HENDREN

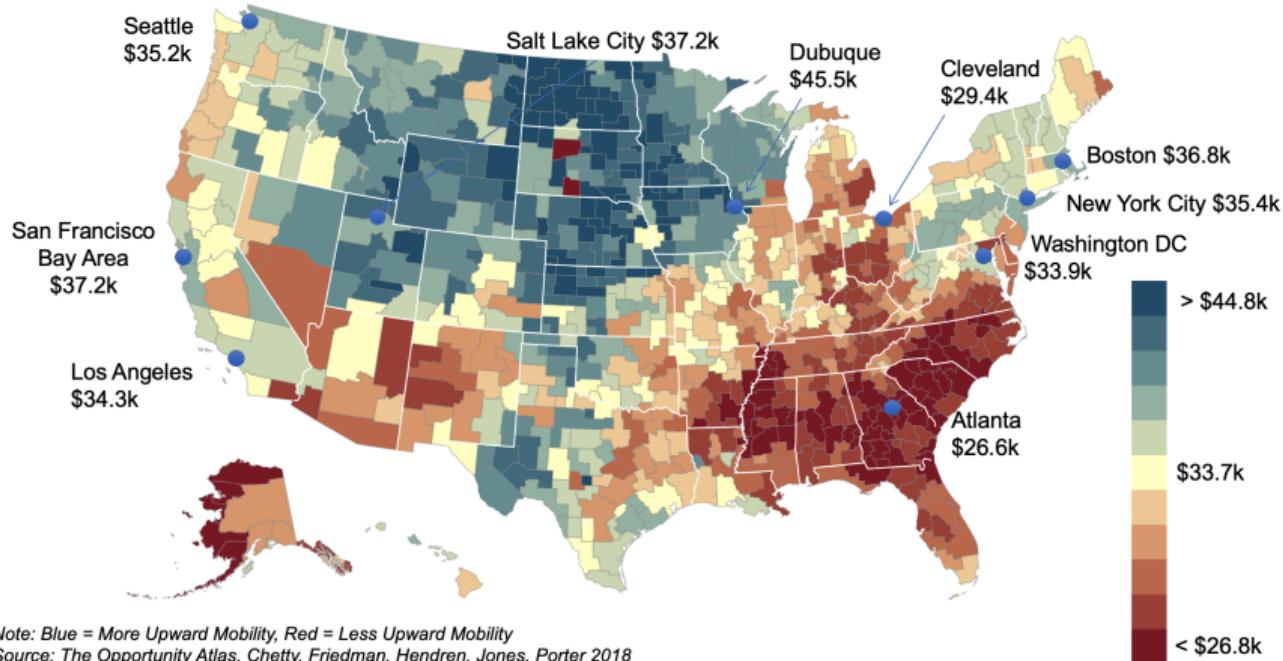
Intro

- ▶ How do children's chances of moving up vary across areas in the US?
- ▶ Are there some areas where kids do better than others? If so, what lessons can we learn from them?
- ▶ Recent studies have used big data to measure how upward mobility varies based on where children grow up
 - ▶ The Opportunity Atlas

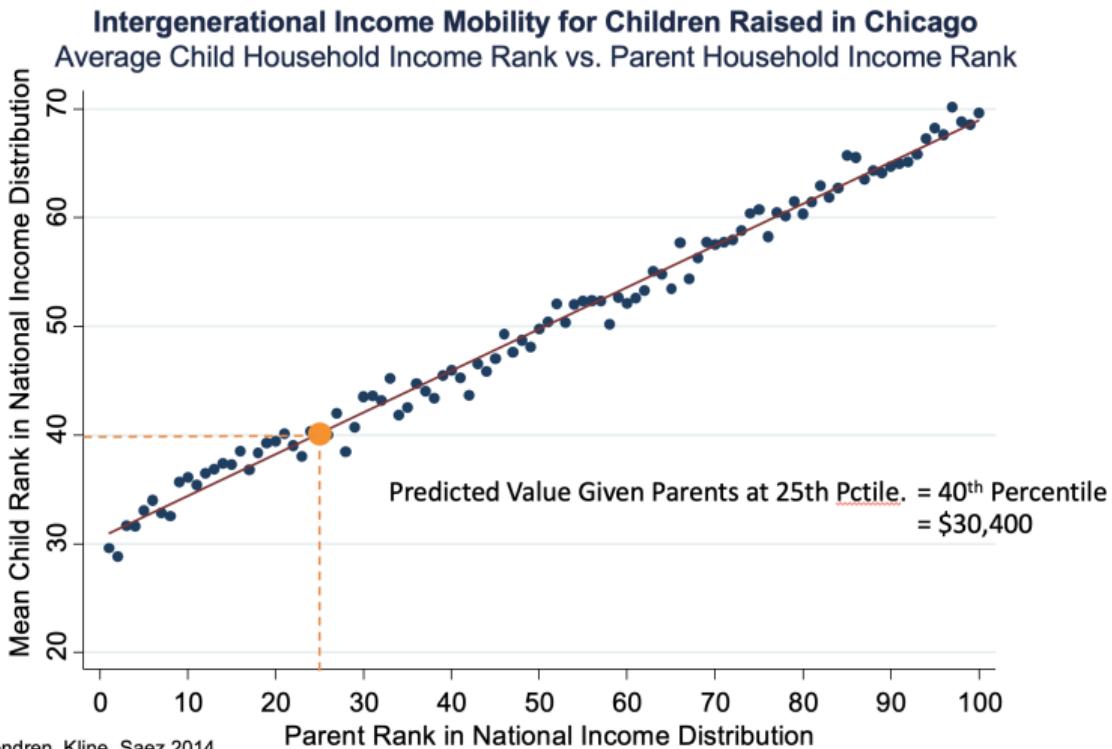
The Opportunity Atlas

The Geography of Upward Mobility in the United States

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



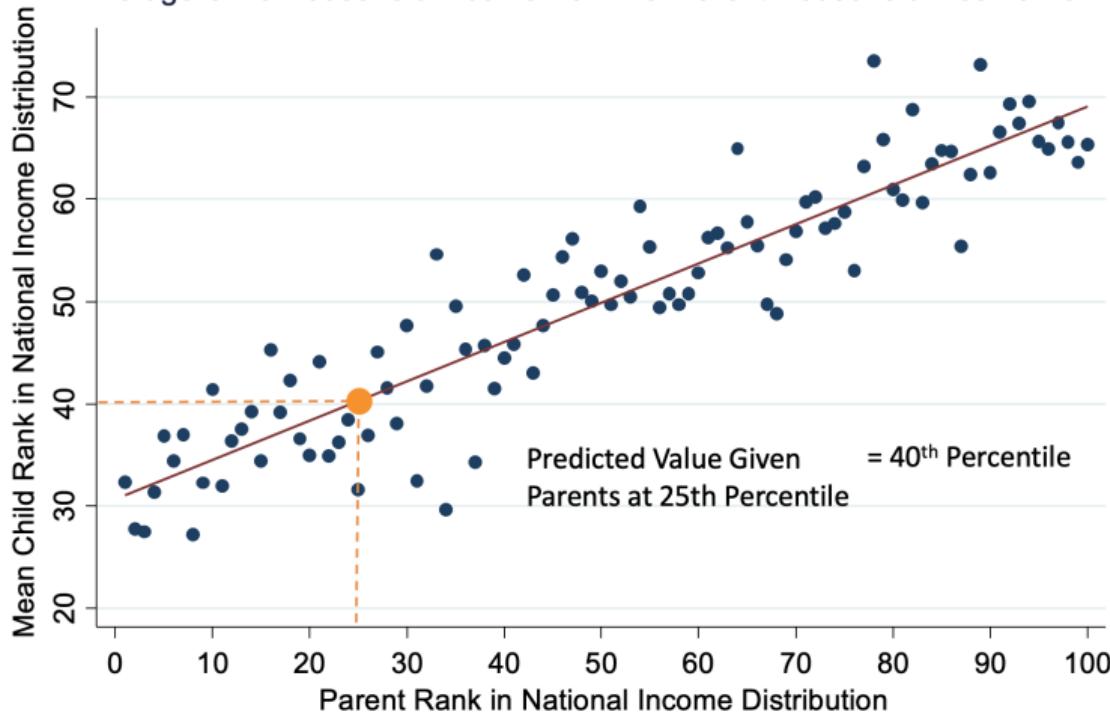
The Opportunity Atlas



The Opportunity Atlas

Intergenerational Income Mobility for Children Raised in a Hypothetical Census Tract

Average Child Household Income Rank vs. Parent Household Income Rank



The Opportunity Atlas

Data Sources and Sample Definitions

- ▶ Data sources: Anonymized 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

The Opportunity Atlas

Measuring Parents' and Children's Incomes in Tax Data

- ▶ Parents' household incomes: average income reported on Form 1040 tax return from 1994-2000
- ▶ Children's incomes measured from tax returns in 2014-15 (ages 31-37)
- ▶ Focus on percentile ranks in national distribution:
 - ▶ Rank children relative to others born in the same year and parents relative to other parents

The Opportunity Atlas

Causal Effects of Neighborhoods vs. Sorting

- ▶ Two very different explanations for variation in children's outcomes across areas:

The Opportunity Atlas

Causal Effects of Neighborhoods vs. Sorting

- ▶ Two very different explanations for variation in children's outcomes across areas:
 - 1 Sorting: different people live in different places
 - 2 Causal effects: places have a causal effect on upward mobility for a given person

The Opportunity Atlas

Identifying Causal Effects of Neighborhoods

- ▶ Objective is to determine how much a child's potential outcomes would improve on average if he were to grow up in an area where the permanent residents' outcomes are 1 percentile point higher.

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Identifying Causal Effects of Neighborhoods

- ▶ Objective is to determine how much a child's potential outcomes would improve on average if he were to grow up in an area where the permanent residents' outcomes are 1 percentile point higher.
- ▶ Ideal experiment?

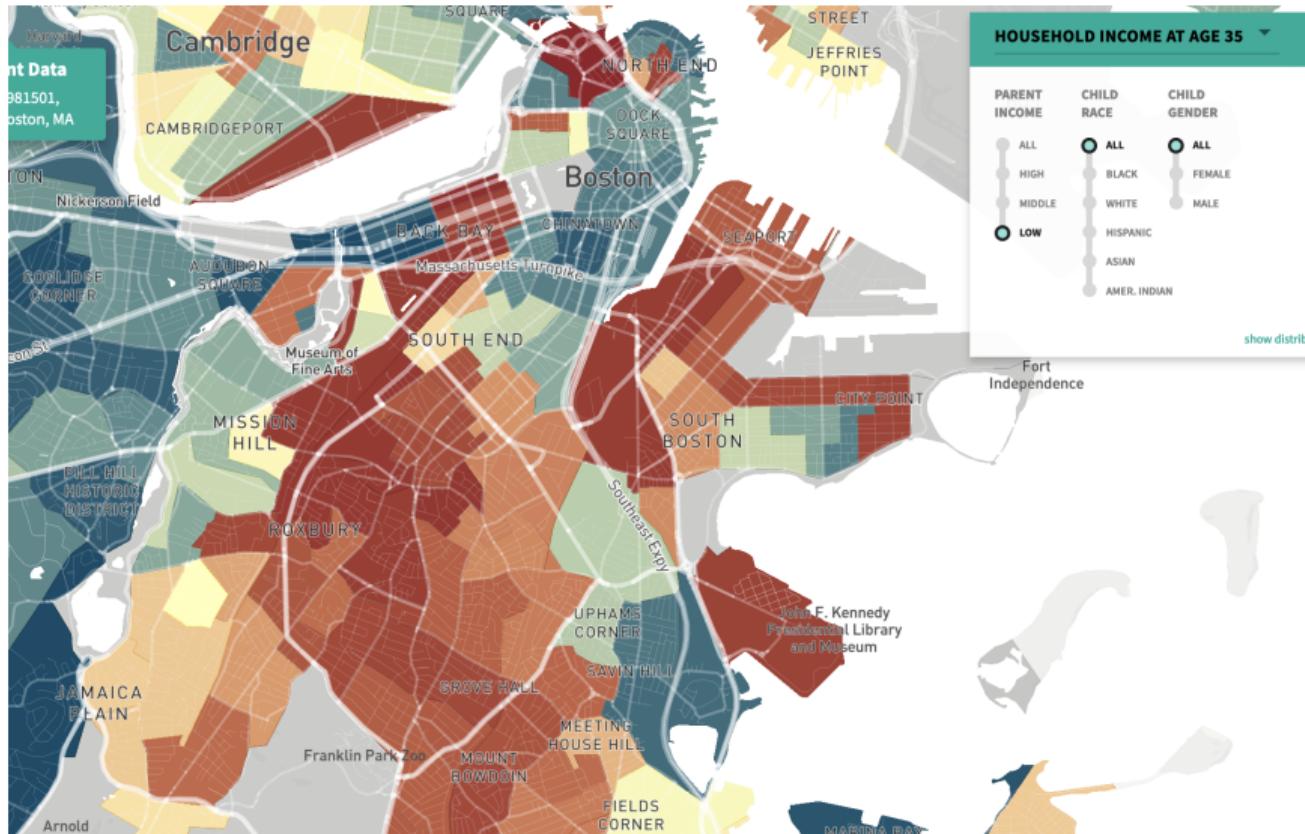
The Opportunity Atlas

Identifying Causal Effects of Neighborhoods

- ▶ Ideal experiment?
- ▶ they approximate this experiment using a quasi-experimental design
- ▶ Study 3 million families who move across Census tracts in observational data
- ▶ Key idea: exploit variation in age of child when family moves to identify causal effects of environment

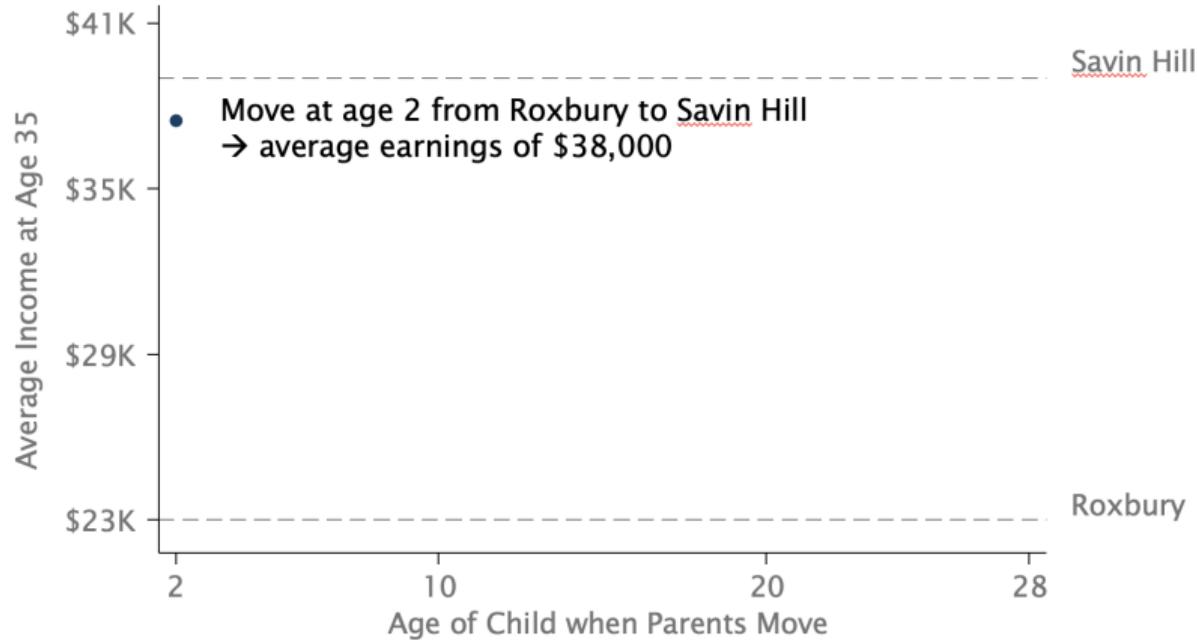
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Identifying Causal Effects of Neighborhoods



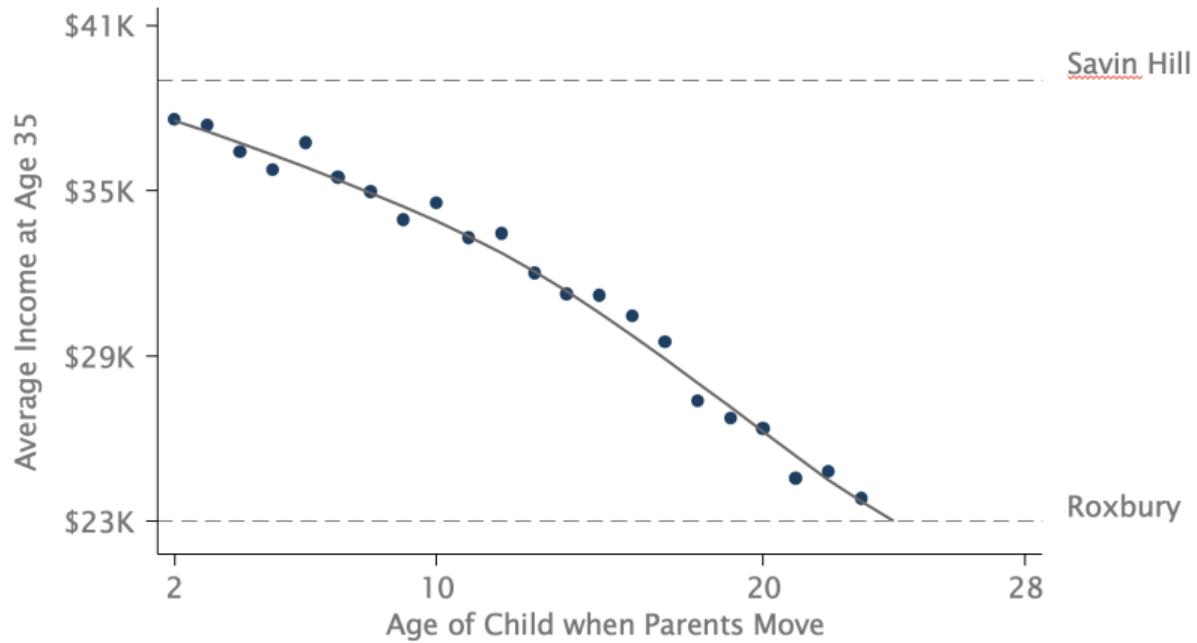
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Identifying Causal Effects of Neighborhoods



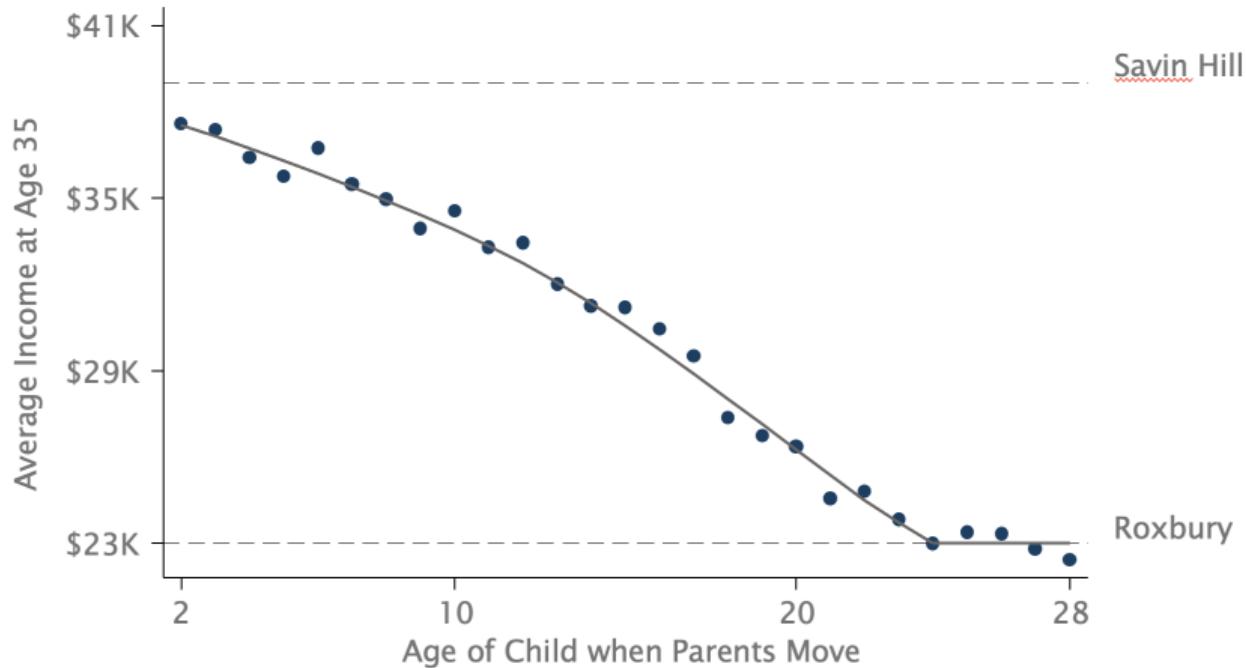
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Identifying Causal Effects of Neighborhoods



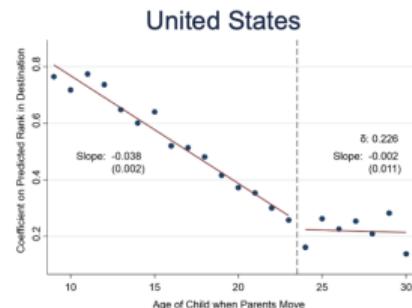
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Identifying Causal Effects of Neighborhoods

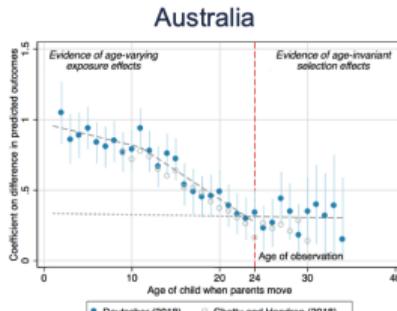


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Identifying Causal Effects of Neighborhoods

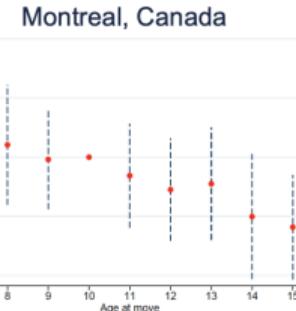


Source: Chetty and Hendren (QJE 2018)

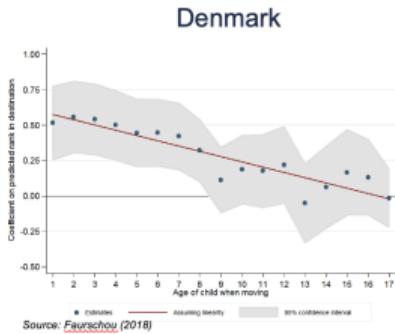


Source: Deutscher (2018)

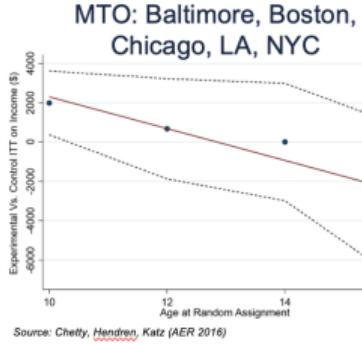
Source: Chetty and Hendren (2018)



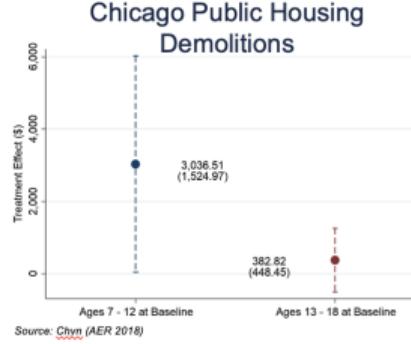
Source: Laliberté (2018)



Source: Fan Chung (2018)



Source: Chetty, Hendren, Katz (AER 2016)



Source: Chetty (AER 2018)

The Opportunity Atlas

Identifying Causal Effects of Neighborhoods

- ▶ Key assumption: timing of moves to a better/worse area unrelated to other determinants of child's outcomes
- ▶ This assumption might not hold for two reasons:

The Opportunity Atlas

Identifying Causal Effects of Neighborhoods

- ▶ Key assumption: timing of moves to a better/worse area unrelated to other determinants of child's outcomes
- ▶ This assumption might not hold for two reasons:
 - 1 Parents who move to good areas when their children are young might be different from those who move later
 - 2 Moving may be related to other factors (e.g., change in parents' job, income) that affect children directly

Neighborhood Effects

- ▶ We have shown that the neighborhood where people live has important implications for outcomes.
- ▶ Observational data make it difficult to disentangle the multiple factors involved in the residential location choice.
 - ▶ Disparities in income, differences in information about neighborhood attributes
 - ▶ Housing/neighborhood preferences that also affect residential sorting behavior
 - ▶ Discrimination
 - ▶ etc.

Intro

- ▶ I'm going to discuss Chetty et al (2014) AER

The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment[†]

*By RAJ CHETTY, NATHANIEL HENDREN, AND LAWRENCE F. KATZ**

- ▶ Disclaimer: these slides are based on their slides

Motivation

- ▶ Substantial disparities in economic outcomes across low vs. high poverty neighborhoods [e.g., Wilson 1987, Jencks and Mayer 1990, Cutler and Glaeser 1997]
- ▶ These disparities motivated the HUD Moving to Opportunity (MTO) experiment in the mid 1990's
- ▶ Offered a randomly selected subset of families living in high-poverty housing projects housing vouchers to move to lower-poverty areas
- ▶ Large literature on MTO has found significant effects on adult health and subjective well-being
- ▶ But these studies have consistently found that the MTO treatments had no impact on earnings or employment rates of adults and older youth [e.g. Katz, Kling, and Liebman 2001, Oreopoulos 2003, Sanbonmatsu et al. 2011]

Revisit MTO

- ▶ They revisit the MTO experiment and focus on its impacts on children who were young when their families moved to better neighborhoods
- ▶ Re-analysis motivated by a companion paper that presents quasi-experimental evidence on neighborhood effects [Chetty and Hendren 2015]
- ▶ Key finding: childhood exposure effects
- ▶ Every year in a better area during childhood → better outcomes in adulthood
- ▶ Implies that gains from moving to a better area are larger for children who move when young

Revisit MTO

- ▶ In light of this evidence on childhood exposure effects, they returned to MTO data to examine treatment effects on young children
- ▶ Link MTO data to tax data to analyze effects of MTO treatments on children's outcomes in adulthood
- ▶ Children they study were not old enough to observe outcomes in adulthood at the time of the MTO Final Impacts Evaluation (which used data up to 2008)

Moving to Opportunity Experiment

- ▶ HUD Moving to Opportunity Experiment implemented from 1994-1998
- ▶ 4,600 families at 5 sites: Baltimore, Boston, Chicago, LA, New York
- ▶ Families randomly assigned to one of three groups:
 - ▶ Experimental: housing vouchers restricted to low-poverty (< 10%) Census tracts
 - ▶ Section 8: conventional housing vouchers, no restrictions
 - ▶ Control: public housing in high-poverty (50% at baseline) areas

Moving to Opportunity Experiment



Data

- ▶ MTO data obtained from HUD
 - ▶ 4,604 households and 15,892 individuals
 - ▶ Primary focus: 8,603 children born in or before 1991
- ▶ Link MTO data to federal income tax returns from 1996-2012
 - ▶ Approximately 85% of children matched
 - ▶ Match rates do not differ significantly across treatment groups
 - ▶ Baseline covariates balanced across treatment groups in matched data

Estimation I

► Estimation 1:

$$y_i = \alpha + \beta_E Exp_i + \beta_S S8_i + \delta s_i + \epsilon_i \quad (1)$$

- Experimental take-up: 48% for young children, 40% for older children
- Section 8 take-up: 65.8% for young children, 55% for older children

Estimation II

- ▶ Experimental take-up: 48% for young children, 40% for older children
- ▶ Section 8 take-up: 65.8% for young children, 55% for older children

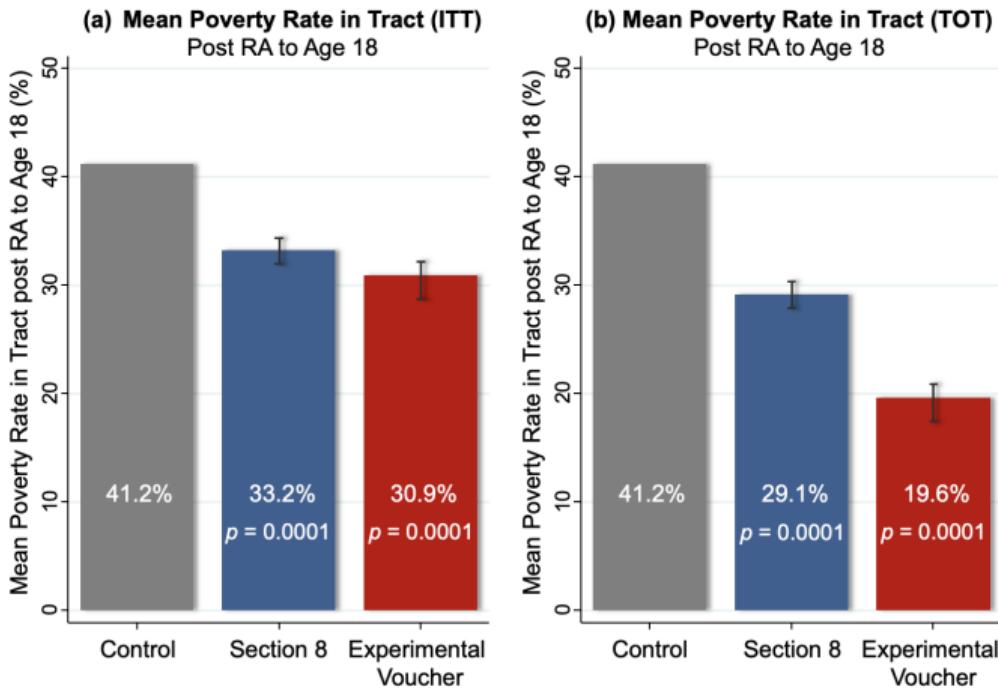
$$y_i = \alpha + \beta_E TakeExp_i + \beta_S TakeS8_i + \delta s_i + \epsilon_i \quad (2)$$

Results I: Where they live

- ▶ "First degree" effects of MTO experiment on poverty rates
- ▶ Measure mean poverty rates from random assignment to age 18 at tract level using Census data
- ▶ Use poverty rates as an index of nbhd. quality, but note that MTO treatments naturally changed many other features of neighborhoods too

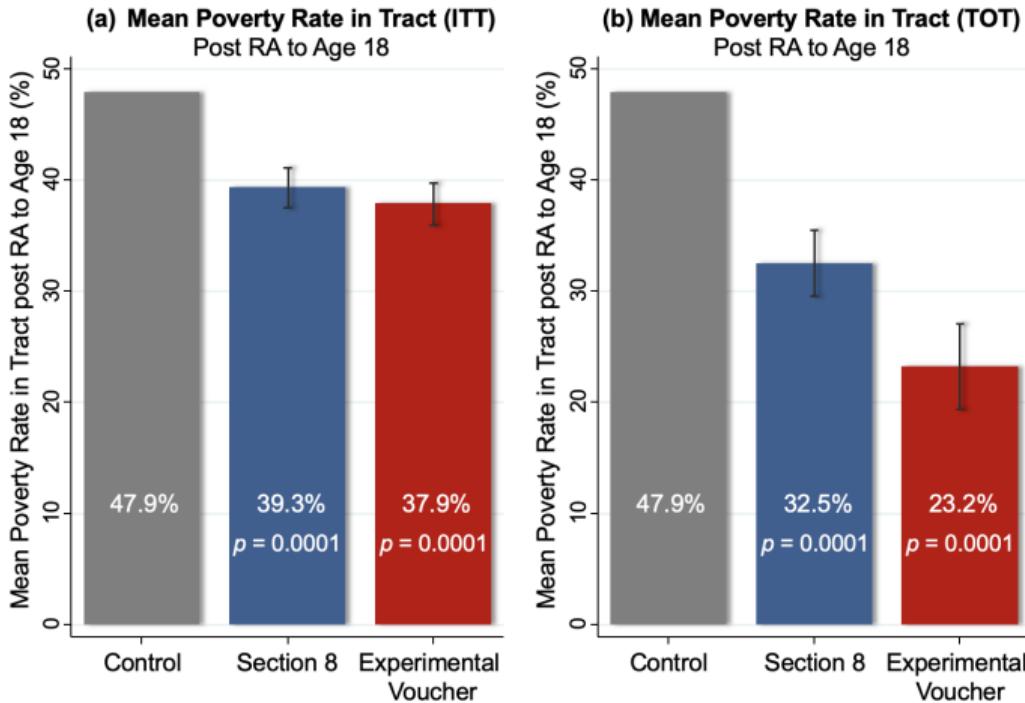
Results I: Where they live

Impacts of MTO on Children Below Age 13 at Random Assignment



Results I: Where they live

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

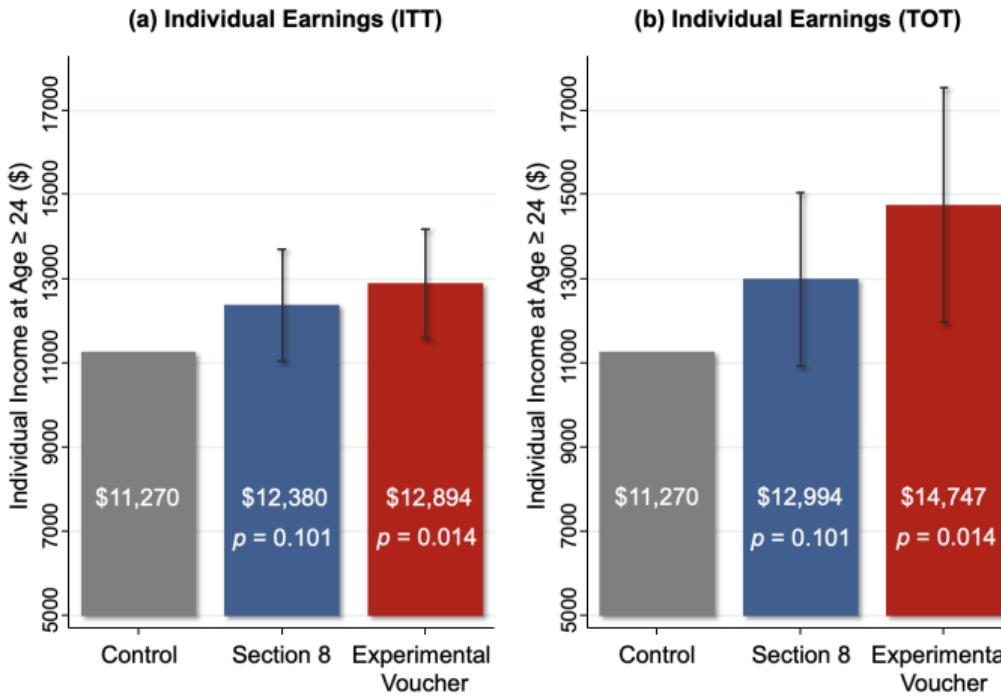


Results II: Treatment Effects on Outcomes in Adulthood below age 13 at RA

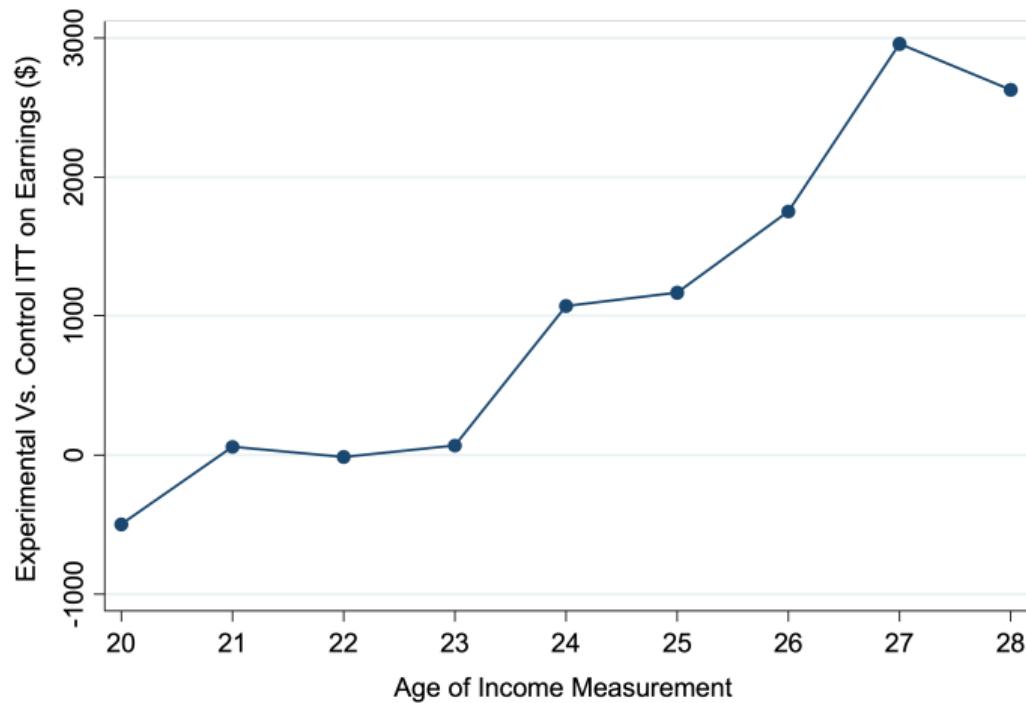
- ▶ Now turn to impacts on outcomes in adulthood
- ▶ Begin by analyzing effects on children below age 13 at RA
- ▶ Start with individual earnings (W-2 earnings + self-employment income)
 - ▶ Includes those who don't file tax returns through W-2 forms
- ▶ Measured from 2008-12, restricting to years in which child is 24 or older
 - ▶ Evaluate impacts at different ages after showing baseline results

Results II: Treatment Effects on Outcomes in Adulthood below age 13 at RA

Impacts of MTO on Children Below Age 13 at Random Assignment

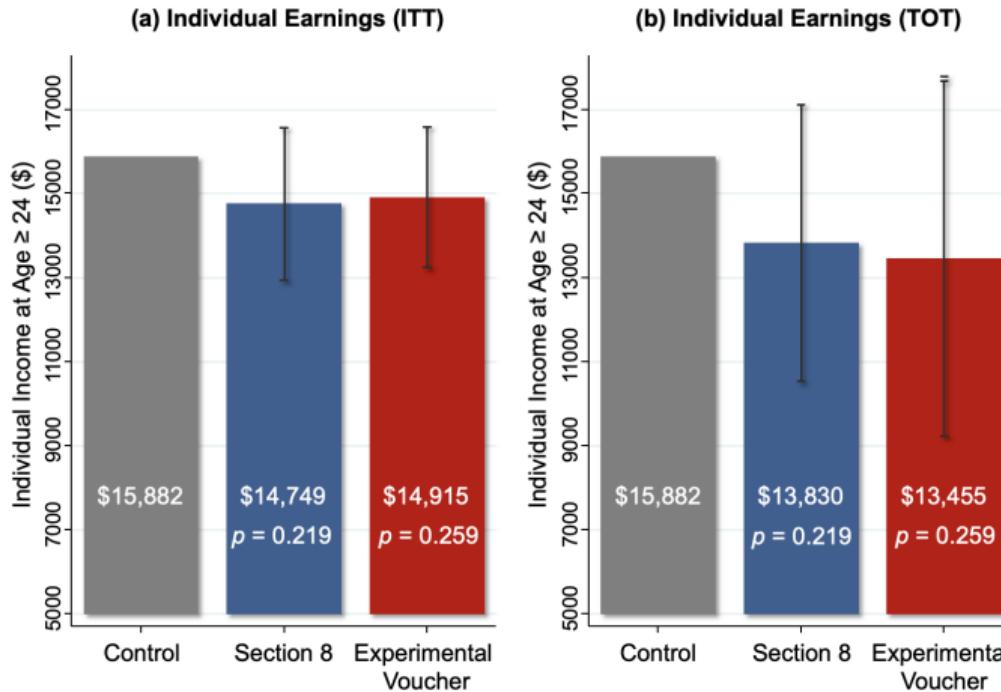


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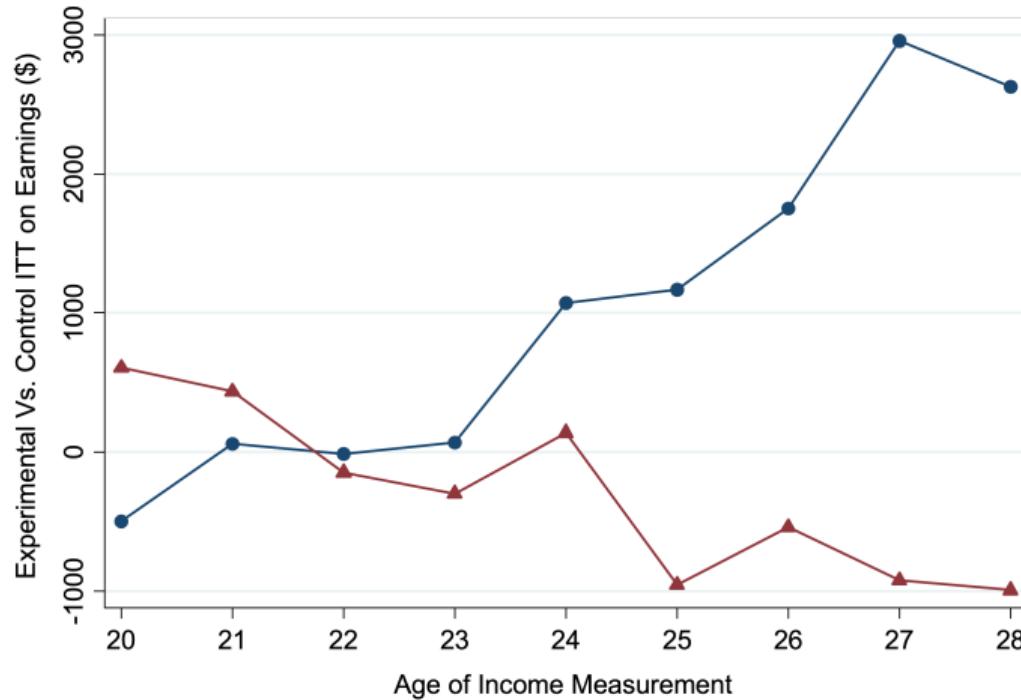


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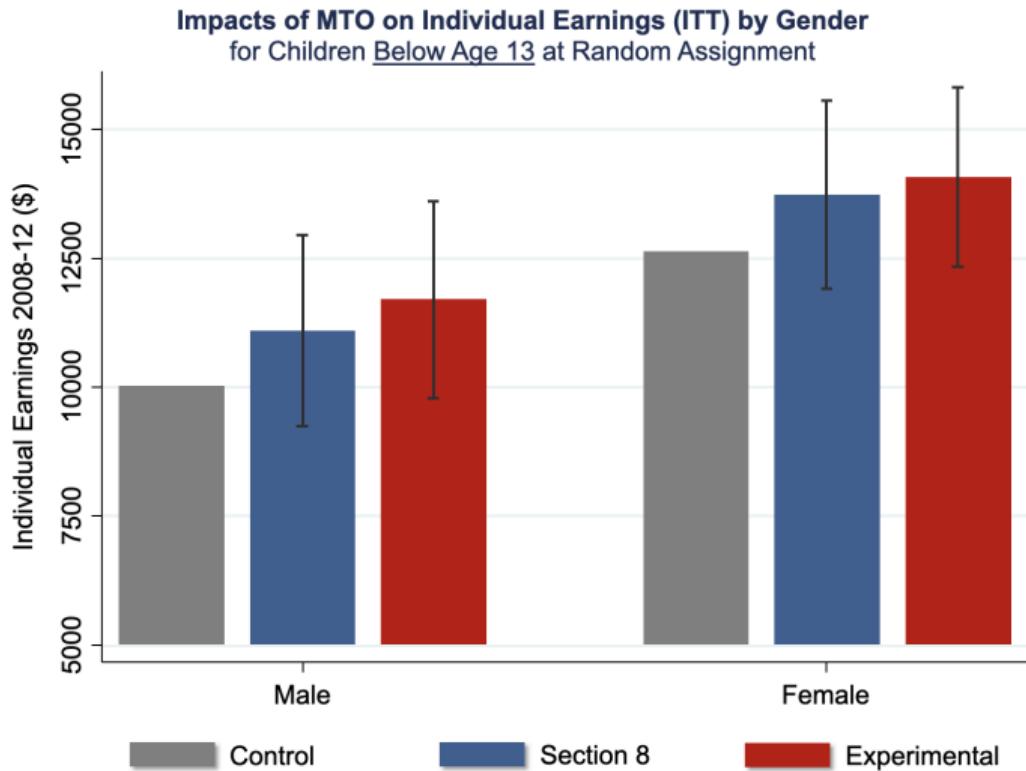
Impacts of MTO on Children Age 13-18 at Random Assignment



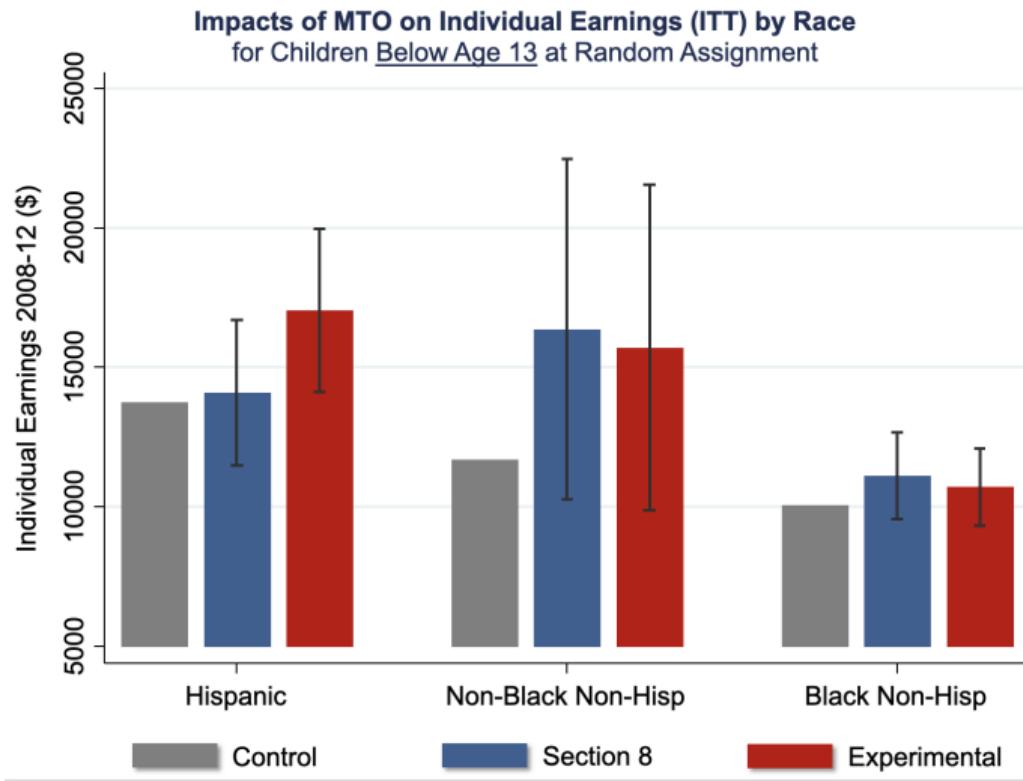
Results II: Treatment Effects on Outcomes in Adulthood ages 13-18 at random assignment



Results III: Heterogeneity



Results III: Heterogeneity



MTO Limitations

- ▶ MTO experiment shows that neighborhoods matter, but has two limitations:
- ▶ Sample size insufficient to determine which ages of childhood matter most
- ▶ Does not directly identify which neighborhoods are good or bad

Conclusion: Implications for Housing Voucher Policy

- ▶ Housing vouchers can be very effective but must be targeted carefully
 - ▶ Vouchers should be targeted at families with young children
 - ▶ 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

Conclusion: Policy Lessons

- ▶ How can we improve neighborhood environments for disadvantaged youth?
- ▶ Short-term solution: Provide targeted housing vouchers at birth conditional on moving to better (e.g. mixed-income) areas
- ▶ Taxpayers may ultimately gain from this investment
- ▶ Long-term solution: improve neighborhoods with poor outcomes, concentrating on factors that affect children