

Causal Effect of Neighborhoods

Economics of Public and Social Issues

Jonathan Moreno-Medina

ECO3253, UTSA

Fall 2022

Plan for today

Reminder: Today is deadline for submission

1. Clarifications about project
2. Causal effects of neighborhoods
3. Regression Analysis (work in couples for 15 mins)

Clarifications for project

1. No need to submit anything. I will use time stamps for your work. Remember you should use the **project1** tab
2. When you create the Quarto/RMarkdown file, **do not change anything besides title and author** between the --- lines (this is called YAML code).

```
---
```

```
title: "Project 1"
author: "Your name here"
format: html
editor: visual
---
```

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

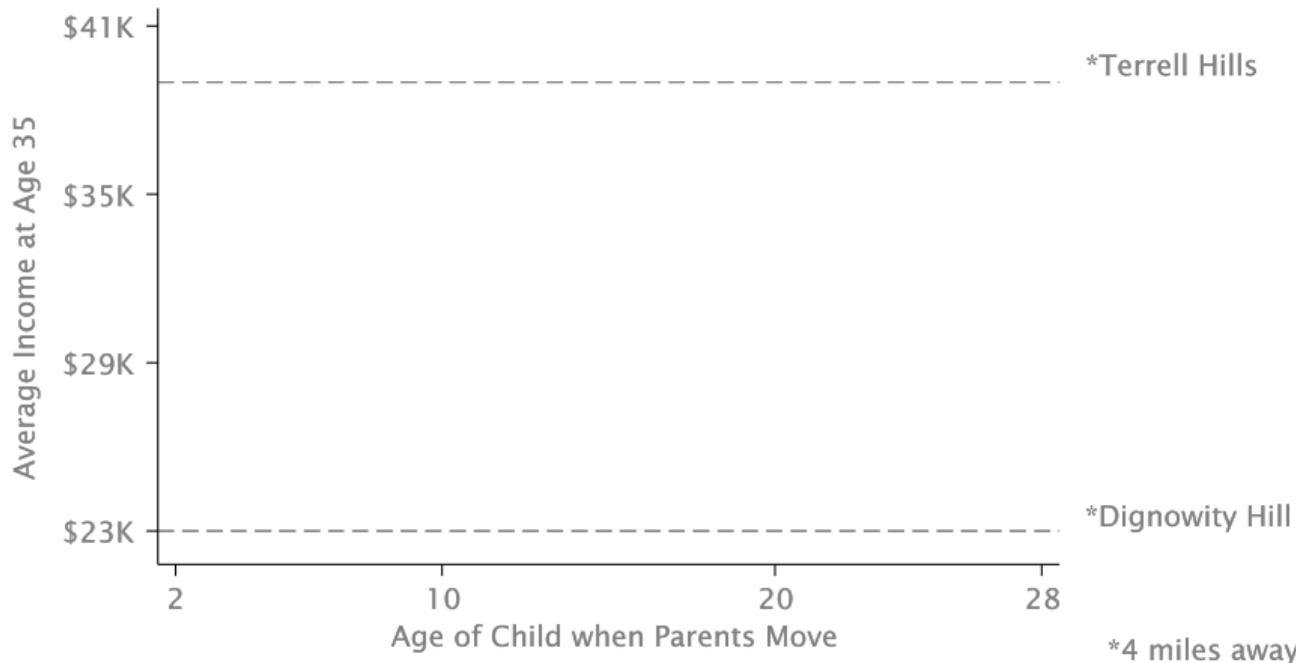
Identifying Causal Effects of Neighborhoods

- ▶ Ideal experiment: randomly assign children to neighborhoods and compare outcomes in adulthood
- ▶ We 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

Income Gain from Moving to a Better Neighborhood

Income Gain from Moving to a Better Neighborhood

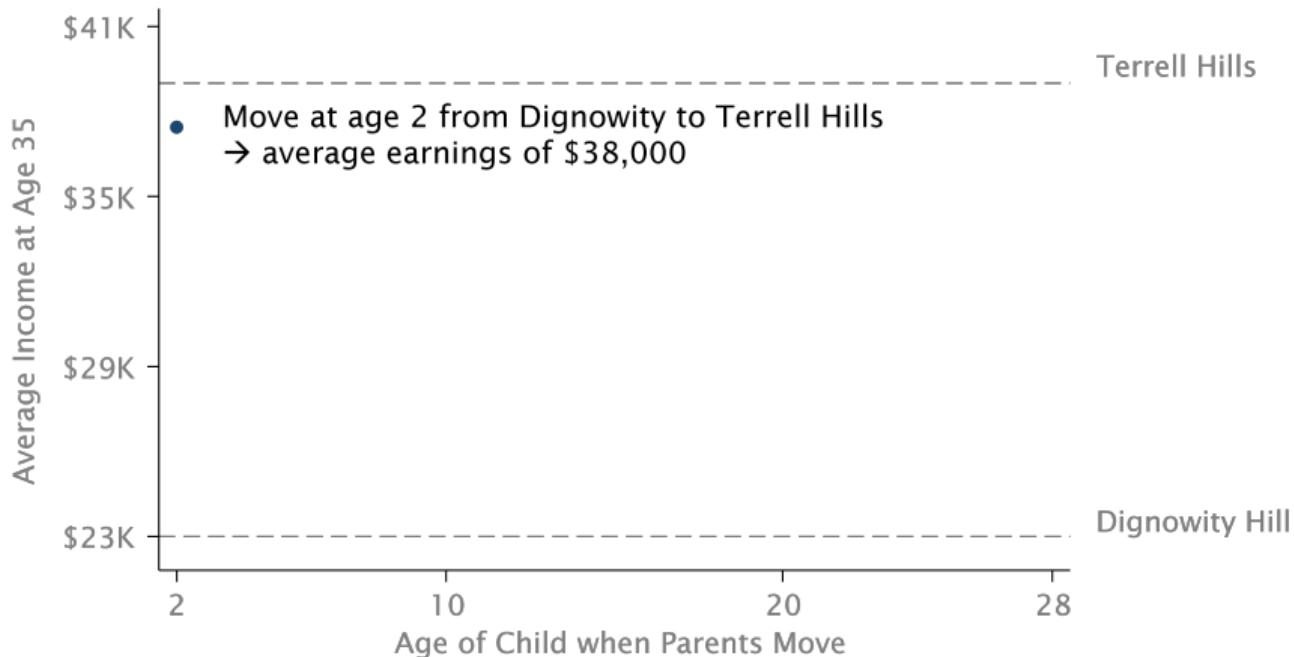
By Child's Age at Move



Income Gain from Moving to a Better Neighborhood

Income Gain from Moving to a Better Neighborhood

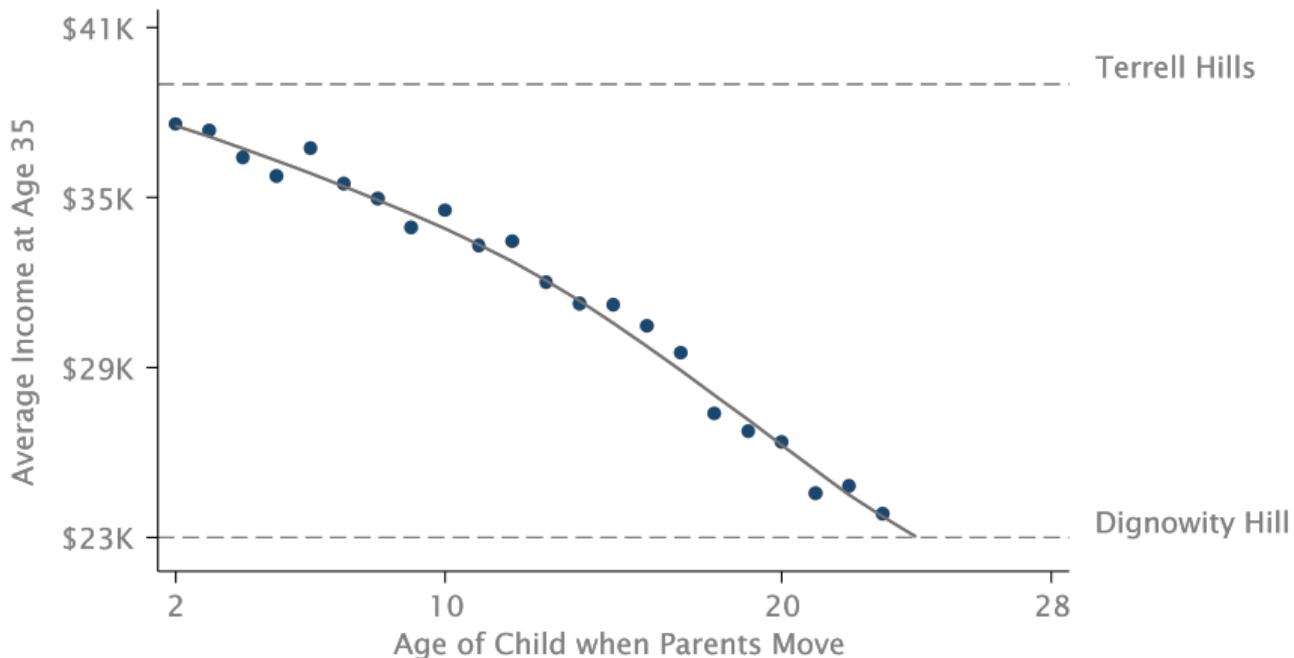
By Child's Age at Move



Income Gain from Moving to a Better Neighborhood

Income Gain from Moving to a Better Neighborhood

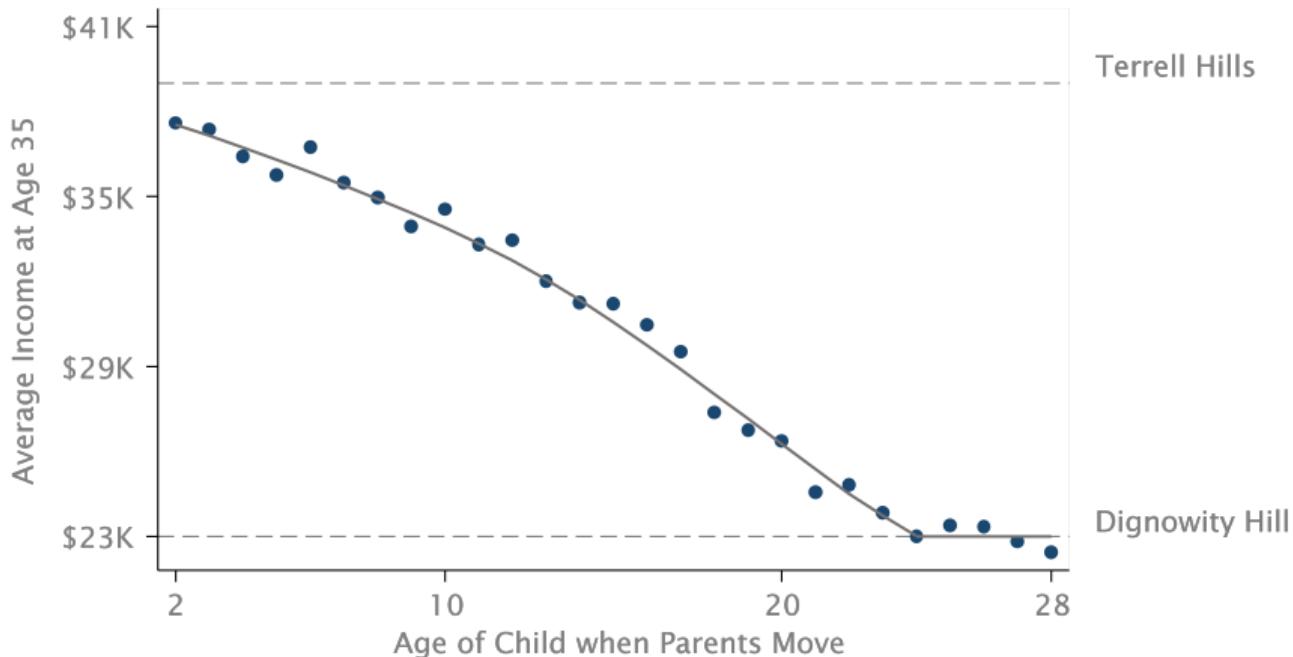
By Child's Age at Move



Income Gain from Moving to a Better Neighborhood

Income Gain from Moving to a Better Neighborhood

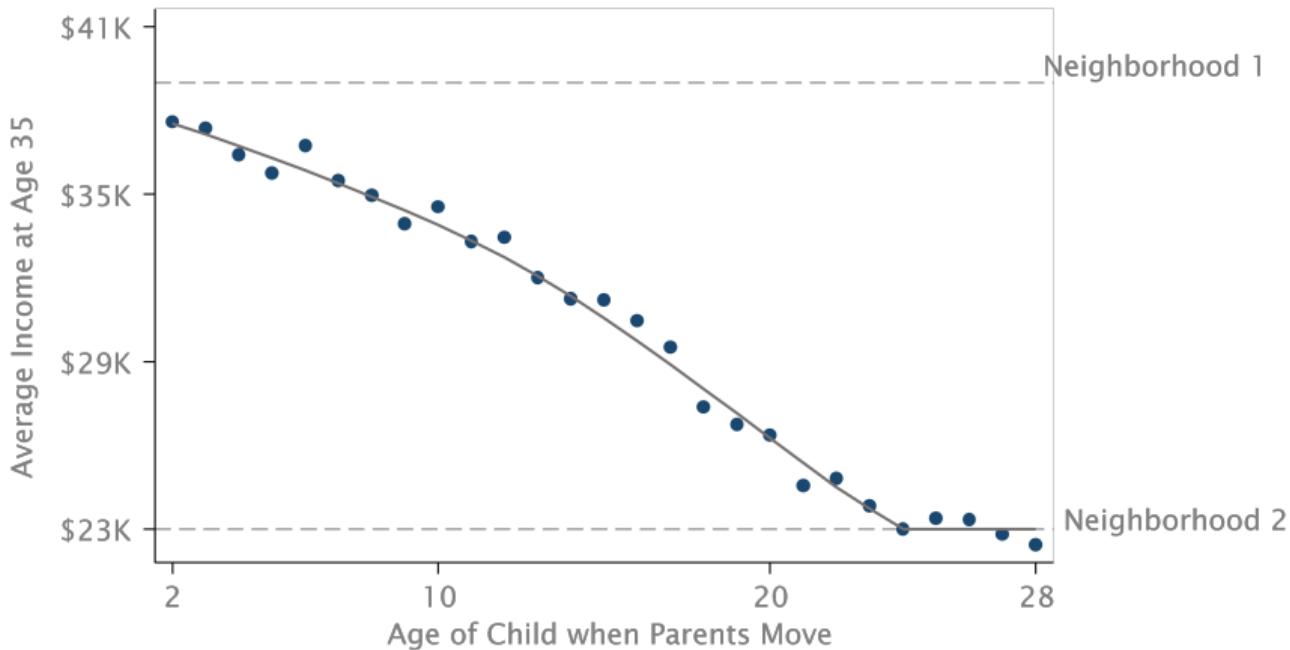
By Child's Age at Move



Income Gain from Moving to a Better Neighborhood

Income Gain from Moving to a Better Neighborhood

By Child's Age at Move



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) that affect children directly

Identifying Causal Effects of Neighborhoods

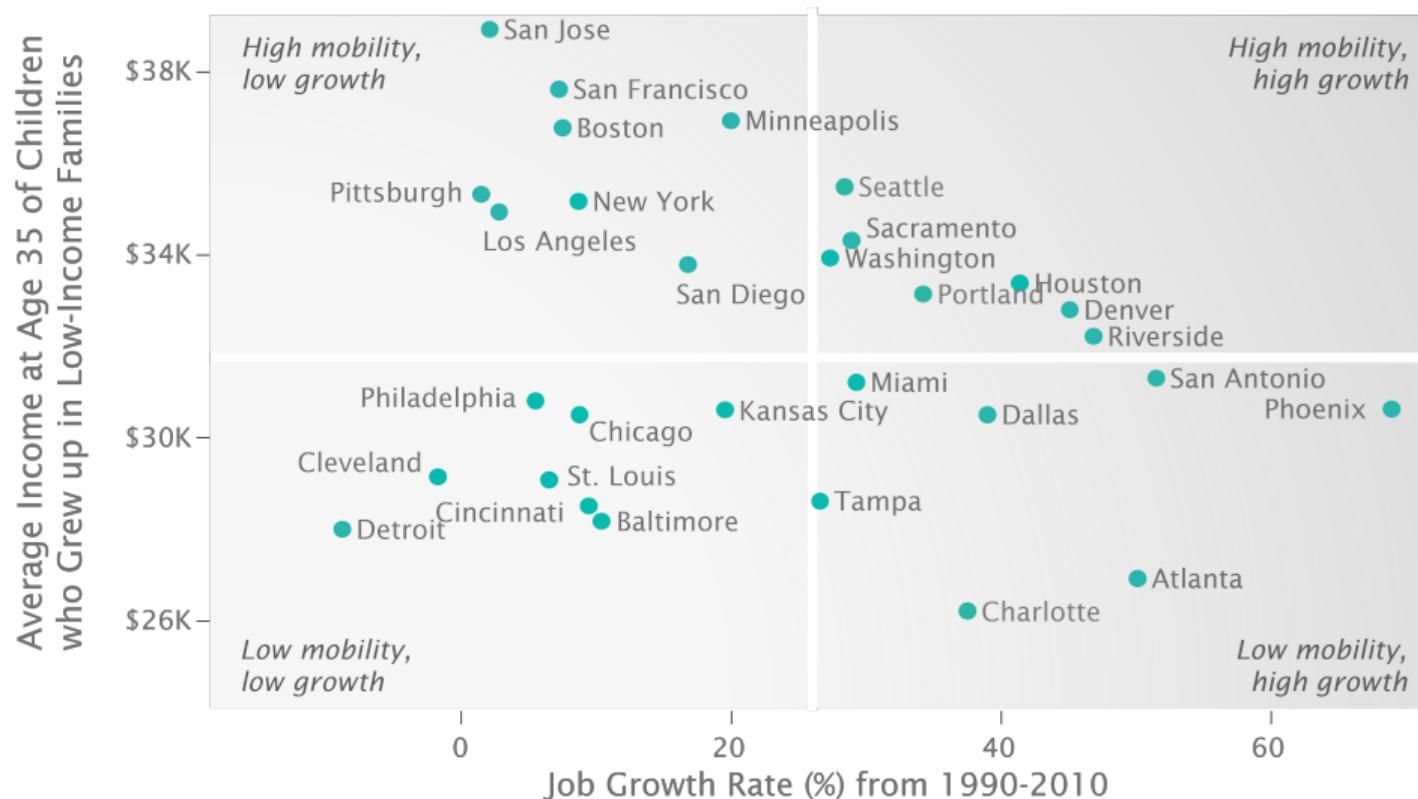
- ▶ Two approaches to evaluating validity of this assumption:
 1. Compare siblings' outcomes to control for family effects
 2. Use differences in neighborhood effects across subgroups to implement "placebo" tests
 - ▶ Ex: some places (e.g., low-crime areas) have better outcomes for boys than girls
 - ▶ Move to a place where boys have high earnings son improves in proportion to exposure but daughter does not
- ▶ Conclude that about two-thirds of the variation in upward mobility across areas is due to causal effects

Characteristics of High-Mobility Areas

Why Does Upward Mobility Differ Across Areas?

- ▶ Why do some places produce much better outcomes for disadvantaged children than others?
- ▶ Begin by characterizing the properties of areas with high rates of upward mobility using correlational analysis
- ▶ Do places with higher mobility tend to have better jobs, schools, different institutions, ...?

Upward Mobility vs. Job Growth in the 30 Largest Metro Areas



Racial Segregation in Atlanta

Residents: White (blue), Black (green), Asian (red), Hispanic (orange)

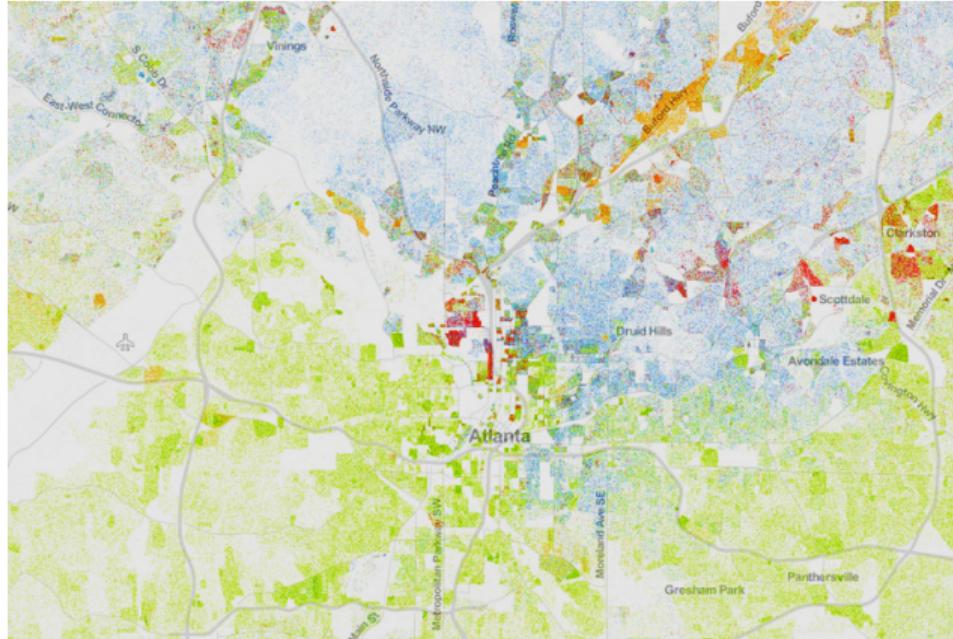


Figure 1: Source: Source: Cable (2013) based on Census 2010

Racial Segregation in Sacramento

Residents: White (blue), Black (green), Asian (red), Hispanic (orange)



Figure 2: Source: Source: Cable (2013) based on Census 2010

Racial Segregation in San Antonio

Residents: White (blue), Black (green), Asian (red), Hispanic (orange)



Figure 3. San Antonio, TX (2010) based on Census 2010 data

Five Strongest Correlates of Upward Mobility

1. Segregation
2. Income Inequality
 - ▶ Places with smaller middle class have much less mobility
3. School Quality
 - ▶ Higher expenditure, smaller classes, higher test scores correlated with more mobility
4. Family Structure
 - ▶ Areas with more single parents have much lower mobility
 - ▶ Strong correlation even for kids whose own parents are married
5. Social Capital
 - ▶ “It takes a village to raise a child”
 - ▶ Putnam (1995): “Bowling Alone”

New Map of Social Capital

A few weeks ago Chetty and co-authors published a paper and a website exploring social capital across the US:

- ▶ <https://socialcapital.org/>

Check the correlation yourself

Go to the Section on [Simple and Multivariate Regression](#) and check for yourself the correlation of kfr_pooled_p25 and at least one of these:

- ▶ gsmn_math_g3_2013
- ▶ ann_avg_job_growth_2004_2013
- ▶ frac_coll_plus2000
- ▶ frac_coll_plus2010
- ▶ med_hhinc1990

Policies to Improve Upward Mobility

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

Affordable Housing Policies in the United States

- ▶ Many potential policies to help low-income families move to better neighborhoods:
 - ▶ Subsidized housing vouchers to rent better apartments
 - ▶ Mixed-income affordable housing developments (LIHTC – Low Income Housing Tax Credit)
 - ▶ 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

Based on 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

- ▶ 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 (\$10,000)?

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 treatment effect of voucher on child i :

$$G_i = Y_i(V = 1) - Y_i(V = 0)$$

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 in the lingo of tech firms)
- ▶ 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 is the average treatment effect of getting the voucher (average value of G_i)
 - ▶ 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:
 - ▶ $\text{True Impact} = \text{Estimated Impact}/\text{Compliance Rate}$