Big Data and Economics

Neighborhoods and Upward Mobility

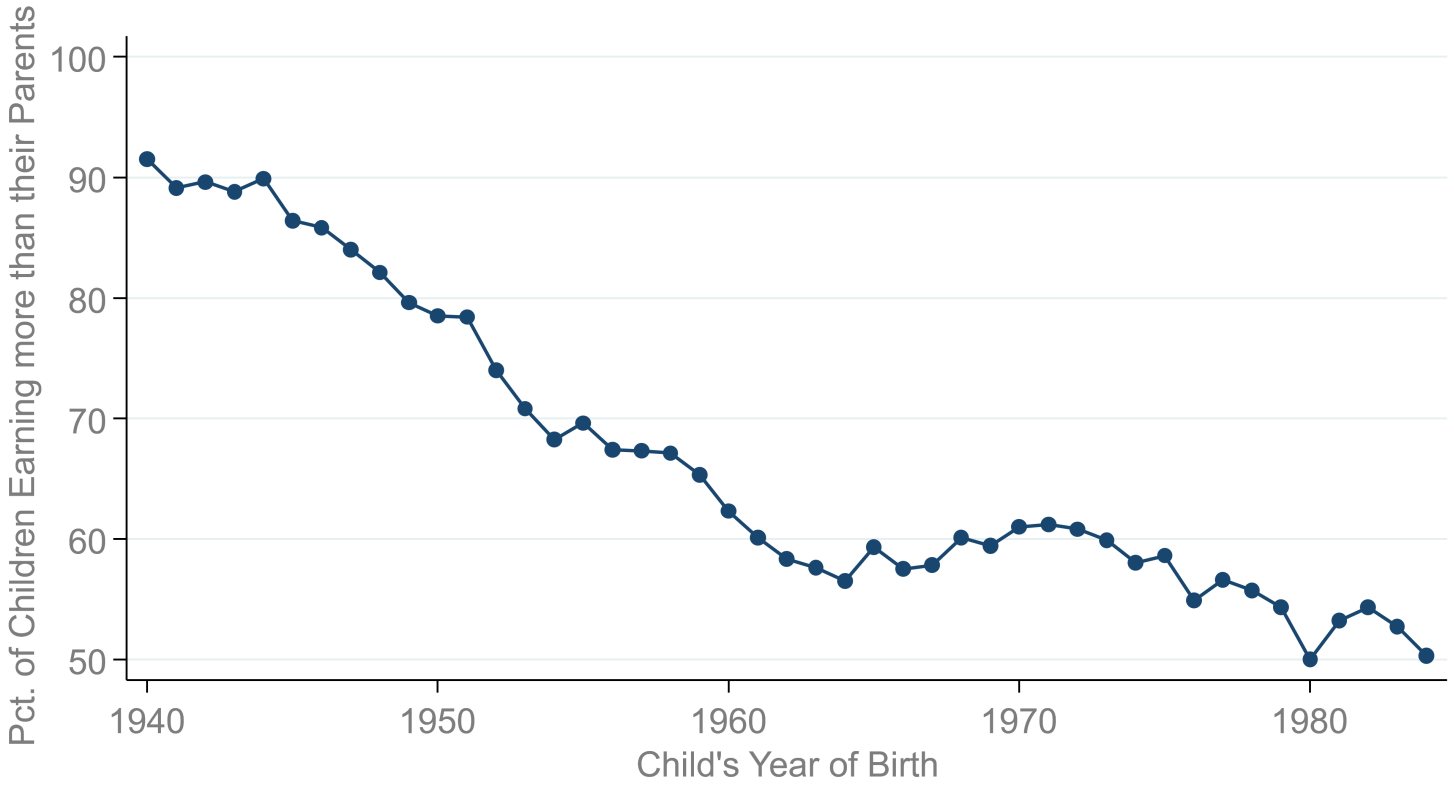
Kyle Coombs
Bates College | EC/DCS 368

Table of contents

Prologue

Prologue

- Today's lecture is a little different than the last few
- We're talking about an application of big data to a big question: why do some people move up the income ladder and others don't?
- This is a big question in economics and public policy
- Chetty answered it using big data and spatial analysis
    - By big I mean: essentially all tax returns in the USA from 1989-2015
- He released summaries of the data publicly in 2018 as the Opportunity Atlas
- These show tons of descriptive measures of income mobility at various levels of geography: state, county, and Census Tract



Source: Chetty et al. (2014)

Why is the "American Dream" Fading?

- Why are children's chances of climbing the income ladder falling in the USA?
  - What can be done to reverse this trend?
- Need to go beyond macroeconomic data to ansawer this question. Why?
  - Too many changes happening over time and across space to separate out the causal factors.
  - Also: only a handful of data points (classic macro problem)

Enter the Opportunity Atlas

- Created in 2018, the Opportunity Atlas offers one measure of how income mobility differs by location in the USA
    - If some areas have more mobility than others, can we learn why and apply those lessons elsewhere?
- Data sources:
    - Anonymized Census data (2000, 2010 ACS) covering U.S. population
    - Federal income tax returns from 1989-2015.
- Method: Link parents based on dependent claiming on tax returns
- Target sample: Children born between 1978-1983 (U.S. citizens and authorized immigrants who arrived as children)

There's bound to be a messy with this much data, so they create an analysis sample

- **Analysis sample**: 20.5 million children, 96% coverge of target sample

Toolkit to use these data

- Data cleaning and wrangling
- Data visualization
- Spatial analysis
- Regression analysis

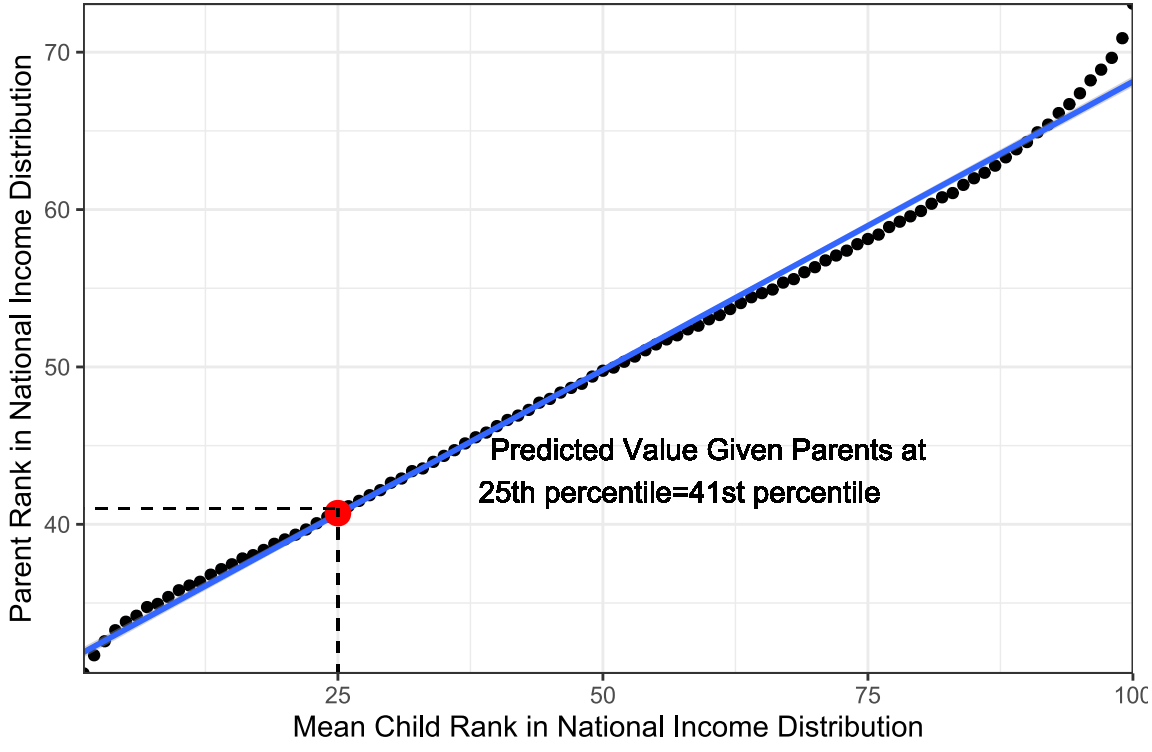
Incomes in Tax Data

- Parent household incomes: average income reported on Form 1040 tax return from 1994-2000
- Children incomes measured from tax returns in 2014-15 (ages 31-37)
- But income levels differ over time! How do we compare them?
  - Use percentile ranks in the *national* distribution
  - Rank children relative to others born in same year and parents relative to other parents
- What is a percentile?

Incomes in Tax Data

- Parent household incomes: average income reported on Form 1040 tax return from 1994-2000
- Children incomes measured from tax returns in 2014-15 (ages 31-37)
- But income levels differ over time! How do we compare them?
    - Use percentile ranks in the *national* distribution
    - Rank children relative to others born in same year and parents relative to other parents
- What is a percentile?
- **Income percentile**: The fraction of the national income distribution that a person's income exceeds
- Take average income percentile of children by parental income percentile

Average Child Income Percentile by



Source: The Opportunity Atlas

Geographic Variation in Upward Mobility

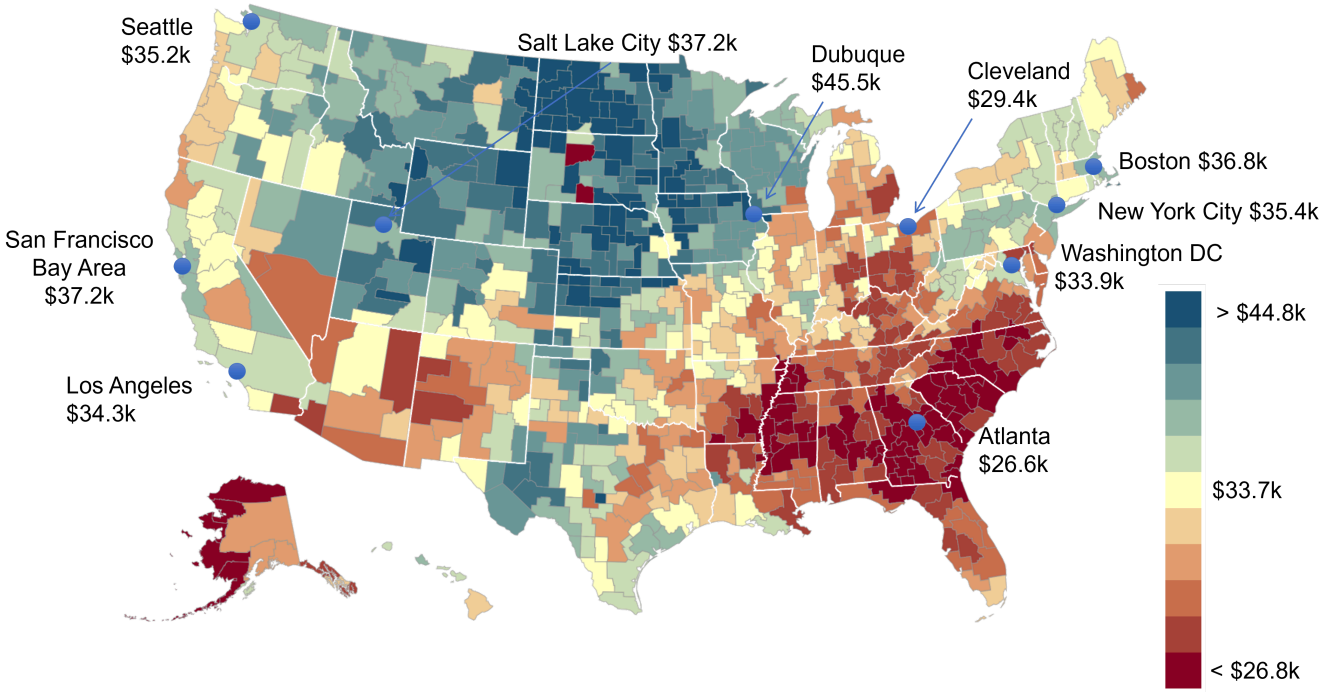
What is mobility for a given area?

- Run this same regression of income ranks by Census tract, county, or commuting zone in the USA[1]
    - Census tracts are small geographic areas that contain 1,200-8,000 people
- For simplicity, Chetty et al. (2018) report the average income percentile of children whose parents were at the 25th percentile of the national income distribution
- This is a single measure of upward mobility that is easy to understand and compare across areas
    - It is not the only measure, but it is a good one
- **Big data tip**: Sensibly summary statisics make big data more useful
    - The right statistic depends on the question you're asking
- Where do you think has the lowest upward mobility? The highest?

[1] Technical detail: Weight each child by fraction of childhood (up to 23) in a given area to account for movement across areas during childhood

The Geography of Upward Mobility in the United States

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



Note: Blue = More Upward Mobility, Red = Less Upward Mobility Source: The Opportunity Atlas

All that data and still limitations?

- They worked with the near universe of tax returns in the USA from 1989-2015
- Yet, they still have limitations
- What are a few?

All that data and still limitations?

- They worked with the near universe of tax returns in the USA from 1989-2015
- Yet, they still have limitations
- What are a few?
- Underscores a key point: data limitations are a fact of life no matter how much data you have
- You are always simplifying the world to make it fit into data
- We use models to make sense of what those limitations are
- Even if you do not think you are using a model, you are

What model? I didn't write one

- A model is a simplification of the world
- It outlines the variables that you assume are systematically related to each other
- e.g. Chetty et al. use tax data to measure income mobility
    - Unreported income is not included
    - Do you think unreported income is systematically underreported for some groups? In some areas?
    - To some extent this can be tested
- Can anyone think of examples of places where hidden models are used to interpret data?

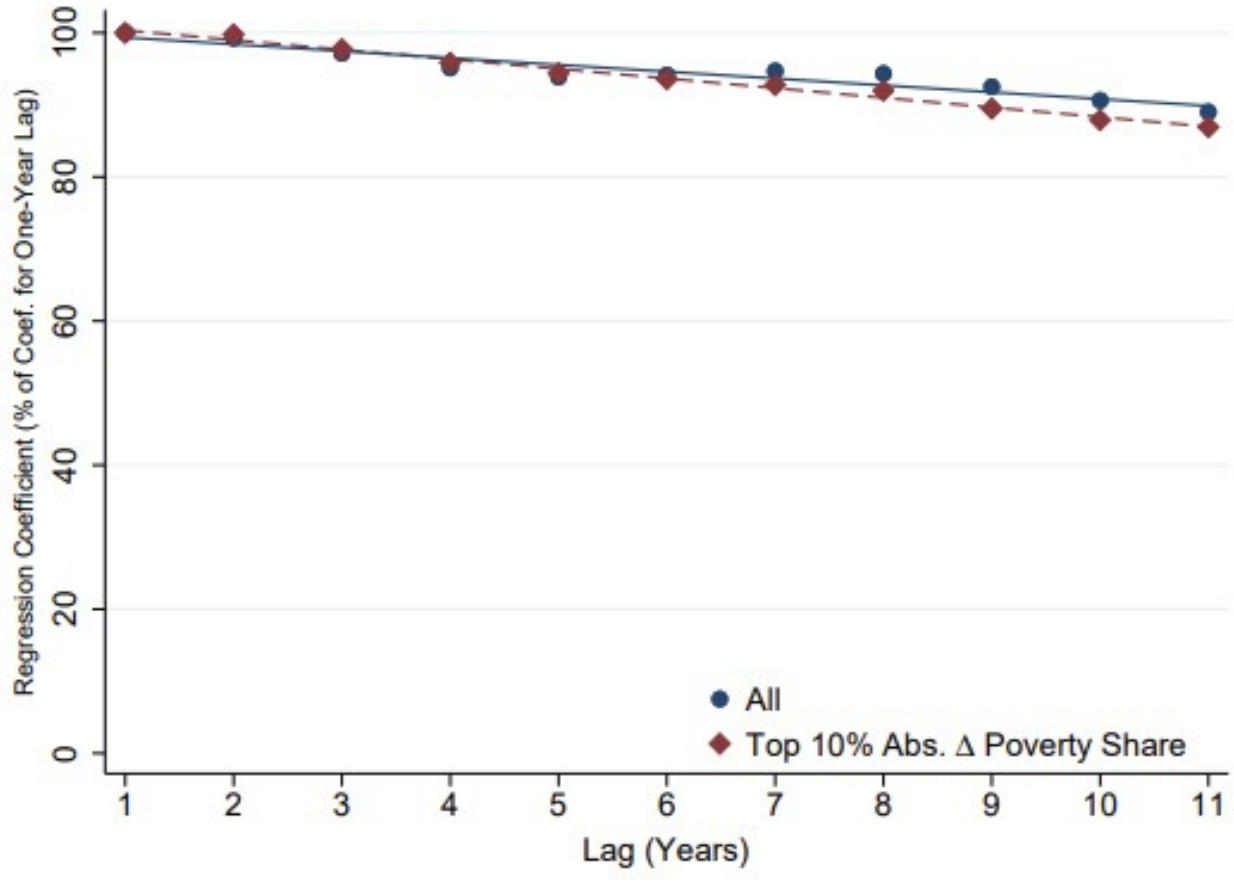
What model? I didn't write one

- A model is a simplification of the world
- It outlines the variables that you assume are systematically related to each other
- e.g. Chetty et al. use tax data to measure income mobility
  - Unreported income is not included
  - Do you think unreported income is systematically underreported for some groups? In some areas?
  - To some extent this can be tested
- Can anyone think of examples of places where hidden models are used to interpret data?
- Economic wellbeing summarized by income percentile
- GDP per capita as an indicator of economic development
- More lead paint in old buildings $\Rightarrow$ Pre-1950s housing proxies for lead exposure
- New construction is slow, so pre-1950s housing measured today likely holds for the past

Inferences about today

Chetty et al. extrapolate from cohorts born in the 80s to make inferences about today

- Assumption: mobility is not systematically changing over time, but it may lose precision
- Tests for "correlation" between mobility measures for cohorts born earlier in history

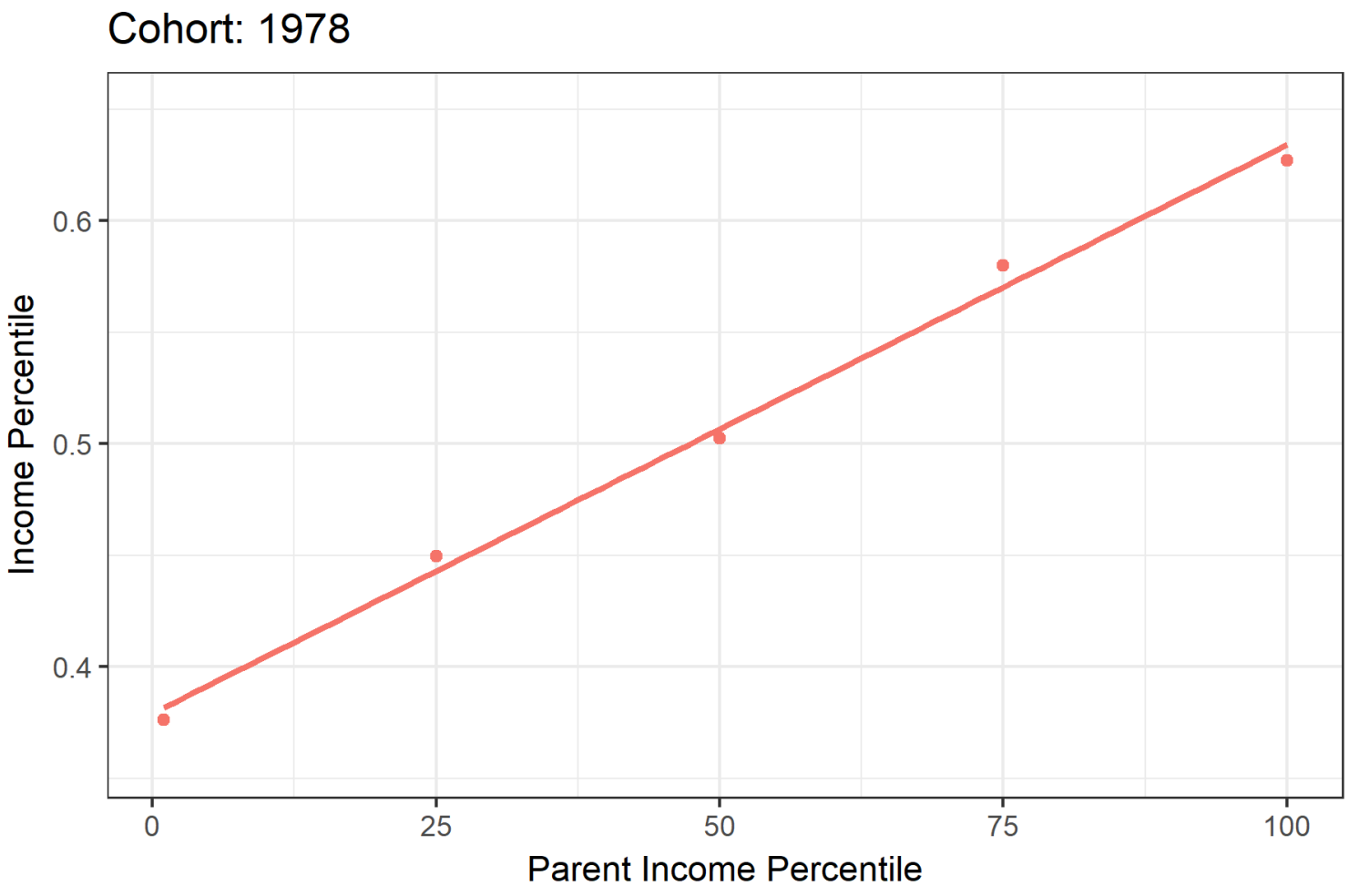


Sometimes more data is the answer

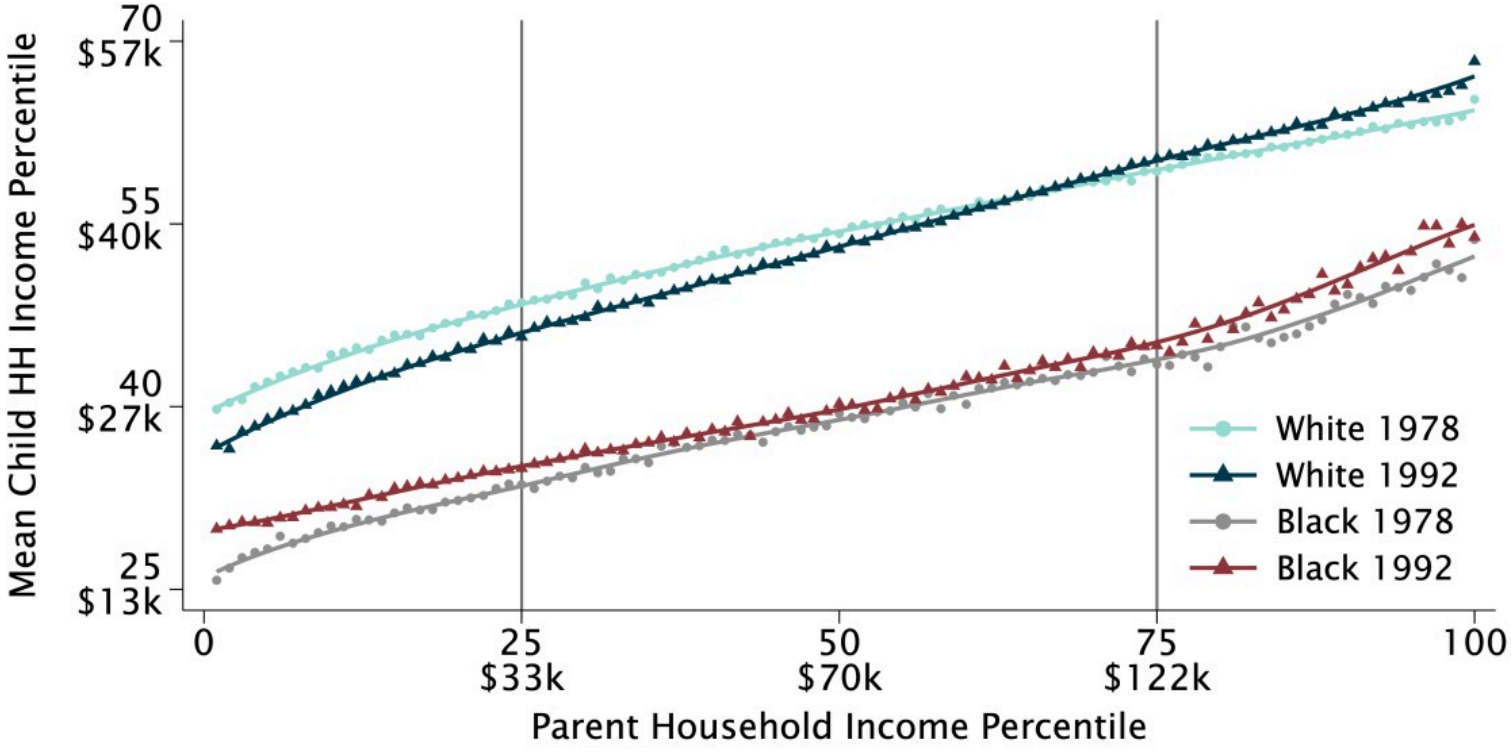
- After a few years, the Opp Atlas team (Chetty, Dobbie, Goldman, Porter, and Yang 2024) updated with more data
- They repeat the same analysis for cohorts born between 1978 and 1992[2]
    - Measure adulthood income from 2005 to 2019
- Able to look at how mobility has changed over time by cohort, location, other demographics
- Indications that mobility has increased over time for some, but not all groups

[2] I'm in the data!

Mobility trends shift over time



Racial differences



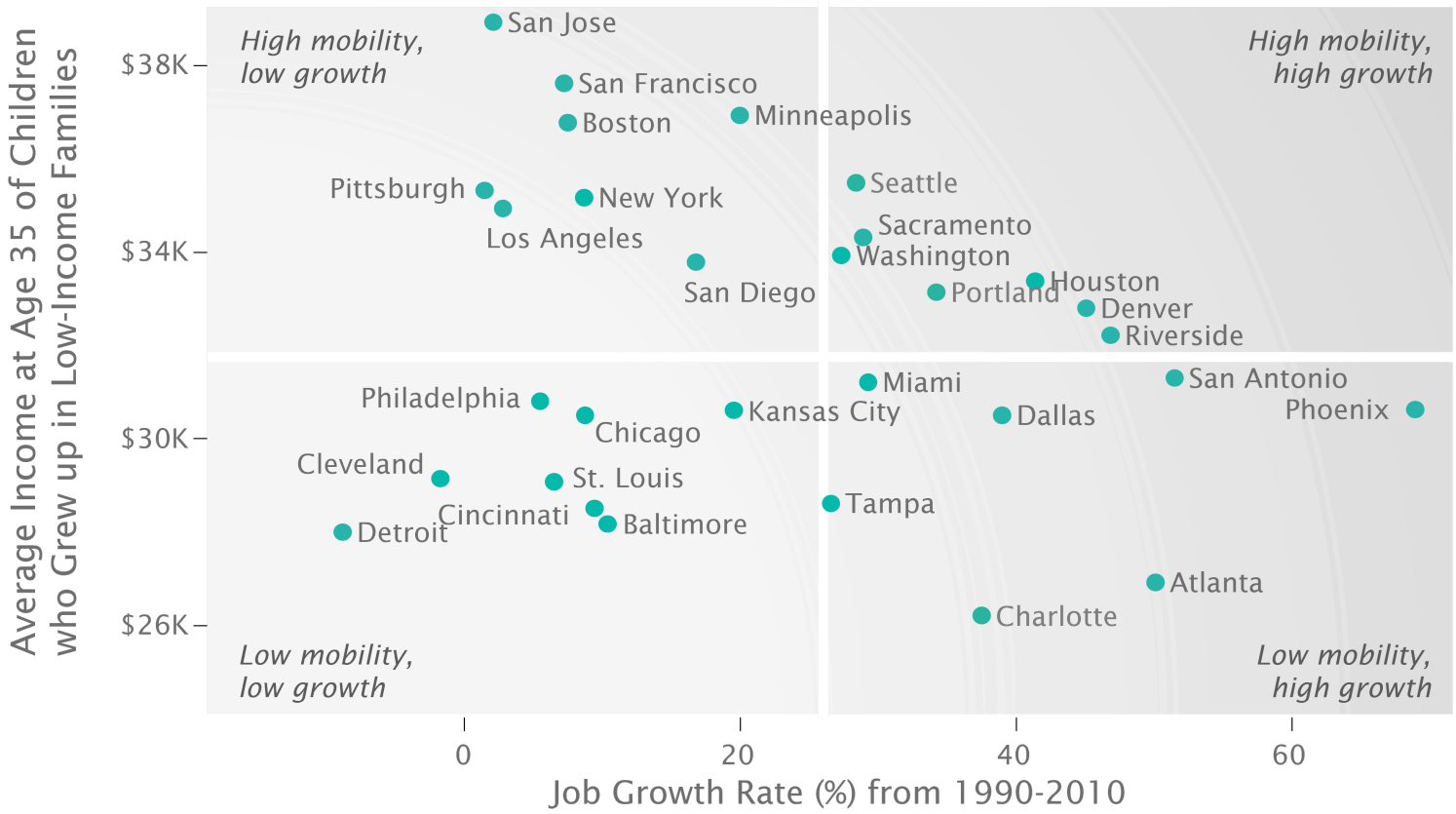
Characteristics of High-Mobility Areas

Why does upward mobility differ?

Armed with a summary measure of upward mobility, we can ask:

- Why do some areas have more upward mobility than others?
- Spatial and correlational analysis is a good place to start
- What are potential characteristics of high mobility areas?
    - Better jobs?
    - Better schools?
    - Institutional differences?
    - Culture?

Upward Mobility vs. Job Growth



How to calculate a correlation

- Quick review: what is a correlation?
- Mathematically:

$$\text{Correlation} = \frac{\text{Cov}(X, Y)}{\text{SD}(X)\text{SD}(Y)}$$

- Intuitively, what is it?

How to calculate a correlation

- Quick review: what is a correlation?
- Mathematically:

$$\text{Correlation} = \frac{\text{Cov}(X, Y)}{\text{SD}(X)\text{SD}(Y)}$$

- Intuitively, what is it?
- It is a measure of how two variables move together normalized to be between -1 and 1
- What are some ways to calculation a correlation in R?

```
corr ← cor(outcomes$kfr_p25, outcomes$kfr_p75)
print(paste("This correlation between 25th and 75th percentile mobility is:", corr))
```

```
## [1] "This correlation between 25th and 75th percentile mobility is: -0.684480995406698"
```

Correlations using regression

- One handy way to calculate a correlation is to use regression, exploiting the formula for the coefficient

In a regression, the coefficient on X:

$$\beta = \frac{\text{Cov}(X, Y)}{\text{Var}(X)}$$

$$\text{Cov}(X, Y) = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})$$

$$\text{Var}(X) = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2$$

- Subtract means and divide by the standard deviation, or "z-score," we'll calculate the correlation with a regression coefficient

- Why do this?

    - It is easy to interpret a coefficient
    - It is easy to get a confidence interval
    - It is easy to control for other variables
    - Great way to normalize wildly different variables

Let's test it out

```
# library(fixest); library(broom) # already loaded
# Finish this code!
# I renamed kfr_pooled_pooled_p25 to kfr_p25 and kfr_pooled_pooled_p75 to kfr_p75
outcomes ← mutate(outcomes,
  kfr_p25_demean=,
  kfr_p75_demean=)

results ← feols(kfr_p75_demean ~ kfr_p25_demean, data=outcomes)
#diff ← round(results$coefficients[['kfr_p25_demean']] - corr,16)
diff ← NA
etable(results) %>% # table it
  kable() %>% # make it prettier
  print() # print it
print(paste("Correlation function and z-scored regression approach are within",diff,"of each other"))
```

Correlation vs. Regression

```
##
##
## |                |results            |
## |:---------------|:------------------|
## |Dependent Var.: |kfr_p75_demean     |
## |                |                   |
## |Constant        |3.08e-14 (0.1953)  |
## |kfr_p25_demean  |-0.6845** (0.2022) |
## |________________ |_________________ |
## |S.E. type       |IID                |
## |Observations    |15                 |
## |R2              |0.46851            |
## |Adj. R2         |0.42763            |

## [1] "Correlation function and z-scored regression approach are within 1e-16 of each other"
```

Actual correlates

1. Segregation: Greater racial and income segregation associated with lower levels of mobility
2. Income Inequality: Places with smaller middle class have 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 lower mobility
    - Strong correlation even for kids whose *own* parents are married
    - This result is a puzzling one and the focus of much recent and (somewhat controversially) reported on research
5. Social Capital
    - It takes a village to raise a child
    - Chetty et al. (2023) leveraged Facebook Data to create the Social Capital Atlas

Why do we care about correlation?

- We all know correlation is not causation
- We'll discuss this in-depth after break if you don't believe me
- So why are we talking about correlation at all?
- One of the first steps in understanding a complex system is to understand how variables are related
- This is especially true when we have a lot of data
- Plus, almost ever causal relationship is just a correlation with a story
    - Story might be: I ran an experiment and found a correlation with a randomly assigned treatment
    - But the story might be: I assume some natural variation in the data is like a random assignment and I found a correlation

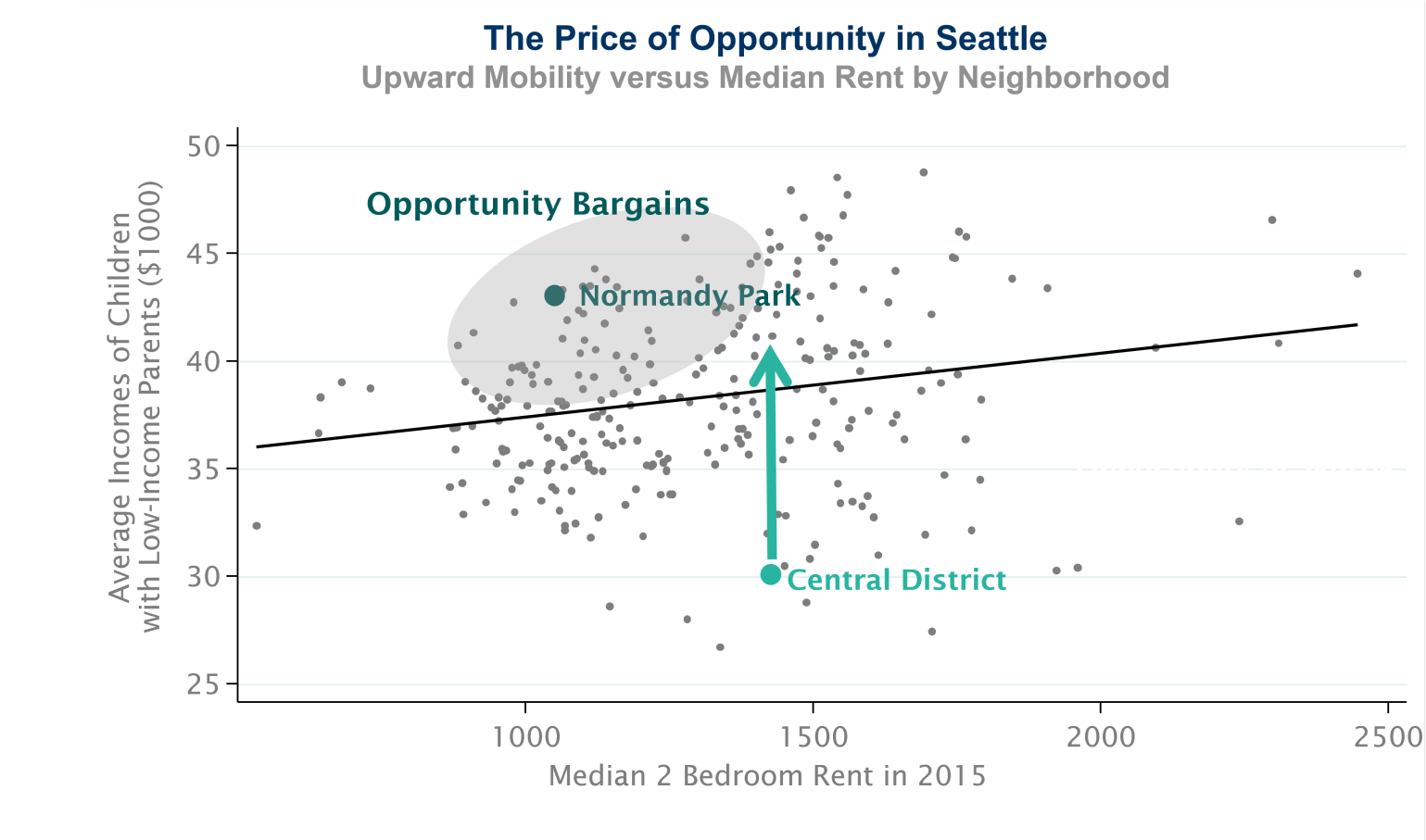
Spatial Correlation and Decay

Big question: why don't people move?

- If some areas have more mobility than others, why don't people move to those areas?
- Is it rent?

The Price of Opportunity in Seattle

Upward Mobility vs Median Rent by Neighborhood



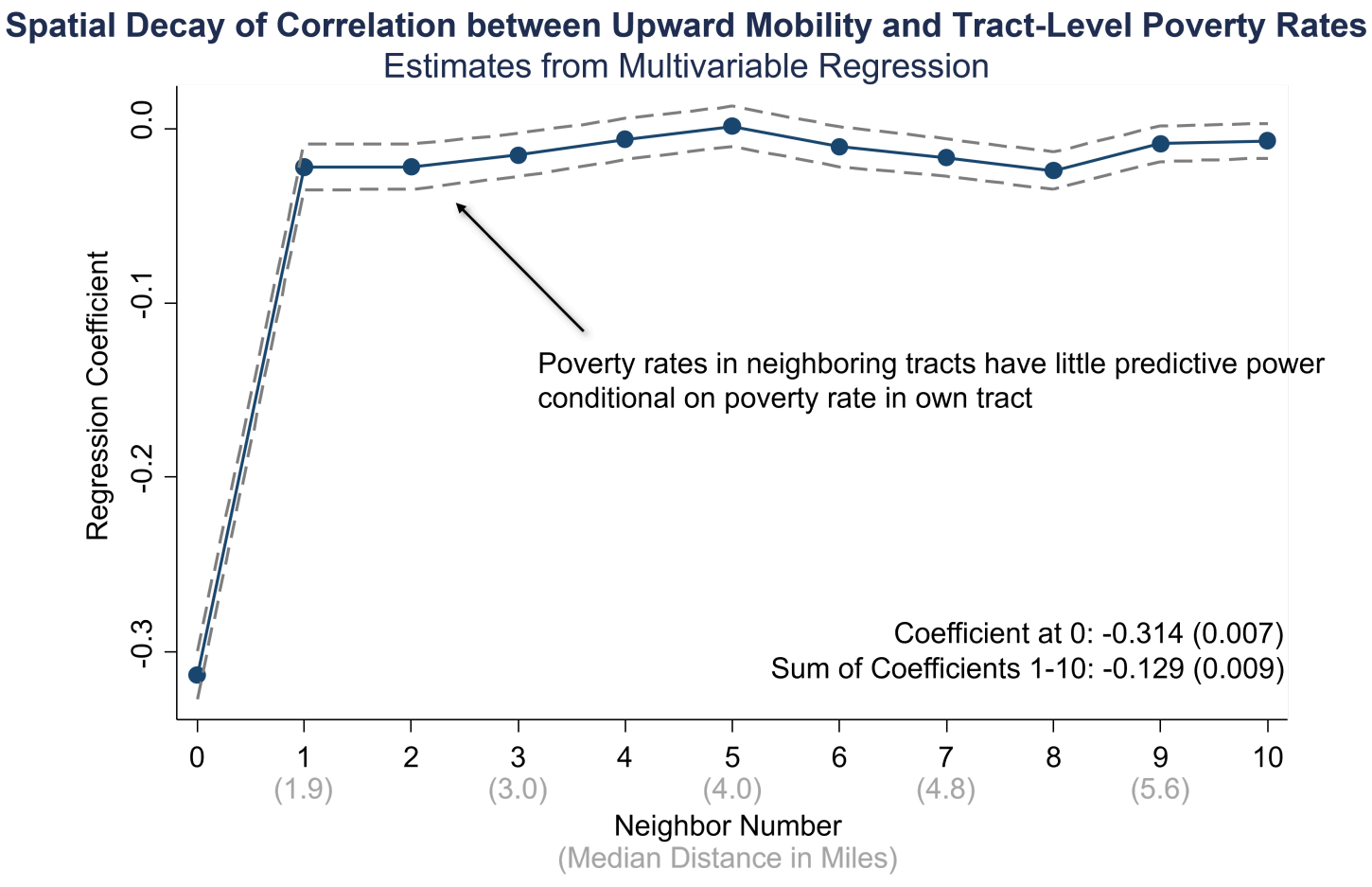
Big question: why don't people move?

- Initial experiments indicate benefits exist from moving (we'll see later)
- If some areas have more mobility than others, why don't people move to those areas?
- Is it rent?
- Other costs of moving?
- Maybe they do not want to move as far?
- Overall, this is not a highly effective approach

Well what if we invest locally?

- What if we invest in the areas that have low mobility? (place-based approach)
- Would there be spillovers between locations?
  - It is tough to improve one neighborhood (e.g. a tract), let alone many at once
  - Do we have to improve them all at once to help people?
- The answer to this question changes the policy approach

Spatial decay suggests localized effects



Overall Takeaways

- Correlation evidence is suggestive, but not causal
- Causality requires a more focused approach
- We will build this toolkit in the next few lectures

Next lecture: Spatial Analysis and Opportunity Atlas