Improving Equality of Opportunity
New Insights from Big Data

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The American Dream?

Chance that a child born to parents in the bottom fifth of the income distribution reaches the top fifth:
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- **USA**: 7.5% (Chetty, Hendren, Kline, Saez 2014)
- **UK**: 9.0% (Blanden and Machin 2008)
- **Denmark**: 11.7% (Boserup, Kopczuk, and Kreiner 2013)
- **Canada**: 13.5% (Corak and Heisz 1999)
The American Dream?

Chance that a child born to parents in the bottom fifth of the income distribution reaches the top fifth:

<table>
<thead>
<tr>
<th>Country</th>
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<th>Probability</th>
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Chances of achieving the “American Dream” are almost **two times higher in Canada** than in the U.S.
The Fading American Dream
Percent of Children Earning More than Their Parents, by Year of Birth

Source: Chetty, Grusky, Hell, Hendren, Manduca, Narang 2017
How Can We Increase Upward Mobility?

- Empirical evidence on the determinants of economic mobility across generations has been limited because of a lack of longitudinal data.
  - Most empirical work on inequality has used cross-sectional data to study poverty or income differences within a single generation.
- This talk presents an overview of recent research on economic mobility using longitudinal administrative data (based on work with John Friedman, Nathan Hendren, and many others).
  - Trace the roots of outcomes such as poverty and incarceration back to the environment in which people grew up.
- Focus here on variation across neighborhoods as a lens to understand determinants of opportunity.
1. Data and Methods
2. The Geography of Opportunity
3. Causal Effects of Neighborhoods
1. Data and Methods

2. The Geography of Opportunity

3. Causal Effects of Neighborhoods
Data Sources and Sample Definitions


- 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
Income Definitions

- Parents’ pre-tax household incomes: mean Adjusted Gross Income from 1994-2000, assigning non-filers zeros

- Children’s pre-tax incomes measured in 2014-15 (ages 31-37)

- To mitigate lifecycle bias, focus on percentile ranks in national distribution:
  - Rank children relative to others in their birth cohort and parents relative to other parents
Intergenerational Mobility in the United States

Mean Child Household Income Rank vs. Parent Household Income Rank

Predicted Value Given Parents at 25th Percentile = 41st Percentile = $31,900

Source: Chetty, Friedman, Hendren, Jones, Porter (2018)
1. Data and Methods
2. The Geography of Opportunity
3. Causal Effects of Neighborhoods
The Geography of Opportunity and Policy Targeting

- Begin with a descriptive characterization of the geography of opportunity: how rates of upward income mobility vary across areas.

- Why is this descriptive analysis useful?
  - Many policies target areas based on characteristics such as the poverty rates.
  - Tax policies (e.g., Opportunity zones), local services (e.g., pre-school programs), …

- For such “tagging” applications, observed outcomes are of direct interest in standard optimal tax models [Akerlof 1978]
  - Isolating causal effects of neighborhoods not necessarily relevant.
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: Chetty, Friedman, Hendren, Jones, Porter 2019
Two Americas: The Geography of Upward Mobility for Black vs. White Men

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

Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: Chetty, Hendren, Jones, Porter 2018
The Geography of Upward Mobility for Black vs. White Women
Average Household Income for Women with Parents Earning $27,000 (25th percentile)

Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: Chetty, Hendren, Jones, Porter 2018
Income Mobility for Black vs. White Men Raised in High-Income Families

Follow the lives of these 19,940 Americans and see where they end up as adults:

- **Black men**
  - Grew up rich: 852 (26%)
  - Upper-middle-class adult: 705 (22%)
  - Middle-class adult: 646 (20%)
  - Lower-middle-class adult: 541 (17%)
  - Poor adult: 554 (17%)

- **White men**
  - Grew up rich: 1,411 (43%)
  - Upper-middle-class adult: 741 (23%)
  - Middle-class adult: 488 (15%)
  - Lower-middle-class adult: 298 (9%)
  - Poor adult: 254 (8%)

Source: Chetty, Hendren, Jones, Porter 2018; New York Times 2018
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: Chetty, Friedman, Hendren, Jones, Porter 2019
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile

Number of Jobs Within 5 Miles
High-Paying Jobs Within 5 Miles
Job Growth 2004-2013

Magnitude of Race-Controlled Signal Correlation

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

Average Income at Age 35 of Children who Grew up in Low-Income Families

Job Growth Rate (%) from 1990-2010

High mobility, low growth

Low mobility, low growth

High mobility, high growth

Low mobility, high growth
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile

Number of Jobs Within 5 Miles
High-Paying Jobs Within 5 Miles
Job Growth 2004-2013
2000 Employment Rate

Positive  
Negative

Magnitude of Race-Controlled Signal Correlation

0 0.2 0.4 0.6 0.8
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile

Number of Jobs Within 5 Miles
High-Paying Jobs Within 5 Miles
Job Growth 2004-2013
2000 Employment Rate
Share Above Poverty Line
Mean Household Income
Mean 3rd Grade Math Score
Share College Grad.

- Positive
- Negative

Magnitude of Race-Controlled Signal Correlation
Spatial Decay of Correlation with Tract-Level Poverty Rate
Mean Child Household Income Rank (Parents $p=25$), White Children

Coefficient at 0: -0.314 (0.007)
Sum of Coefficients 1-10: -0.129 (0.009)
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)
Spatial Decay of Correlation with Block-Level Poverty Rate
Mean Child Household Income Rank (Parents p=25), White Children

Coefficient at 0: -0.057 (0.001)
Sum of Coefficients 1-40: -0.224 (0.014)
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25\textsuperscript{th} Percentile

- Number of Jobs Within 5 Miles
- High-Paying Jobs Within 5 Miles
- Job Growth 2004-2013
- 2000 Employment Rate
- Share Above Poverty Line
- Mean Household Income
- Mean 3rd Grade Math Score
- Share College Grad.
- Share Single Parent Households
- Census Return Rate (“Social Capital”)

Correlation Magnitude:
- Positive
- Negative

Magnitude of Race-Controlled Signal Correlation

Census Return Rate ("Social Capital")
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile

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- Share Single Parent Households
- Census Return Rate ("Social Capital")
- Share Black
- Share Hispanic

Positive
Negative

Magnitude of Race-Controlled Signal Correlation

0 0.2 0.4 0.6 0.8
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 25th Percentile

Number of Jobs Within 5 Miles
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Job Growth 2004-2013
2000 Employment Rate
Share Above Poverty Line
Mean Household Income
Mean 3rd Grade Math Score
Share College Grad.
Share Single Parent Households
Census Return Rate ("Social Capital")

Share Black
Share Hispanic

R-Squared of All Covars. = 0.504

Positive
Negative
Do Cities Offer Greater Opportunities for Upward Mobility?
Average Income for White Children with Parents Earning $25,000 in North Carolina

- Charlotte
- Winston-Salem
- Raleigh
- Durham

Income Levels:
- $63k
- $36k
- $20k
Do Cities Offer Greater Opportunities for Upward Mobility?
Average Income for White Children with Parents Earning $25,000 in Iowa

- $20k: < 29.5
- $36k: 44.6
- $63k: > 64.3
Hypothetical Opportunity Zones using Upward Mobility Estimates

- < 31.4 ($22k)
- 43.7 (35k)
- > 59.4 ($55k)
1. Data and Methods

2. The Geography of Opportunity

3. Causal Effects of Neighborhoods
Neighborhood Choice and Causal Effects of Place

- Where should a family seeking to improve their children’s outcomes live?

- Answer matters both to individual families and potentially for policy design
  - Ex: Many affordable housing programs (e.g., Housing Choice Vouchers) have explicit goal of helping low-income families access “higher opportunity” areas

- For these questions, critical to understand whether observational variation is driven by causal effects of place or selection
Identifying Causal Effects of Place

- Identify causal effects using two research designs:

  1. **Moving-to-Opportunity (MTO) Experiment**: Compare observational predictions to treatment effects of MTO experiment on children's earnings [Chetty, Hendren, Katz 2016]

  2. **Movers Quasi-Experiment**: Analyze outcomes of children who move at different ages across all tracts [Chetty and Hendren 2018]
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago

- Ida B. Wells Homes
- Stateway Gardens
- Robert Taylor Homes

- ● = Control
- △ = Section 8
- ◆ = Experimental
Earnings of Young Children in MTO Experiment vs. Observational Predictions from Opportunity Atlas

- Black circle = Control
- Orange triangle = Section 8
- Blue diamond = Experimental

Mean Indiv. Earnings in MTO (with site FE)

Mean Indiv. Earnings for Children with Parents at p=10 in Opportunity Atlas (with site FE)

Chetty, Hendren, and Katz (2016, Online Appendix Table 7, Panel B)
Earnings of Young Children in MTO Experiment vs. Observational Predictions from Opportunity Atlas

- Correlation = 0.60
- Slope = 0.71

Chetty, Hendren, and Katz (2016, Online Appendix Table 7, Panel B)
Quasi-Experimental Estimates

- MTO experiment shows that observational estimates predict causal effects of moving in a small set of neighborhoods

- Now extend this approach to all areas using a quasi-experimental design in observational data
To begin, consider families who move across Census tracts when child is exactly 5 years old

- Regress child’s income rank in adulthood $y_i$ on mean rank of children with same parental income level in destination tract:

$$y_i = \alpha_{qo} + b_m \bar{y}_{pd} + \eta_i$$

- Include parent decile ($q$) by origin ($o$) fixed effects to identify $b_m$ purely from differences in destinations

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**Estimating Exposure Effects in Observational Data**
Movers’ Income Ranks vs. Mean Ranks of Children in Destination
For Children Who Move at Age 5

Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.
Coefficient on Observational Outcome in Destination

Childhood Exposure Effects on Household Income Rank at Age 24

Age of Child When Parents Move
Childhood Exposure Effects on Household Income Rank at Age 24

Coefficient on Observational Outcome in Destination

 Selection Effect

Age of Child When Parents Move
Childhood Exposure Effects on Household Income Rank at Age 24

Ident. Assumption: Selection effect constant across ages
→ Shape before age 23 reflects causal effects of exposure

Selection Effect
δ = 0.346

Slope (Age>23): -0.008 (0.005)
Childhood Exposure Effects on Household Income Rank at Age 24

Coefﬁcient on Observational Outcome in Destination

Age of Child When Parents Move

Slope (Age<=23): -0.025 (0.002)

Slope (Age>23): -0.008 (0.005)

Selection Effect δ = 0.346

Ident. Assumption: Selection effect constant across ages
→ Shape before age 23 reﬂects causal effects of exposure
Identifying Causal Exposure Effects

- Use two approaches to evaluate validity of key assumption, following Chetty and Hendren (2018):
  1. Sibling comparisons to control for family fixed effects
  2. Outcome-based placebo tests exploiting heterogeneity in place effects by gender, quantile, and outcome
    - Ex: moving to a place where boys have high earnings → son improves in proportion to exposure but daughter does not
## Gender-Specific Childhood Exposure Effects on Household Income Rank

**Regression Estimates Based on One-Time Movers Across Tracts**

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Child Household Income Rank at Age 24</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Males</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Prediction for Males</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Prediction for Females</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Num. of Obs.</td>
<td>1,146,000</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses
Childhood Exposure Effects Around the World

**United States**

- **Source:** Chetty, Friedman, Hendren, Jones, Porter (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)
Improving Childhood Environments

- Moving at birth from tract at 25th percentile of distribution of upward mobility to a tract at 75th percentile within county → $206,000 gain in lifetime earnings

- Two paths to improving neighborhoods in which children in low-income families grow up:
  1. Reduce segregation by helping families move to higher opportunity areas
  2. Place-based investments to improve outcomes in low-opportunity areas
Feasibility of moving to opportunity approach relies on being able to find affordable housing in high-opportunity neighborhoods.

How does the housing market price the amenity of better outcomes for children?
The Price of Opportunity in Chicago
Children’s Mean Income Ranks in Adulthood vs. Median Rents in Chicago, by Tract

Correlation = 0.50
Opportunity Bargain Neighborhoods in Chicago

- Evergreen
- Alsip
- Marionette
- Ida B. Wells Homes
- Stateway Gardens
- Robert Taylor Homes

Legend:
- Black dot = Control
- Triangle = Section 8
- Diamond = Experimental
- Circle = Opp. Bargains
Predicted Impacts of Moving to Opportunity Bargain Neighborhoods in Chicago

Mean Indiv. Earnings in MTO (with site FE)

- **Black Dot** = Control
- **Orange Triangle** = Section 8
- **Brown Diamond** = Experimental: Poverty Rate-Based Targeting
- **Orange Circle** = Opp. Bargain: Outcome-Based Targeting

Mean Indiv. Earnings for Children with Parents at p=10 in Opportunity Atlas (with site FE)
Randomized trial to help families with vouchers move to “opportunity bargain” areas using three approaches:

- Information + financial assistance
- Landlord recruitment
- Brokerage services
Moving to opportunity can be helpful in reducing segregation, but ultimately is not a fully scalable approach.

In parallel, important to invest in low-opportunity places.

- Many place-based efforts focus on the labor market (e.g., tax credits for employers).
- Our results call for a place-based focus on human-capital development instead.

We do not yet know which place-based investments (schools, mentoring programs, crime reduction, physical infrastructure) are most effective.

- Currently studying impacts of historical place-based policies on prior residents using longitudinal data.
Equality of Opportunity and Economic Growth

- Traditional interest in equality of opportunity is based on principles of justice
- But improving opportunities for upward mobility can also increase economic growth
- To illustrate, focus on innovation
  - Study the lives of 750,000 patent holders in the U.S. by linking universe of patent applications to tax data [Bell, Chetty, Jaravel, Petkova, van Reenen 2018]
Patent Rates vs. Parent Income Percentile

Patent rate for children with parents in top 1%:
8.3 per 1,000

Patent rate for children with parents below median:
0.85 per 1,000
Patent Rates vs. 3rd Grade Math Test Scores

No. of Inventors per Thousand Children

3rd Grade Math Test Score (Standard Deviations Relative to Mean)
Patent Rates vs. 3rd Grade Math Test Scores for Children with Low vs. High Income Parents

No. of Inventors per Thousand Children

3rd Grade Math Test Score (Standard Deviations Relative to Mean)

- Par. Inc. Below 80th Percentile
- Par. Inc. Above 80th Percentile
High-ability children much more likely to become inventors if they are from high-income families.
The Origins of Inventors in America
Patent Rates per 1000 Children by Area where Child Grew Up

San Francisco 3.8
San Jose 5.4

Minneapolis 4.9
Madison 4.3
Detroit 3.8

Inventors per 1000 Children

- >3.1
- 1.5
- <0.4
- Insufficient Data
Lost Einsteins

If women, minorities, and children from low-income families invent at the same rate as high-income white men, the number of inventors in America would quadruple.
Supporting Future Work on Equality of Opportunity

1. Publicly available data: Local area statistics discussed here are all publicly available and can be used to study a variety of questions
Supporting Future Work on Equality of Opportunity

1. Publicly available data: Local area statistics discussed here are all publicly available and can be used to study a variety of questions

2. Global network: Supporting other researchers who are constructing and analyzing analogous statistics in other countries
The Geography of Intergenerational Mobility in India

Source: Asher and Novosad (2018)
Note: Figure shows mean educational rank attained by sons born to fathers born in bottom half of education distribution
Supporting Future Work on Equality of Opportunity

1. Publicly available data: Local area statistics discussed here are all publicly available and can be used to study a variety of questions.

2. Global network: Supporting other researchers who are constructing and analyzing analogous statistics in other countries.

3. Training the next generation of researchers and policy makers.
Online Course: Using Big Data to Solve Economic and Social Problems

www.opportunityinsights.org/course