The Opportunity Atlas
Mapping the Childhood Roots of Social Mobility

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Disclaimer: Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The statistical summaries reported in these slides have been cleared by the Census Bureau's Disclosure Review Board release authorization number CBDRB-FY18-319. All values in the tables and figures that appear in this presentation have been rounded to four significant digits as part of the disclosure avoidance protocol. Unless otherwise noted, source for all tables and figures: authors calculations based on Census 2000 and 2010, tax returns, and American Community Surveys 2005-2015.
Growing body of evidence shows that where children grow up has substantial causal effects on their prospects for upward income mobility


Natural question: which neighborhoods offer the best opportunities for children?

- Previous work either focuses on a small set of neighborhoods (e.g., Moving to Opportunity experiment) or broad geographies
We construct publicly available estimates of children’s earnings in adulthood (and other long-term outcomes) by Census tract and subgroup, for the entire U.S.

- Granular definition of neighborhoods: 70,000 Census tracts; 4,200 people per tract

Key difference from prior work on geographic variation: identify roots of outcomes such as poverty and incarceration by tracing them back to where children grew up

- Large literature on place-based policies and local labor markets has documented importance of place for production [e.g., Moretti 2011, Glaeser 2011, Moretti 2013, Kline & Moretti 2014]

- Here we focus on the role of place in the development of human capital and show that patterns differ in important ways
1. Data
2. Methods to Construct Tract-Level Estimates
3. Observational Variation and Targeting
4. Causal Effects and Neighborhood Choice
1 Data

2 Methods to Construct Tract-Level Estimates

3 Observational Variation and Targeting

4 Causal Effects and Neighborhood Choice
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
Variable 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)
  - Non-filers assigned incomes based on W-2’s (available since 2005)

- To mitigate lifecycle bias, focus on percentile ranks: rank children relative to others in their birth cohort and parents relative to other parents

- Also examine other outcomes: marriage, teenage birth, incarceration, …
1. Data

2. Methods to Construct Tract-Level Estimates

3. Observational Variation and Targeting

4. Causal Effects and Neighborhood Choice
Empirical Objectives

- Goal: estimate children’s expected outcomes given their parent’s income percentile $p$, race $r$, and gender $g$, conditional on growing up from birth in tract $c$:

$$\bar{y}_{cprg} = E[y_i | c(i) = c, p(i) = p, r(i) = r, g(i) = g]$$

- Focus on tracts where kids grow up given evidence that childhood location is what matters for outcomes in adulthood [Chetty, Hendren, Katz 2016; Chetty and Hendren 2018]

- Two challenges:
  1. Not enough data to estimate $y_{cprg}$ non-parametrically in every cell
  2. Relatively few kids stay in a single tract for their entire childhood
Estimating Mean Outcomes by Tract

- In each tract $c$, for each race $r$ and gender $g$, regress children’s outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \varepsilon_{icprg}$$

- Function $f_{rg}$ estimated non-parametrically in national data, by race and gender
Mean Child Household Income Rank vs. Parent Household Income Rank

Children’s Mean Household Income Rank (Ages 31-37) vs. Parent Household Income Rank

($22K) ($43K) ($69K) ($105K) ($1.5M)
Incarceration Rates vs. Parent Household Income Rank
Black Men

Pct. of Men Incarcerated on April 1, 2010 (Ages 27-32)

Parent Household Income Rank

($22K) ($43K) ($69K) ($105K) ($1.5M)
Estimating Mean Outcomes by Tract

- In each tract $c$, for each race $r$ and gender $g$, regress children’s outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \epsilon_{icprg}$$

- Function $f_{rg}$ estimated non-parametrically in national data, by race and gender

  - Key assumption: shape of conditional expectation of outcome given parental income at national level is preserved in each tract, up to an affine transformation

  - We validate this assumption by testing effects of including higher-order terms and using non-parametric estimates at broader geographies
In each tract $c$, for each race $r$ and gender $g$, regress children’s outcomes on a smooth function of parent rank:

$$y_{icprg} = \alpha_{crg} + \beta_{crg} \times f_{rg}(p_{icrg}) + \epsilon_{icprg}$$

Function $f_{rg}$ estimated non-parametrically in national data, by race and gender

Finally, account for the fact that many children move across tracts in childhood

- Weight children in each tract-level regression by fraction of childhood (up to age 23) spent in that tract
Focus on predicted values at selected parental income percentiles, especially \( p=25 \) (low income)

- Extrapolate to all percentiles even in areas with predominantly low- or high-income populations

- Mask cells with fewer than 20 children in the relevant subgroup

- To limit disclosure risk, add noise to tract-level estimates; SD of noise added is typically an order of magnitude smaller than standard error

Translate mean rank outcomes to dollar values based on income distribution of children in their mid-30s (in 2015) for ease of interpretation
1. Data

2. Methods to Construct Tract-Level Estimates

3. Observational Variation and Targeting

4. Causal Effects and Neighborhood Choice
Observational Variation and Targeting

- Many policies target areas based on characteristics such as the poverty rate
  - E.g. tax policies (Empowerment zones, Opportunity zones) and local services (Head Start, mentoring programs)

- For such “tagging” applications, observed outcomes are of direct interest in standard optimal tax models [Akerlof 1978, Nichols and Zeckhauser 1982]
  - Isolating causal effects of neighborhoods not necessarily relevant

- Motivated by these applications, begin with a descriptive characterization of how children’s outcomes vary across tracts
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
Mean Household Income for Children in Los Angeles with Parents Earning $27,000 (25th percentile)
Mean Household Income for Children in Los Angeles with Parents Earning $27,000 (25th percentile)

WATTS:
Mean Household Income = $23,800 ($3,600)
Mean Household Income for Black Men in Los Angeles with Parents Earning $27,000 (25th percentile)

WATTS, Black Men:
Mean Household Income = $7,286 ($2,576)
Mean Household Income for Black Men in Los Angeles with Parents Earning $27,000 (25th percentile)

- WATTS, Black Men: Mean Household Income = $7,286 ($2,576)
- COMPTON, Black Men: Mean Household Income = $19,141 ($2,149)
Mean Individual Income for **Black Women** in Los Angeles with Parents Earning $27,000 (25th percentile)

**WATTS, Black Women**: Mean Household Income = $19,489 ($1,985)

**COMPTON, Black Women**: Mean Household Income = $21,509 ($1,850)
Incarceration Rates for **Black Men** in Los Angeles with Parents Earning < $2,200 (1st percentile)

**WATTS, Black Men**
Share Incarcerated on April 1, 2010
= 44.1% (9.3%)
Incarceration Rates for **Black Men** in Los Angeles with Parents Earning < $2,200 (1\textsuperscript{st} percentile)

**WATTS, Black Men**: Share Incarcerated on April 1, 2010
- Share Incarcerated on April 1, 2010 = 44.1% (9.3%)

**COMPTON, Black Men**: Share Incarcerated on April 1, 2010
- Share Incarcerated on April 1, 2010 = 6.2% (5.0%)
Incarceration Rates for **Hispanic Men** in Los Angeles with Parents Earning < $2,200 (1st percentile)

**WATTS, Hispanic Men:**
Share Incarcerated on April 1, 2010 = 4.5% (2.8%)

**COMPTON, Hispanic Men:**
Share Incarcerated on April 1, 2010 = 1.4% (0.8%)
Example illustrates three general results on targeting:

1. Children’s outcomes vary widely across nearby tracts → neighborhood where children grow up is a useful tag for policy interventions
Share of Signal Variance of Tract-Level Mean Child Income Rank (Parent p = 25) Explained at Different Levels of Geography

Percentage of Signal Variance

Tract
County
CZ

All Races  White  Black  Hispanic
Share of Signal Variance of Tract-Level Mean Child Income Rank (Parent p = 25) Explained at Different Levels of Geography

- Tract
- High School Catchment Area
- County
- CZ

Percentage of Signal Variance

All Races

White

Black

Hispanic
Share of Signal Variance of Tract-Level Mean Child Income Rank (Parent p = 25) Explained at Different Levels of Geography
Example illustrates three general results on targeting:

1. Children’s outcomes vary widely across nearby tracts → location where children grow up is a useful tag for policy interventions.

2. Substantial heterogeneity within areas across subgroups/outcomes cond. on parent income → neighborhoods not well described by a single-factor model.
### Correlations Between Outcomes Across Census Tracts within CZs
Children with Parents at 25th Percentile, Race-Adjusted

<table>
<thead>
<tr>
<th></th>
<th>Household Income Rank</th>
<th>Individual Income Rank</th>
<th>Employment Rate</th>
<th>Incarceration Rate</th>
<th>Teenage Birth Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Income Rank</td>
<td>1</td>
<td>0.963</td>
<td>0.444</td>
<td>-0.755</td>
<td>-0.872</td>
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<tr>
<td>Individual Income Rank</td>
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<td>0.570</td>
<td>-0.756</td>
<td>-0.841</td>
<td></td>
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<tr>
<td>Employment Rate</td>
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<td></td>
<td>-0.367</td>
<td></td>
<td>-0.314</td>
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<tr>
<td>Incarceration Rate</td>
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<td></td>
<td></td>
<td>1</td>
<td>0.820</td>
</tr>
<tr>
<td>Teenage Birth Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Note: Correlations estimated by splitting families into two random samples, estimating correlations across the two samples, and adjusting for sampling error.
Upward Mobility vs. Teenage Birth Rates Across Tracts
White Women with Parents at 25th Percentile of Income Distribution

SD(Indiv Income Rank | Teen Birth Rate in Top Decile: 3.55)
SD(Indiv Income Rank | Teen Birth Rate in Bottom Decile: 7.64)
## Correlation of Mean Income Ranks by Tract Across Racial Groups within CZs
Children with Parents at 25th Percentile

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
<th>Asian</th>
<th>American Indian &amp; Alaska Natives</th>
<th>Parents at 75th Pctile, Same Race</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>1</td>
<td>0.573</td>
<td>0.580</td>
<td>0.523</td>
<td>0.636</td>
<td>0.604</td>
</tr>
<tr>
<td>Black</td>
<td>1</td>
<td>0.546</td>
<td>0.357</td>
<td>0.436</td>
<td>0.454</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>1</td>
<td>0.374</td>
<td>0.602</td>
<td></td>
<td>0.353</td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>1</td>
<td></td>
<td>0.267</td>
<td></td>
<td>0.465</td>
<td></td>
</tr>
<tr>
<td>American Indian &amp; Alaska Natives</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>0.357</td>
<td></td>
</tr>
</tbody>
</table>

Note: Signal correlations adjusted for sampling error in the outcome variables
Targeting Place-Based Policies

- Example illustrates three general results on targeting:
  1. Children’s outcomes vary widely across nearby tracts \(\rightarrow\) location where children grow up is a useful tag for policy interventions
  2. Substantial heterogeneity *within* areas across subgroups and outcomes conditional on parent income \(\rightarrow\) neighborhoods not well described by a single-factor model
  3. Outcome-based measures contain new information relative to traditional measures used to target policies, such as poverty rates or job 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

Magnitude of Race-Controlled Signal Correlation

Positive  Negative

0  0.2  0.4  0.6  0.8
Upward Mobility vs. Job Growth in the 50 Largest Commuting Zones

Correlation (across all CZs): -0.03
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.

Magnitude of Race-Controlled Signal Correlation

- Positive
- Negative
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)
**Spatial Decay of Correlation with Tract-Level Poverty Rate**

Mean Child Household Income Rank (Parents p=25), White Children

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

Coeficient 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 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.
- Share Single Parent Households
- Census Return Rate
- Share Black
- Share Hispanic
- Population Density

R-Squared of All Covars. = 0.504
Do Cities Offer Greater Opportunities for Upward Mobility?
Average Income for White Children with Parents Earning $25,000 in North Carolina

- Charlotte: < 29.5 ($20k)
- Winston-Salem: 29.5 - 44.6 ($20k - $36k)
- Raleigh: > 44.6 ($36k+)
- Durham: > 64.3 ($63k+)
Do Cities Offer Greater Opportunities for Upward Mobility?
Average Income for White Children with Parents Earning $25,000 in Iowa

- Less than $29.5 (less than $20k)
- $29.5 to $44.6 ($20k to $36k)
- Greater than $44.6 ($36k)

[Map showing income distribution across Iowa]
Using Location as a Tag for Policy

- Tract-level estimates of children’s appear to provide new information that could be helpful in identifying areas where opportunity is most lacking.

- Practical challenge in using these estimates to inform policy: they come with a lag, since one must wait until children grow up to observe their earnings.

- Statistic of interest for policy is rate of social mobility for children today, which is inherently unobservable.

- Key conceptual question: are historical estimates useful predictors of opportunity for current cohorts?
Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

- Assess predictive value of historical estimates in two steps:

  1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power
Autocovariance of Tract-Level Estimates

Mean Household Income at Age 26 for Children with Parents at p=25
Autocovariance of Tract-Level Poverty Rates Using Publicly Available Census Data

Regression Coefficient (% of Coef. for Three-Year Lag) vs. Lag (Years)
Do Historical Estimates Provide Useful Guidance for Recent Cohorts?

- Assess predictive power of historical estimates in two steps:

1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power

2. Compare predictive power of historical outcomes to observable characteristics such as poverty rate and single parent share

   - When predicting upward mobility for 1989 cohort, incremental R-squared of covariates is 20% of the R-squared of upward mobility for 1979 cohort

   - Correlation of predicted values using models with vs. without neighborhood characteristics exceeds 0.85
Assess predictive power of historical estimates in two steps:

1. Examine serial correlation of outcomes across tracts within CZs to assess decay in predictive power

2. Compare predictive power of historical outcomes to observable characteristics such as poverty rate and single parent share
   - When predicting upward mobility for 1989 cohort, incremental R-squared of covariates is 20% of the R-squared of upward mobility for 1979 cohort
   - Correlation of predicted values using models with vs. without neighborhood characteristics exceeds 0.85

→ Tract-level estimates of outcomes provide informative (but imperfect) predictors of economic opportunity for children today
Hypothetical Opportunity Zones using Upward Mobility Estimates

<table>
<thead>
<tr>
<th>Opportunity Zone Tracts</th>
<th>CHILDREN’S MEAN H.H. INC. IN ADULTHOOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 59.4 ($55k)</td>
<td>35.4</td>
</tr>
<tr>
<td>43.7 (35k)</td>
<td>26,227</td>
</tr>
<tr>
<td>&lt; 31.4 ($22k)</td>
<td>43.7</td>
</tr>
<tr>
<td></td>
<td>34,973</td>
</tr>
</tbody>
</table>
Preferential Admission Tracts to Selective Chicago Public Schools

CHILDREN’S MEAN H.H. INC. IN ADULTHOOD

Inside Tier 1 Tracts = 32.1
$22,720

Outside Tier 1 Tracts = 37.3
$28,143

> 59.4 ($55k)
43.7 (35k)
< 19.5 ($9.9k)
Hypothetical Admission Tracts using Upward Mobility Estimates

CHILDREN’S MEAN H.H. INC. IN ADULTHOOD

Inside Tier 1 Tracts = 27.8
$18,286

Outside Tier 1 Tracts = 38.7
$29,624

< 19.5 ($9.9k)
43.7 (35k)
> 59.4 ($55k)
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
  
  2. **Movers Quasi-Experiment**: Analyze outcomes of children who move at different ages across all tracts
Moving to Opportunity Experiment

- 4,600 families at 5 sites from 1994-98: Baltimore, Boston, Chicago, LA, New York

- Families randomly assigned to one of three groups:
  1. Control: public housing in high-poverty (50% at baseline) areas
  2. Section 8: conventional housing vouchers, no restrictions
  3. Experimental: housing vouchers restricted to low-poverty (<10%) Census tracts

- Chetty, Hendren, and Katz (2016) show that children who moved using vouchers when young (<age 13) earn more; those who move at older ages do not
Moving To Opportunity Experiment: Origin and Destination Locations in Chicago

- Calumet Heights
- Cottage Grove Heights
- Riverdale
- Oakland
- Washington Park
- Grand Crossing

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

- **Control**
- **Section 8**
- **Experimental**

Chetty, Hendren, and Katz (2016, Online Appendix Table 7, Panel B)
Correlation = 0.60
Slope = 0.71

Earnings of Young Children in MTO Experiment vs. Observational Predictions from Opportunity Atlas

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, following Chetty and Hendren (2018)
  - Much larger sample size permits a more precise characterization of how neighborhoods affect outcomes
  - Briefly summarize key results here
To begin, consider families who move 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:

$$y_i = \alpha_{qo} + b_m \bar{y}_p a + \eta_i$$

Include parent decile ($q$) by origin ($o$) fixed effects to identify $b_m$ purely from differences in destinations
Movers’ Income Ranks vs. Mean Ranks of Children in Destination
For Children Who Move at Age 5

Slope: 0.815
(0.031)

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

Selection Effect
Childhood Exposure Effects on Household Income Rank at Age 24

Ident. Assumption: Selection effect constant across ages

$\delta = 0.346$

Shape before age 23 reflects causal effects of exposure

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

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

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

Selection Effect \( \delta = 0.346 \)
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
<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>No Age Interactions</th>
<th>Family FEs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Age &lt;= 23</td>
<td>-0.027</td>
<td>-0.026</td>
<td><strong>-0.021</strong></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Age &gt; 23</td>
<td>-0.008</td>
<td>-0.004</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Num. of Obs.</td>
<td>2,814,000</td>
<td>2,814,000</td>
<td>2,814,000</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses
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 $\rightarrow$ son improves in proportion to exposure but daughter does not
<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>-0.024</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>
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</tbody>
</table>

Note: Standard errors in parentheses.
# Childhood Exposure Effects on Other Outcomes

For **Male** Children of All Races

<table>
<thead>
<tr>
<th></th>
<th>Income Rank at 24</th>
<th>Married at 30</th>
<th>Incarceration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean Income Rank at 24</td>
<td>-0.024 (0.002)</td>
<td>-0.005 (0.006)</td>
<td>0.001 (0.002)</td>
</tr>
<tr>
<td>Frac. Married at 30</td>
<td>0.000 (0.001)</td>
<td>-0.022 (0.003)</td>
<td>0.000 (0.001)</td>
</tr>
<tr>
<td>Incarceration Rate</td>
<td>-0.001 (0.007)</td>
<td>-0.009 (0.016)</td>
<td>-0.032 (0.005)</td>
</tr>
<tr>
<td>Num. of Obs.</td>
<td>1,132,000</td>
<td>824,000</td>
<td>734,000</td>
</tr>
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</table>

Note: Standard errors in parentheses
## Childhood Exposure Effects on Other Outcomes

For **Female** Children of All Races

<table>
<thead>
<tr>
<th></th>
<th>Income Rank at 24</th>
<th>Married at 30</th>
<th>Teen Birth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Mean Income Rank at 24</strong></td>
<td>-0.032 (0.003)</td>
<td>0.002 (0.007)</td>
<td>-0.003 (0.003)</td>
</tr>
<tr>
<td><strong>Frac. Married at 30</strong></td>
<td>-0.003 (0.001)</td>
<td>-0.029 (0.002)</td>
<td>0.004 (0.001)</td>
</tr>
<tr>
<td><strong>Teen Birth</strong></td>
<td>-0.005 (0.002)</td>
<td>-0.010 (0.004)</td>
<td>-0.026 (0.002)</td>
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<td>1,068,000</td>
<td>776,000</td>
<td>1,347,000</td>
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</table>

Note: Standard errors in parentheses
### Childhood Exposure Effects on Household Income Rank at Age 24
Regression Estimates Based on One-Time Movers Across Tracts

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Good and Bad Moves</th>
<th>Large Moves</th>
<th>Observed Components of Opportunity</th>
<th>Unobserved Components of Opportunity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age &lt;= 23</td>
<td>-0.027</td>
<td></td>
<td>-0.046</td>
<td>-0.020</td>
<td>-0.025</td>
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<td>(0.017)</td>
<td>(0.001)</td>
<td>(0.003)</td>
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<td>Age &lt;= 23,</td>
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<td></td>
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<td></td>
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<td>Good Moves</td>
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<td></td>
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<tr>
<td></td>
<td>(0.002)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Age &lt;= 23,</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Bad Moves</td>
<td>-0.027</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td>Num. of Obs.</td>
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<td>22,500</td>
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<td>2,692,000</td>
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</tbody>
</table>

Note: Standard errors in parentheses
Predictive Power of Outcomes in Own Tract vs. Neighboring Tract

Average Childhood Exposure Effect

Neighbor Number (Median Distance in Miles)

Predictive Power of Poverty Rates in Actual Destination vs. Neighboring Tracts
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

Feasibility of such moves 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?
Children’s Mean Income Ranks in Adulthood vs. Median Rents in Chicago, by Tract

Children with Parents at 25th Percentile

Mean Child Household Income Rank Given Parents at 25th Percentile

Median Two-Bedroom Rent in 1990 (2015 $)

National Signal Corr (within CZ): 0.439
Residual Standard Deviation of Mean Ranks Across Tracts Within CZs
Controlling for Rent and Commute Time

<table>
<thead>
<tr>
<th>Description</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal SD within CZs</td>
<td>5.15</td>
</tr>
<tr>
<td>Controlling for Rent</td>
<td>4.63</td>
</tr>
<tr>
<td>Controlling for Rent + Commute</td>
<td>4.60</td>
</tr>
</tbody>
</table>
The Price of Opportunity

- What explains the existence of areas that offer good outcomes for children but have low rents in spatial equilibrium?
  - One explanation: these areas have other disamenities
  - Alternative explanation: lack of information or barriers such as discrimination
    [DeLuca et al 2016, Christensen and Timmins 2018]
Correlation Between Rents and Observable vs. Unobservable Component of Outcomes

For Children with Parents at 25th Percentile

Correlation Between Median Rent and Mean Ranks

Observable Component: 0.472

Unobservable Component: 0.031
Opportunity Bargains

- Potential scope to improve outcomes by helping low-income families with young children move to higher opportunity areas

- Could also benefit taxpayers
  - If a child were to grow up in an above-average tract instead of a below-average tract in terms of observed earnings, taxpayers would gain ~$41,000

- Illustrate how we can identify such areas by looking for “opportunity bargains” in Moving to Opportunity data
Predicted Impacts of Moving to “Opportunity Bargain” Areas in MTO Cities

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

- = Control
- = Section 8
- = Experimental: Poverty Rate-Based Targeting
- = Opp. Bargain: Outcome-Based Targeting

Creating Moves to Opportunity RCT

Mean Indiv. Earnings in MTO (with site FE)
Moving To Opportunity Experiment: Origin (Control Group) Locations in Chicago

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

Key:
- ● = Control
- ▲ = Section 8
- ◆ = Experimental
- ○ = Opp. Bargains
Predicted Impacts of Moving to “Opportunity Bargain” Areas in MTO Cities

- **Control**
- **Section 8**
- **Experimental: Poverty Rate-Based Targeting**
- **Opp. Bargain: Outcome-Based Targeting**

**Mean Indiv. Earnings in MTO (with site FE)**

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

- **Baltimore**
- **Boston**
- **Chicago**
- **LA**
- **NY**
Heterogeneity in the Price of Opportunity

- Price of opportunity itself is highly heterogeneous across metro areas and subgroups

- Policies such as land use regulation may play a role in determining this price in equilibrium...
Relationship Between Land Regulation and the Price of Opportunity

Correlation (Pop-Wt.) = 0.550 (0.053)

Note: figure excludes Statesboro and Colby for scaling purposes
Conclusions and Future Work

- Children’s outcomes vary sharply across neighborhoods, and we can now measure and potentially address these differences with greater precision.

- Two directions for future work that we hope will be facilitated by these publicly available data:
  1. Understanding the causal mechanisms that produce differences in neighborhood quality in spatial equilibrium.
  2. Supporting policy interventions to improve economic opportunity at a local level.
Supplementary Results
Reliability of Tract-Level Estimates

- Each tract typically contains about 300 children in the cohorts we examine.

- Some of the variation across tracts therefore reflects sampling error rather than signal.

- Assess relative importance of signal vs. noise by examining reliability of the estimates.

- As a benchmark to gauge significance of differences in maps that follow:

  - Average standard errors on mean ranks are typically 2 percentiles (~$2K) in pooled data and 3-4 percentiles in subgroups ($3K-$4K).

  - Average standard errors for incarceration rates are 3-4 pp.
Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates
For Children With Parents at 25th Percentile

Total SD = 6.51 ($7,024)
Noise SD = 1.97
Signal SD = 6.20
Reliability $\rho = \text{Sig. Var./Tot. Var.} = 90.8\%$
Standard Deviation and Reliability of Tract-Level Mean Income Rank Estimates
For Children With Parents at 25th Percentile

- All Races: ρ = 90.8%
- White: ρ = 78.0%
- Black: ρ = 69.0%
- Hispanic: ρ = 62.5%
Mean Child Household Income Rank vs. Parent Household Income Rank
By Race

Child Mean Household Income Rank vs. Parent Household Income Rank

By Race

- White
- Black
- Hispanic

Parent Household Income Rank

Child Mean Household Income Rank
School Catchment Zones in Mecklenburg County: Boundaries vs. Assignment of Tracts to Catchment Zones

- High School Catchment Boundary
- Tract Boundary
Correlations between Tract-Level Covariates and Household Income Rank
Race-Adjusted, Parent Income at 75th Percentile

R-Squared of All Covars. = 0.417

- 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
- Share Black
- Share Hispanic
- Population Density

Owing to race adjustments, the share single parent households and share Hispanic show a negative correlation with household income rank.
Upward Mobility for Whites vs. Job Growth in the 50 Largest Commuting Zones

Correlation (across all CZs): 0.02
Upward Mobility vs. Job Growth in the 30 Largest MSAs

Correlation (across all MSAs): -0.07
Childhood Exposure Effects on Household Income Ranks at Ages 24 and 30

Coefficient on Observational Outcome in Destination

Age of Child When Parents Move

- Age 24
- Age 30
Predicted Impacts of Moving to “Opportunity Bargain” Areas in CZ
Restricting to Tracts with Minority Share Above 20%

Mean Indiv. Earnings in MTO (with site FE)

- $5,000
- $8,000
- $11,000
- $14,000

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

= Control
= Section 8
= Experimental: Poverty Rate-Based Targeting
= Opp. Bargain: Outcome-Based Targeting

Baltimore Boston Chicago LA NY
Percentile Difference Between Opportunity Atlas Measures of Mean Child Income in Adulthood And Area Deprivation Index Measure of Neighborhood Quality

Note: Blue = areas where Opportunity Atlas ranking is higher than Area Deprivation Index (Singh 2003); red is the converse.