Part 2: Efficient Redistribution through Places/Mobility?

Nathaniel Hendren

(Based on joint work with Raj Chetty and Larry Katz)

Harvard University and NBER

August, 2015

The opinions expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Internal Revenue Service or the U.S. Treasury Department. This work is a component of a larger project examining the effects of eliminating tax expenditures on the budget deficit and economic activity. Results reported here are contained in the SOI Working Paper “The Economic Impacts of Tax Expenditures: Evidence from Spatial Variation across the U.S.,” approved under IRS contract TIRNO-12-P-00374.
Part 1: Redistribution is not free

Part 2: find the least expensive method of redistribution

Two types of policies:

- Ex-post “redistributive” policies targeted towards adults
  - EITC, income tax
  - Food Stamps
  - Job Training
  - Etc.

- Ex-ante “mobility” policies targeted towards children
  - Public schools, S-Chip, Harlem Children’s Zone, etc.
Introduction

- Growing evidence that may be more efficient to promote redistribution through mobility / investment in children

- **Health.** Medicaid to children decreases long-run public expenditure on health transfers (Wherry et al. 2015)

- **Education.** Impact of teachers on long-run earnings (Chetty et al. 2013)

- This lecture: Place.

  - Theory of how neighborhood environments play role in persistent inequality and immobility: Durlauf (1996)


    - Neighborhoods have significant childhood exposure effects
Outline of Lecture

- Background: Geographical variation in intergenerational mobility in the U.S. [Chetty, Hendren, Kline, Saez QJE 2014]

- Part 1: Childhood Exposure Effects
  - Estimate fraction of variance across areas due to causal effects of place

- Part 2: Causal Estimates by County
  - Decompose variation across areas into sorting and causal effect of each county
Data

- Data source: de-identified data from 1996-2012 tax returns
- Children linked to parents based on dependent claiming
- Focus on children in 1980-1993 birth cohorts
  - Approximately 50 million children
Variable Definitions

- Parent income: mean pre-tax household income between 1996-2000
  - For non-filers, use W-2 wage earnings + SSDI + UI income

- Child income: pre-tax household income at various ages

- Results robust to varying definitions of income and age at which child’s income is measured

- Focus on percentile ranks in **national** income distribution
  - Rank children relative to others in the same birth cohort
  - Rank parents relative to other parents
The Geography of Intergenerational Mobility in the U.S.
We conceptualize neighborhood effects as the sum of effects at different geographies (hierarchical model)

\[ \mu_{nbhd} = \mu_{CZ} + \mu_{County} + \mu_{Zip} + \mu_{Block} \]

Our primary estimates are at the commuting zone (CZ) and county level

- CZ’s are aggregations of counties analogous to MSAs
  [Tolbert and Sizer 1996; Autor and Dorn 2013]

Variance of place effects at broad geographies is a lower bound for total variance of neighborhood effects
Intergenerational Mobility by CZ

- Begin with a descriptive characterization of children’s outcomes in each CZ

- Focus on “permanent residents” of CZs
  - Permanent residents = parents who stay in CZ c between 1996-2012
  - Note that children who grow up in CZ c may move out as adults

- Characterize relationship between child’s income rank and parent’s income rank \( p \) for each CZ c and birth cohort s
Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago
Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago

\[ \mathcal{Y}_{0, \text{Chicago, 1985}} = \mathbb{E}[\text{Child Rank} \mid p = 0, c = \text{Chicago}, s = 1985] \]
Predict outcome for child in CZ c using slope + intercept of rank-rank relationship.

$$y_{p,\text{Chicago,1985}} = y_{0,\text{Chicago,1985}} + (\text{Rank-Rank Slope}) \times p$$
The Geography of Intergenerational Mobility in the United States
Predicted Income Rank at Age 26 for Children with Parents at 25th Percentile
The Geography of Intergenerational Mobility in the United States
Predicted Income Rank at Age 26 for Children with Parents at 25th Percentile

Part 1: What happens if you move to a lighter county?
Part 2: Decompose map into sorting and causal effect for each county.
Part 1
Impact of Exposure to a Better Neighborhood
We identify causal effects of neighborhoods by analyzing childhood exposure effects.

Exposure effect at age $m$: impact of spending year $m$ of childhood in an area where permanent residents’ outcomes are 1 percentile higher.

Ideal experiment: randomly assign children to new neighborhoods $d$ starting at age $m$ for the rest of childhood.

Regress income in adulthood ($y_i$) on mean outcomes of prior residents:

$$y_i = \alpha + \beta_m \bar{y}_{pds} + \epsilon_i \quad (1)$$

Exposure effect at age $m$ is $\beta_{m-1} - \beta_m$. 
We estimate exposure effects by studying families that move across CZ’s with children at different ages in observational data.

Of course, choice of neighborhood is likely to be correlated with children’s potential outcomes.

Ex: parents who move to a good area may have latent ability or wealth \( \theta_i \) that produces better child outcomes.

Estimating (1) in observational data yields a coefficient

\[
b_m = \beta_m + \delta_m
\]

where

\[
\delta_m = \frac{Cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})}
\]

is a standard selection effect.
But identification of exposure effects does not require that *where* people move is orthogonal to child’s potential outcomes.

Instead, requires that *timing* of move to better area is orthogonal to child’s potential outcomes.

**Assumption 1.** Selection effects do not vary with child’s age at move:

\[ \delta_m = \delta \text{ for all } m \]

Certainly plausible that this assumption could be violated.

- Ex: parents who move to better areas when kids are young may have better unobservables.

First present baseline estimates and then evaluate this assumption in detail.
To begin, consider subset of families who move with a child who is exactly 13 years old

Regress child’s income rank at age 26 $y_i$ on predicted outcome of permanent residents in destination:

$$y_i = \alpha_{qos} + b_m \bar{y}_{pds} + \eta_{1i}$$

Include parent decile (q) by origin (o) by birth cohort (s) fixed effects to identify $b_m$ purely from differences in destinations
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
Child Age 13 at Time of Move, Income Measured at Age 26

Mean (Residual) Child Rank in National Income Distribution

Predicted Diff. in Child Rank Based on Permanent Residents in Dest. vs. Orig.

Slope: $b_{13} = 0.628$ (0.048)
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Ages 26

Coefficient on Predicted Rank in Destination ($b_m$)
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Ages 26

Coefficient on Predicted Rank in Destination ($b_m$)

$b_m > 0$ for $m > 26$: Selection Effects

$b_m$ declining with $m$: Exposure Effects
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Ages 24, 26, or 28

Coefficient on Predicted Rank in Destination ($b_m$)

Age of Child when Parents Move (m)

Income at Age 24
Income at Age 26
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Ages 24, 26, or 28

Coefficient on Predicted Rank in Destination ($b_m$)

Coeficient on Predicted Rank in Destination ($b_m$) vs. Age of Child when Parents Move ($m$)

- Blue dots: Income at Age 24
- Red dots: Income at Age 26
- Green dots: Income at Age 28

Age of Child when Parents Move (m)

Income at Age 24
Income at Age 26
Income at Age 28
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Age = 24

Coefficient on Predicted Rank in Destination

Slope: -0.038
(0.002)

Slope: -0.002
(0.011)

δ: 0.226

Age of Child when Parents Move

Spec
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Age = 24

Coefficient on Predicted Rank in Destination

Assumption 1: $\delta_m = \delta$ for all $m$

$\Rightarrow$ Causal effect of moving at age $m$ is $\beta_m = b_m - \delta$
Family Fixed Effects: Sibling Comparisons

Slope (Age $\leq$ 23): -0.043 (0.003)

Slope (Age $>$ 23): -0.003 (0.013)

$\delta$ (Age $>$ 23): 0.008

Coefficient on Predicted Rank in Destination ($b_m$)
Family Fixed Effects: Sibling Comparisons
with Controls for Change in Income and Marital Status at Move

Slope (Age ≤ 23): -0.042 (0.003)

Slope (Age > 23): -0.003 (0.013)

δ (Age > 23): 0.015

Coefficient on Predicted Rank in Destination (b_m)
Time-Varying Unobservables

- Family fixed effects do not rule out time-varying unobservables (e.g. wealth shocks) that affect children in proportion to exposure time

  - Core problem: we do not know what triggered the move

- Two approaches to evaluate such confounds:
  1. Experimental variation: Moving to Opportunity experiment
  2. Outcome-based placebo (overidentification) tests
Outcome-Based Placebo Tests

- General idea: exploit heterogeneity in place effects across subgroups to obtain overidentification tests of exposure effect model

- For example, exposure model predicts convergence to permanent residents’ outcomes not just on means but across *entire* distribution
  - Variance of earnings for children of permanent residents in SF is higher than for children of permanent residents in Boston
  - Exposure model predicts that children who move to SF at younger ages should be more likely to end up in tails than those who move to Boston

- Difficult to know exactly where in the income distribution child will fall as an adult when moving
  - Unlikely that unobserved factor $\theta_i$ would replicate distribution of outcomes in destination area in proportion to exposure time
### Exposure Effects on Upper-Tail and Lower-Tail Outcomes
Comparisons of Impacts at P90 and Non-Employment

<table>
<thead>
<tr>
<th></th>
<th>Child Rank in top 10%</th>
<th>Child Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Distributional Prediction</td>
<td>0.043</td>
<td>0.040</td>
</tr>
<tr>
<td>Mean Rank Prediction</td>
<td>0.022</td>
<td>0.004</td>
</tr>
<tr>
<td>(Placebo)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>
Outcome-Based Placebo Tests

- We implement similar placebo tests using variation in place effects across birth cohorts and across genders.

- Exposure effect is fully determined by own-cohort and own-gender place effect.

- When a family with a daughter and son moves to a place where boys do especially well, son does better in proportion to exposure but daughter does not.

→ We conclude based on these tests that timing-of-move design yields unbiased estimates of neighborhoods’ causal exposure effects.

- How do these findings fit with results from MTO experiment?
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:
  
  1. Experimental: housing vouchers restricted to low-poverty (<10%) Census tracts
  
  2. Section 8: conventional housing vouchers, no restrictions
  
  3. Control: public housing in high-poverty (50% at baseline) areas

- 48% of eligible households in experimental voucher group “complied” and took up voucher
Most Common MTO Residential Locations in New York

- Control
  - King Towers
  - Harlem
- Experimental
  - Wakefield
  - Bronx
- Section 8
  - Soundview
  - Bronx
MTO Experiment: Exposure Effects?

- Existing research on MTO:
  - Little impact of moving to a better area on earnings and other economic outcomes

- Work has focused on adults and older youth at point of move [e.g., Kling, Liebman, and Katz 2007]

- What about the young kids?


- Does MTO improve outcomes for children who moved when young?

  - Link MTO data to tax data to study children’s outcomes in mid-20’s
Impacts of MTO on Children Below Age 13 at Random Assignment

(a) Individual Earnings (ITT)

<table>
<thead>
<tr>
<th>Group</th>
<th>Individual Income at Age ≥ 24 ($)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$11,270</td>
<td>0.101</td>
</tr>
<tr>
<td>Section 8</td>
<td>$12,380</td>
<td>0.014</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>$12,894</td>
<td></td>
</tr>
</tbody>
</table>

(b) Individual Earnings (TOT)

<table>
<thead>
<tr>
<th>Group</th>
<th>Individual Income at Age ≥ 24 ($)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$11,270</td>
<td>0.101</td>
</tr>
<tr>
<td>Section 8</td>
<td>$12,994</td>
<td>0.014</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>$14,747</td>
<td></td>
</tr>
</tbody>
</table>
Impacts of MTO on Children Below Age 13 at Random Assignment

(a) College Attendance (ITT)
- Control: 16.5%
- Section 8: 17.5%
- Experimental Voucher: 19.0%
- p = 0.028

(b) College Quality (ITT)
- Control: $20,915
- Section 8: $21,547
- Experimental Voucher: $21,601
- p = 0.014, p = 0.003
Impacts of MTO on Children Age 13-18 at Random Assignment

(a) Individual Earnings (ITT)

(b) Individual Earnings (TOT)

<table>
<thead>
<tr>
<th>Group</th>
<th>Individual Income at Age ≥ 24 ($)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$15,882</td>
<td>0.259</td>
</tr>
<tr>
<td>Section 8</td>
<td>$14,749</td>
<td>0.219</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>$14,915</td>
<td>0.259</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group</th>
<th>Individual Income at Age ≥ 24 ($)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$15,882</td>
<td>0.219</td>
</tr>
<tr>
<td>Section 8</td>
<td>$13,830</td>
<td>0.259</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>$13,455</td>
<td>0.259</td>
</tr>
</tbody>
</table>
Impacts of MTO on Children Age 13-18 at Random Assignment

(a) College Attendance (ITT)

<table>
<thead>
<tr>
<th>Group</th>
<th>College Attendance, Ages 18-20 (%)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>15.6%</td>
<td>0.091</td>
</tr>
<tr>
<td>Section 8</td>
<td>12.6%</td>
<td>0.013</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>11.4%</td>
<td></td>
</tr>
</tbody>
</table>

(b) College Quality (ITT)

<table>
<thead>
<tr>
<th>Group</th>
<th>Mean College Quality, Ages 18-20 ($)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$21,638</td>
<td>0.168</td>
</tr>
<tr>
<td>Section 8</td>
<td>$21,041</td>
<td>0.022</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>$20,755</td>
<td></td>
</tr>
</tbody>
</table>
Impacts of MTO on Children \textit{Age 13-18} at Random Assignment

(a) ZIP Poverty Share in Adulthood (ITT)

- Control: 23.6% \(p = 0.184\)
- Section 8: 22.7% \(p = 0.418\)
- Experimental Voucher: 23.1%

(b) Birth with no Father Present (ITT)

- Females Only
- Control: 41.4% \(p = 0.857\)
- Section 8: 40.7% \(p = 0.242\)
- Experimental Voucher: 45.6%
Impacts of Experimental Voucher by Age of Random Assignment

Household Income, Age ≥ 24 ($)

Experimental Vs. Control ITT on Income ($)

Age at Random Assignment

Experimental Vs. Control ITT on Income ($)
Part 2
Estimates of Causal Place Effects
Estimating Causal Effects of Each County

- Part 1 of our analysis establishes that neighborhoods matter, but it does not tell us which places are good and which are not.

- Part 2: estimate causal effects of each county and CZ in the U.S. on children’s earnings in adulthood.
We characterize each county and CZ’s causal effect in four steps

1. Estimate fixed effects of each county using movers
2. Estimate variance components of latent variable model of nbhd. effects
3. Construct optimal predictors (shrunk estimates) of each county’s effect
4. Characterize features of areas that produce high vs. low levels of mobility
Step 1: Fixed Effects Estimation

- Apply exposure-time design to estimate causal effects of each area in the U.S. using a fixed effects model
  - Focus exclusively on movers, **without** using data on permanent residents

- Intuition: suppose children who move from Manhattan to Queens at younger ages earn more as adults
  - Can infer that Queens has positive exposure effects relative to Manhattan

- Build on this logic to estimate fixed effects of all counties using five million movers, identifying purely from differences in *timing* of moves across areas
Estimate place effects $\mu = (\mu_1, ..., \mu_N)$ using fixed effects for origin and destination interacted with exposure time:

$$y_i = \left( T_c - m \right) \frac{\mu_d 1 \{ d(i) = d \} - \mu_o 1 \{ o(i) = o \}}{\text{Dest. FE}} + \text{Orig. FE.} + \alpha_{odps} + \eta_i$$

Place effects are allowed to vary linearly with parent income rank:

$$\mu_c = \mu^0_c + \mu^P_c P$$

Include origin-by-destination fixed effects (to isolate variation in exposure) and quadratic birth cohort controls (to eliminate time trends)
CZ Fixed Effect Estimates for Child’s Income Rank at Age 26
For Children with Parents at 25th Percentile of Income Distribution

Note: Estimates represent annual exposure effects on child’s rank in income distribution at age 26
Step 2: Estimation of Variance Components

- Fixed effect estimates are the sum of latent causal effect of each place $\mu_{pc}$ and estimation error $\varepsilon_{pc}$

- Variance of fixed effects therefore overstates true variance of causal effects of place

- Estimate magnitude of neighborhood effects by subtracting noise variance (due to sampling error) from total variance
Estimation of Variance Components

- Signal SD of annual exposure effect is $\sigma_\mu = 0.17$ percentiles = 0.5% across counties for parents at 25th percentile
  - 1 SD better county from birth $\rightarrow$ 10% earnings gain
  - $1/3$ as large as 1 SD increase in parent income

- For children at p75 (high-income families), signal SD of annual exposure effects = 0.16 percentiles = 0.3% effect on mean earnings

- Correlation of place effects for p25 and p75 across counties is $+0.3$
  - Places that are better for the poor are not worse for the rich
Variance components allow us to quantify degree of signal vs. noise in each fixed effect estimates

- In largest counties, signal accounts for 75% of variance
- In smaller counties, more than half of the variance is due to noise
- Therefore raw fixed effect estimates do not provide reliable predictions of each county’s causal effect on a given child
Step 3: Optimal Forecasts of Place Effects

- Construct more reliable forecasts using a simple shrinkage estimator

- Goal: forecast each county’s causal effect, minimizing mean-squared-error of prediction

- Optimal forecast is a weighted average of raw fixed effect based on movers and prediction based on permanent residents
  - Permanent residents’ effects are very precise (large samples) but are biased by selection
  - Fixed effect estimates based on movers are noisy but unbiased estimates of each county’s causal effect
To derive optimal forecast, consider hypothetical experiment of randomly assigning children from an average place to new places.

Regress outcomes $y_i$ on fixed-effect estimate and stayers prediction:

$$y_{ipc} = \alpha + \rho_{1,pc} \bar{y}_{pc} + \rho_{2,pc} \hat{\mu}_{pc}$$

This yields regression coefficients:

$$\rho_{1,pc} = \beta \frac{\sigma^2_{\varepsilon,pc}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}} \quad \rho_{2,pc} = \frac{\sigma^2_{\nu,p}}{\sigma^2_{\nu,p} + \sigma^2_{\varepsilon,pc}}$$

where $\sigma^2_{\nu}$ is residual variance of fixed effects after regressing on stayers.

Optimal forecast weights movers fixed effect more heavily in large counties (less noise) and permanent residents more heavily in small counties.
Predicted Exposure Effects on Child’s Income Level at Age 26 by CZ
For Children with Parents at 25th Percentile of Income Distribution

Note: Estimates represent % change in earnings from spending one more year of childhood in CZ
Exposure Effects on Income in the New York CSA
For Children with Parents at 25th Percentile of Income Distribution

Causal Exposure Effects Per Year:
Bronx NY: - 0.54 %
Bergen NJ: + 0.69 %
Exposure Effects on Income in the New York CSA
For Children with Parents at 75th Percentile of Income Distribution

Causal Exposure Effects Per Year:
Bronx NY: - 0.42 %
Bergen NJ: + 0.31 %
Exposure Effects on Income in the Boston CSA
For Children with Parents at 25th Percentile of Income Distribution

Causal Exposure Effects Per Year:
Suffolk MA: - 0.31 %
Middlesex MA: + 0.39 %
Exposure Effects on Income in the Boston CSA
For Children with Parents at 75th Percentile of Income Distribution

Causal Exposure Effects Per Year:
Suffolk MA: -0.18 %
Middlesex MA: +0.03 %
# Annual Exposure Effects on Income for Children in Low-Income Families (p25)

**Top 10 and Bottom 10 Among the 100 Largest Counties in the U.S.**

<table>
<thead>
<tr>
<th>Rank</th>
<th>Top 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
<th>Bottom 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Dupage, IL</td>
<td>0.80</td>
<td>91</td>
<td>Wayne, MI</td>
</tr>
<tr>
<td>2</td>
<td>Fairfax, VA</td>
<td>0.75</td>
<td>92</td>
<td>Orange, FL</td>
</tr>
<tr>
<td>3</td>
<td>Snohomish, WA</td>
<td>0.70</td>
<td>93</td>
<td>Cook, IL</td>
</tr>
<tr>
<td>4</td>
<td>Bergen, NJ</td>
<td>0.69</td>
<td>94</td>
<td>Palm Beach, FL</td>
</tr>
<tr>
<td>5</td>
<td>Bucks, PA</td>
<td>0.62</td>
<td>95</td>
<td>Marion, IN</td>
</tr>
<tr>
<td>6</td>
<td>Norfolk, MA</td>
<td>0.57</td>
<td>96</td>
<td>Shelby, TN</td>
</tr>
<tr>
<td>7</td>
<td>Montgomery, PA</td>
<td>0.49</td>
<td>97</td>
<td>Fresno, CA</td>
</tr>
<tr>
<td>8</td>
<td>Montgomery, MD</td>
<td>0.47</td>
<td>98</td>
<td>Hillsborough, FL</td>
</tr>
<tr>
<td>9</td>
<td>King, WA</td>
<td>0.47</td>
<td>99</td>
<td>Baltimore City, MD</td>
</tr>
<tr>
<td>10</td>
<td>Middlesex, NJ</td>
<td>0.46</td>
<td>100</td>
<td>Mecklenburg, NC</td>
</tr>
</tbody>
</table>

*Exposure effects represent % change in adult earnings per year of childhood spent in county*
## Annual Exposure Effects on Income for Children in High-Income Families (p75)

Top 10 and Bottom 10 Among the 100 Largest Counties in the U.S.

<table>
<thead>
<tr>
<th>Rank</th>
<th>County</th>
<th>Annual Exposure Effect (%)</th>
<th>Rank</th>
<th>County</th>
<th>Annual Exposure Effect (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fairfax, VA</td>
<td>0.55</td>
<td>91</td>
<td>Hillsborough, FL</td>
<td>-0.40</td>
</tr>
<tr>
<td>2</td>
<td>Westchester, NY</td>
<td>0.34</td>
<td>92</td>
<td>Bronx, NY</td>
<td>-0.42</td>
</tr>
<tr>
<td>3</td>
<td>Hudson, NJ</td>
<td>0.33</td>
<td>93</td>
<td>Broward, FL</td>
<td>-0.46</td>
</tr>
<tr>
<td>4</td>
<td>Hamilton, OH</td>
<td>0.32</td>
<td>94</td>
<td>Dist. of Columbia, DC</td>
<td>-0.48</td>
</tr>
<tr>
<td>5</td>
<td>Bergen, NJ</td>
<td>0.31</td>
<td>95</td>
<td>Orange, CA</td>
<td>-0.49</td>
</tr>
<tr>
<td>6</td>
<td>Gwinnett, GA</td>
<td>0.31</td>
<td>96</td>
<td>San Bernardino, CA</td>
<td>-0.51</td>
</tr>
<tr>
<td>7</td>
<td>Norfolk, MA</td>
<td>0.31</td>
<td>97</td>
<td>Riverside, CA</td>
<td>-0.51</td>
</tr>
<tr>
<td>8</td>
<td>Worcester, MA</td>
<td>0.27</td>
<td>98</td>
<td>Los Angeles, CA</td>
<td>-0.52</td>
</tr>
<tr>
<td>9</td>
<td>Franklin, OH</td>
<td>0.24</td>
<td>99</td>
<td>New York, NY</td>
<td>-0.57</td>
</tr>
<tr>
<td>10</td>
<td>Kent, MI</td>
<td>0.23</td>
<td>100</td>
<td>Palm Beach, FL</td>
<td>-0.65</td>
</tr>
</tbody>
</table>

*Exposure effects represent % change in adult earnings per year of childhood spent in county.*
## Annual Exposure Effects on Income for Children in Low-Income Families (p25)

### Male Children

<table>
<thead>
<tr>
<th>Top 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
<th>Bottom 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank</td>
<td>County</td>
<td></td>
<td>Rank</td>
</tr>
<tr>
<td>1</td>
<td>Bucks, PA</td>
<td>0.84</td>
<td>91</td>
</tr>
<tr>
<td>2</td>
<td>Bergen, NJ</td>
<td>0.83</td>
<td>92</td>
</tr>
<tr>
<td>3</td>
<td>Contra Costa, CA</td>
<td>0.72</td>
<td>93</td>
</tr>
<tr>
<td>4</td>
<td>Snohomish, WA</td>
<td>0.70</td>
<td>94</td>
</tr>
<tr>
<td>5</td>
<td>Norfolk, MA</td>
<td>0.62</td>
<td>95</td>
</tr>
<tr>
<td>6</td>
<td>Dupage, IL</td>
<td>0.61</td>
<td>96</td>
</tr>
<tr>
<td>7</td>
<td>King, WA</td>
<td>0.56</td>
<td>97</td>
</tr>
<tr>
<td>8</td>
<td>Ventura, CA</td>
<td>0.55</td>
<td>98</td>
</tr>
<tr>
<td>9</td>
<td>Hudson, NJ</td>
<td>0.52</td>
<td>99</td>
</tr>
<tr>
<td>10</td>
<td>Fairfax, VA</td>
<td>0.46</td>
<td>100</td>
</tr>
</tbody>
</table>

*Exposure effects represent % change in adult earnings per year of childhood spent in county*
## Annual Exposure Effects on Income for Children in Low-Income Families (p25)

**Female Children**

<table>
<thead>
<tr>
<th>Rank</th>
<th>Top 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
<th>Bottom 10 Counties</th>
<th>Annual Exposure Effect (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Dupage, IL</td>
<td>0.91</td>
<td>91</td>
<td>Hillsborough, FL</td>
</tr>
<tr>
<td>2</td>
<td>Fairfax, VA</td>
<td>0.76</td>
<td>92</td>
<td>Fulton, GA</td>
</tr>
<tr>
<td>3</td>
<td>Snohomish, WA</td>
<td>0.73</td>
<td>93</td>
<td>Suffolk, MA</td>
</tr>
<tr>
<td>4</td>
<td>Montgomery, MD</td>
<td>0.68</td>
<td>94</td>
<td>Orange, FL</td>
</tr>
<tr>
<td>5</td>
<td>Montgomery, PA</td>
<td>0.58</td>
<td>95</td>
<td>Essex, NJ</td>
</tr>
<tr>
<td>6</td>
<td>King, WA</td>
<td>0.57</td>
<td>96</td>
<td>Cook, IL</td>
</tr>
<tr>
<td>7</td>
<td>Bergen, NJ</td>
<td>0.56</td>
<td>97</td>
<td>Franklin, OH</td>
</tr>
<tr>
<td>8</td>
<td>Salt Lake, UT</td>
<td>0.51</td>
<td>98</td>
<td>Mecklenburg, NC</td>
</tr>
<tr>
<td>9</td>
<td>Contra Costa, CA</td>
<td>0.47</td>
<td>99</td>
<td>New York, NY</td>
</tr>
<tr>
<td>10</td>
<td>Middlesex, NJ</td>
<td>0.47</td>
<td>100</td>
<td>Marion, IN</td>
</tr>
</tbody>
</table>

*Exposure effects represent % change in adult earnings per year of childhood spent in county*
Step 4: Characteristics of Good Areas

- What types of areas produce better outcomes for low-income children?

- Observed upward mobility is strongly correlated with five factors [CHKS 2014]
  - Segregation, Inequality, School Quality, Social Capital, Family Structure

- Are these characteristics of areas with positive causal effects (good places) or positive selection (good families)?
Step 4: Characteristics of Good Areas

- Decompose observed rank for stayers ($y_{pc}$) into causal and sorting components by multiplying annual exposure effect $\mu_{pc}$ by 20:

  - Causal component = $20\mu_{pc}$
  
  - Sorting component = $y_{pc} - 20\mu_{pc}$

- Regress $y_{pc}$, causal, and sorting components on covariates

  - Standardize covariates so units represent impact of 1 SD change in covariate on child’s percentile rank

    - Multiply by 3 to get percentage effects at p25
Predictors of Exposure Effects For Children at the CZ Level (p25)

Effect of 1 SD Increase in Covariate on Child's Expected Percentile Rank

Fraction Black Residents

Permanent Residents
Predictors of Exposure Effects For Children at the CZ Level (p25)

Effect of 1 SD Increase in Covariate on Child’s Expected Percentile Rank

Causal Correlation: -0.51
Predictors of Exposure Effects For Children at the CZ Level (p25)

Effect of 1 SD Increase in Covariate on Child’s Expected Percentile Rank

- Fraction Black Residents: Causal Correlation -0.51
- Poverty Share: Causal Correlation -0.14
- Racial Segregation: Causal Correlation -0.51
- Gini Coef.: Causal Correlation -0.76
- Fraction Single Moms: Causal Correlation -0.57
- Social Capital: Causal Correlation 0.70
- Student-Teacher Ratio: Causal Correlation -0.34
Predictors of Exposure Effects For Children at the County within CZ Level (p25)

Effect of 1 SD Increase in Covariate on Child’s Expected Percentile Rank

- Fraction Black Residents
  - Causal Correlation: -0.32
- Poverty Share
  - Causal Correlation: -0.23
- Racial Segregation
  - Causal Correlation: -0.37
- Gini Coef.
  - Causal Correlation: -0.41
- Fraction Single Moms
  - Causal Correlation: -0.38
- Social Capital
  - Causal Correlation: 0.15
- Student-Teacher Ratio
  - Causal Correlation: -0.10
Predictors of Exposure Effects For Children at the CZ Level (p75)

- Fraction Black Residents: -0.01
- Poverty Share: -0.06
- Racial Segregation: -0.16
- Gini Coef.: -0.69
- Fraction Single Moms: -0.11
- Social Capital: 0.66
- Student-Teacher Ratio: -0.73

Effect of 1 SD Increase in Covariate on Child’s Expected Percentile Rank
Predictors of Exposure Effects For Children at the County within CZ Level (p75)

Effect of 1 SD Increase in Covariate on Child’s Expected Percentile Rank

- Fraction Black Residents
- Poverty Share
- Racial Segregation
- Gini Coef.
- Fraction Single Moms
- Social Capital
- Student-Teacher Ratio

Causal Correlation:
- Fraction Black Residents: -0.14
- Poverty Share: -0.02
- Racial Segregation: 0.14
- Gini Coef.: -0.06
- Fraction Single Moms: -0.07
- Social Capital: 0.00
- Student-Teacher Ratio: -0.21
Conclusion: Ex-ante versus Ex-post Policies

- Growing body of evidence suggests ex-ante policies targeted to children may be more efficient at providing redistribution

- MTO / Place-based policies
  - No impacts on adults (Kling et al. 2007, ECMA)
  - Strong impacts on young kids (Chetty, Hendren, and Katz 2015)

- Medicaid
  - Adult expansion increases utilization with minimal health impacts (Finkelstein et al. 2015)
  - Medicaid for children decreases long-run costs (Wherry et al 2015)

- Food Stamps / SNAP
  - Distortionary labor impacts on adults (Hoynes and Schanzenbach 2012, AEJ)
  - Positive impacts on children (Hoynes, Schanzenbach, and Almond 2015)

- Lesson: Becker’s model was right – role of human capital formation
Impacts of MTO on Annual Income Tax Revenue in Adulthood for Children Below Age 13 at Random Assignment (TOT Estimates)

- Control: $447.5, p = 0.061
- Section 8: $616.6, p = 0.004
- Experimental Voucher: $841.1, p = 0.004
Download County-Level Data on Social Mobility in the U.S.
www.equality-of-opportunity.org/data

THE EQUALITY OF OPPORTUNITY PROJECT

Downloadable Data

Data from Chetty and Hendren (2015): Causal Effects, Mobility Estimates and Covariates by County, CZ and Birth Cohort

<table>
<thead>
<tr>
<th>Data Description</th>
<th>Stata file</th>
<th>Excel file</th>
<th>ReadMe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online Data Table 1: Preferred Estimates of Causal Place Effects by Commuting Zone</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Data Table 2: Preferred Estimates of Causal Place Effects by County</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Data Table 3: Complete CZ-Level Dataset: Causal Effects and Covariates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Data Table 4: Complete County-Level Dataset: Causal Effects and Covariates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Data Table 5: Pairwise Place Effects by Origin-Destination Pairs of Commuting Zones</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Data Table 6: Parent Income Distribution by Child's Birth Cohort</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Neighborhood Effects on Other Outcomes

- We also find similar exposure effects for other outcomes:
  - College attendance (from 1098-T forms filed by colleges)
  - Teenage birth (from birth certificate data)
  - Teenage employment (from W-2 forms)
  - Marriage
Exposure Effects for College Attendance, Ages 18-23

Slope (Age ≤ 23): -0.037 (0.003)
Slope (Age > 23): -0.021 (0.011)

δ (Age > 23): 0.143
Exposure Effects for Marriage Rate, Age 26

Slope (Age ≤ 23): -0.025 (0.002)

δ (Age > 23): 0.464 (0.005)

Coefficient on Change in Predicted Marriage Rate

Age of Child when Parents Move (m)
Exposure Effects for Teenage Birth: Females and Males

Coefficient on Change in Predicted Teen Birth Rate

Age of Child when Parents Move (m)

- Female
- Male
Identification of Exposure Effects: Summary

Any omitted variable $\theta_i$ that generates bias in the exposure effect estimates would have to:

1. Operate within family in proportion to exposure time
2. Be orthogonal to changes in parent income and marital status
3. Replicate prior residents’ outcomes by birth cohort, quantile, and gender in proportion to exposure time
4. Replicate impacts across outcomes (income, college attendance, teen labor, marriage)

→ We conclude that baseline design exploiting variation in timing of move yields unbiased estimates of neighborhoods’ causal effects