The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates

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May 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.
How much do neighborhood environments affect children’s outcomes?


But experimental studies find no significant effects of moving to better areas on economic outcomes [e.g. Katz, Kling, and Liebman 2001, Oreopoulous 2003, Sanbonmatsu et al. 2011]
We present new quasi-experimental estimates of the effects of neighborhoods on children using data on 5 million movers across U.S. counties.

Also present a re-analysis of the Moving to Opportunity experiment using new data on children’s long-term outcomes.

We find that neighborhoods have significant **childhood exposure effects**.

Every year spent in a better environment improves long-term outcomes.

Results help reconcile conflicting findings in prior work and shed light on the characteristics of good neighborhoods.
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

\[ y_{0,\text{Chicago,1985}} = E[\text{Child Rank} \mid p = 0, c = \text{Chicago}, s = 1985] \]
Mean Child Income Rank at Age 26 vs. Parent Income Rank for Children Born in 1985 and Raised in Chicago

\[ \bar{y}_{p, \text{Chicago, 1985}} = \bar{y}_{0, \text{Chicago, 1985}} + (\text{Rank-Rank Slope}) \times p \]

*Predict outcome for child in CZ c using slope + intercept of rank-rank relationship*
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 Fraction of Variance in this Map is Due to Causal Place Effects?
Part 2: Decompose map into sorting and causal effect for each county
Part 1
Impact of Exposure to a Better Neighborhood
Neighborhood Exposure Effects

- 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:

    $$ y_i = \alpha + \beta_m \bar{y}_{pds} + \epsilon_i $$

    (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
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 \( (b_m) \)

Exposure Effects

\( b_m \) declining with \( m \)

Selection Effects

\( b_m > 0 \) for \( m > 26 \):
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 ($b_m$)

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

Age of Child when Parents Move

Slope: -0.038
(0.002)

Slope: -0.002
(0.011)

δ: 0.226
Movers’ Outcomes vs. Predicted Outcomes Based on Residents in Destination
By Child’s Age at Move, Income Measured at Age = 24

Assumption 1: $\delta_m = \delta$ for all $m$
→ Causal effect of moving at age $m$ is $\beta_m = b_m - \delta$
Family Fixed Effects: Sibling Comparisons

Slope (Age ≤ 23): -0.043 (0.003)
Slope (Age > 23): -0.003 (0.013)

Coefficient on Predicted Rank in Destination ($b_m$)

Age of Child when Parents Move (m)
Family Fixed Effects: Sibling Comparisons
with Controls for Change in Income and Marital Status at Move

Coefficient on Predicted Rank in Destination ($b_m$)

Slope (Age ≤ 23): -0.042 (0.003)
Slope (Age > 23): -0.003 (0.013)

Age of Child when Parents Move (m)

$\delta$ (Age > 23): 0.015
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

- Two approaches to evaluate such confounds:
  1. Outcome-based placebo (overidentification) tests
  2. Experimental/quasi-experimental variation from displacement shocks or randomized incentives to move
Outcome-Based Placebo Tests

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

- Start with variation in place effects across birth cohorts
  - Some areas are getting better over time, others are getting worse
  - Causal effect of neighborhood on a child who moves in to an area should depend on properties of that area while he is growing up
Outcome-Based Placebo Tests

- Parents choose neighborhoods based on their preferences and information set at time of move

  - Difficult to predict high-frequency differences that are realized 15 years later → hard to sort on this dimension

- Key assumption: if unobservables $\theta_i$ correlated with exposure effect for cohort $s$, then correlated with exposure effects for surrounding cohorts $s'$ as well

  \[
  \text{Cov}(\theta_i, m\Delta_{odp,s(i)}|X) > 0 \Rightarrow \text{Cov}(\theta_i, m\Delta_{odp,s'|X, m\Delta_{odp,s(i)}} > 0
  \]

- Under this assumption, selection effects will be manifested in correlation with place effects for surrounding cohorts
Estimates of Exposure Effects Based on Cross-Cohort Variation

Exposure Effect Estimate ($\beta$) vs. Years Relative to Own Cohort
Estimates of Exposure Effects Based on Cross-Cohort Variation

Years Relative to Own Cohort

Exposure Effect Estimate ($\beta$)
Distributional Convergence

Next, implement an analogous set of placebo tests by exploiting heterogeneity across realized distribution of incomes.

Areas differ not just in mean child outcomes but also across distribution.

For example, compare outcomes in Boston and San Francisco for children with parents at 25\(^{th}\) percentile:

- Mean expected rank is 46\(^{th}\) percentile in both cities.
- Probability of reaching top 10\%: 7.3\% in SF vs. 5.9\% in Boston.
- Probability of being in bottom 10\%: 15.5\% in SF vs. 11.7\% in Boston.
Exposure model predicts convergence to permanent residents’ outcomes not just on means but across *entire* distribution

- 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 your child will fall as an adult when moving with a 10 year old

- Also unlikely that unobserved factor $\theta_i$ would replicate distribution of outcomes in destination area in proportion to exposure time

- Does greater exposure to areas that produce stars increase probability of becoming a star, controlling for mean predicted rank?
# Exposure Effects on Upper-Tail and Lower-Tail Outcomes

Comparisons of Impacts at P90 and Non-Employment

<table>
<thead>
<tr>
<th>Distributional Prediction</th>
<th>Child Rank in top 10%</th>
<th>Child Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) 0.043 (0.002)</td>
<td>(4) 0.046 (0.003)</td>
</tr>
<tr>
<td></td>
<td>(2) 0.040 (0.003)</td>
<td>(5) 0.045 (0.004)</td>
</tr>
<tr>
<td></td>
<td>(3) 0.046 (0.003)</td>
<td>(6) 0.045 (0.003)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mean Rank Prediction (Placebo)</th>
<th>Child Rank in top 10%</th>
<th>Child Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) 0.022 (0.002)</td>
<td>(4) 0.021 (0.002)</td>
</tr>
<tr>
<td></td>
<td>(2) 0.004 (0.003)</td>
<td>(5) 0.000 (0.003)</td>
</tr>
<tr>
<td></td>
<td>(3) 0.021 (0.003)</td>
<td>(6) 0.000 (0.003)</td>
</tr>
</tbody>
</table>
Gender Comparisons

- Finally, exploit heterogeneity across genders
- Construct separate predictions of expected income rank conditional on parent income for girls and boys in each CZ
  - Correlation of male and female predictions across CZ’s is 0.90
- Low-income boys do worse than girls in areas with:
  1. More segregation (concentrated poverty)
  2. Higher rates of crime
  3. Lower marriage rates [Autor and Wasserman 2013]
- If unobservable input $\theta_i$ does not covary with gender-specific neighborhood effect, can use gender differences to conduct a placebo test
## Exposure Effect Estimates: Gender-Specific Predictions

<table>
<thead>
<tr>
<th></th>
<th>No Family Fixed Effects</th>
<th>Family Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Own Gender Prediction</td>
<td>0.038</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Other Gender Prediction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Placebo)</td>
<td>0.034</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Sample</td>
<td>Full Sample</td>
<td></td>
</tr>
</tbody>
</table>
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

Coefficient on Change in Predicted Marriage Rate

Slope (Age ≤ 23): -0.025 (0.002)

δ (Age > 23): 0.464
Slope (Age > 23): -0.002 (0.005)

Age of Child when Parents Move (m)
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
We also validate this quasi-experimental design using experimental variation where we know what triggers the move.

We consider two such subsets of moves:

1. Displacement shocks such as plant closures and natural disasters
2. Moving to Opportunity Experiment

Both induce families to move for reasons known to be unrelated to child’s age and potential outcomes.

Focus on the MTO results here in the interest of time.

MTO also provides insights at finer geographies.
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

New York City
MTO Experiment: Exposure Effects?

- Prior research on MTO has found little impact of moving to a better area on earnings and other economic outcomes.
  - This work has focused on adults and older youth at point of move [e.g., Kling, Liebman, and Katz 2007].
- In a companion paper (joint with Larry Katz), we test for childhood exposure effects in MTO experiment:
  

- 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.
Differences between MTO and quasi-experimental designs:

1. Different set of compliers who identify LATE
   - MTO identified from moves induced by vouchers
   - Quasi-experiment from moves that families chose in equilibrium

2. Inclusion of disruption effects from move
   - MTO compares movers to non-movers and therefore incorporates any disruption effect of move
   - Quasi-experimental design compares effect of moving to better vs. worse areas *conditional* on moving $\rightarrow$ fixed cost of move netted out
Impacts of MTO on Children Below Age 13 at Random Assignment

(a) Individual Earnings (ITT)

(b) Individual Earnings (TOT)

Individual Income at Age ≥ 24 ($)

Control: $11,270
Section 8: $12,380, p = 0.101
Experimental Voucher: $12,894, p = 0.014

Control: $11,270
Section 8: $12,994, p = 0.101
Experimental Voucher: $14,747, p = 0.014
Impacts of MTO on Children Below Age 13 at Random Assignment

(a) College Attendance (ITT)

- Control: 16.5%
- Section 8: 17.5% ($p = 0.435$)
- Experimental Voucher: 19.0% ($p = 0.028$)

(b) College Quality (ITT)

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

(a) ZIP Poverty Share in Adulthood (ITT)

- Control: 23.8%
- Section 8: 22.4%
- Experimental Voucher: 22.2%

(b) Birth with no Father Present (ITT) Females Only

- Control: 33.0%
- Section 8: 31.7%
- Experimental Voucher: 28.2%

$p = 0.047$ for Section 8 vs. Control

$p = 0.008$ for Experimental Voucher vs. Control

$p = 0.610$ for Section 8 vs. Experimental Voucher

$p = 0.042$ for Experimental Voucher vs. Control
Impacts of MTO on Children Age 13-18 at Random Assignment

(a) Individual Earnings (ITT)

(b) Individual Earnings (TOT)

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

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<tr>
<td>Individual Income at Age ≥ 24 ($)</td>
<td>$15,882</td>
<td>$13,830</td>
<td>$13,455</td>
</tr>
<tr>
<td>$p$</td>
<td>$p = 0.219$</td>
<td>$p = 0.259$</td>
<td>$p = 0.259$</td>
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</tbody>
</table>
Impacts of MTO on Children  
**Age 13-18** at Random Assignment

(a) College Attendance (ITT)

(b) College Quality (ITT)

<table>
<thead>
<tr>
<th></th>
<th>College Attendance, Ages 18-20 (%)</th>
<th>Mean College Quality, Ages 18-20 ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>15.6%</td>
<td>$21,638</td>
</tr>
<tr>
<td>Section 8</td>
<td>12.6%</td>
<td>$21,041</td>
</tr>
<tr>
<td>Experimental Voucher</td>
<td>11.4%</td>
<td>$20,755</td>
</tr>
</tbody>
</table>

Significant differences indicated by *p* values:

- **College Attendance**:
  - Control vs. Section 8: *p* = 0.091
  - Control vs. Experimental Voucher: *p* = 0.013

- **Mean College Quality**:
  - Control vs. Section 8: *p* = 0.168
  - Control vs. Experimental Voucher: *p* = 0.022
Impacts of MTO on Children \textbf{Age 13-18} at Random Assignment

(a) ZIP Poverty Share in Adulthood (ITT)

(b) Birth with no Father Present (ITT)

Females Only

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Section 8</th>
<th>Experimental Voucher</th>
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<tbody>
<tr>
<td>ZIP Poverty Share (%)</td>
<td>23.6%</td>
<td>22.7%</td>
<td>23.1%</td>
</tr>
<tr>
<td>( p )</td>
<td>0.184</td>
<td>0.418</td>
<td>0.857</td>
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<table>
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<th></th>
<th>Control</th>
<th>Section 8</th>
<th>Experimental Voucher</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth No Father Present (%)</td>
<td>41.4%</td>
<td>40.7%</td>
<td>45.6%</td>
</tr>
<tr>
<td>( p )</td>
<td>0.857</td>
<td>0.242</td>
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Part 2
Estimates of Causal Place Effects
Part 1 of our analysis establishes that each year of childhood exposure to a 1 percentile better CZ/county raises earnings by about 0.035 percentiles.

Extrapolating over 20 years of childhood, implies that causal effects of place account for 70% of variance in intergenerational mobility across areas.

This analysis shows 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, \textbf{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 \textit{timing} of moves across areas.
Estimate place effects $\mu = (\mu_1, ..., \mu_N)$ using fixed effects for origin and destination interacted with exposure time:

$$y_i = \left( T_c - m \right) \begin{bmatrix} \mu_d 1 \{d(i) = d\} - \mu_o 1 \{o(i) = o\} \end{bmatrix} + \alpha_{odps} \text{ orig x Dest FE} + \eta_i$$

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

$$\mu_c = \mu_c^0 + \mu_c^P P$$

Include origin-by-destination fixed effects (to isolate variation in exposure) and quadratic birth cohort controls (to eliminate time trends)

$$\alpha_{odps} = (\alpha_{od}^0 + \alpha_{od}^P P + \psi_{od}^0 s + \psi_{od}^1 s^2 + \psi_{od}^2 sp + \psi_{od}^3 s^2 p)$$
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

  - Signal SD of annual exposure effect is $\sigma_{\mu} = 0.13$ percentiles at CZ level and $\sigma_{\mu} = 0.17$ percentiles across counties for parents at 25th percentile
We use ranks instead of dollars because ranks have less noise

But for interpreting units, useful to think in terms of $ and % increases

Regress mean child income on mean child rank at parent income rank $p$ to obtain a scaling factor to translate ranks to dollars

At parent $p=25$: 1 percentile = $818 = 3.1\%$ of mean income

At parent $p=75$: 1 percentile = $840 = 2.1\%$ of mean income

Note that we obtain very similar (but noisier) estimates if we estimate exposure effects on dollars directly
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 $\sigma^2_{\varepsilon}$ 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 Rank at Age 26 by CZ
For Children with Parents at 25th Percentile of Income Distribution

Note: Estimates represent change in rank from spending one more year of childhood in CZ.
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>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>Dupage, IL</td>
<td>0.80</td>
<td>91</td>
<td>Wayne, MI</td>
<td>-0.57</td>
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<tr>
<td>2</td>
<td>Fairfax, VA</td>
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<td>92</td>
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<tr>
<td>3</td>
<td>Snohomish, WA</td>
<td>0.70</td>
<td>93</td>
<td>Cook, IL</td>
<td>-0.64</td>
</tr>
<tr>
<td>4</td>
<td>Bergen, NJ</td>
<td>0.69</td>
<td>94</td>
<td>Palm Beach, FL</td>
<td>-0.65</td>
</tr>
<tr>
<td>5</td>
<td>Bucks, PA</td>
<td>0.62</td>
<td>95</td>
<td>Marion, IN</td>
<td>-0.65</td>
</tr>
<tr>
<td>6</td>
<td>Norfolk, MA</td>
<td>0.57</td>
<td>96</td>
<td>Shelby, TN</td>
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</tr>
<tr>
<td>7</td>
<td>Montgomery, PA</td>
<td>0.49</td>
<td>97</td>
<td>Fresno, CA</td>
<td>-0.67</td>
</tr>
<tr>
<td>8</td>
<td>Montgomery, MD</td>
<td>0.47</td>
<td>98</td>
<td>Hillsborough, FL</td>
<td>-0.69</td>
</tr>
<tr>
<td>9</td>
<td>King, WA</td>
<td>0.47</td>
<td>99</td>
<td>Baltimore City, MD</td>
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</tr>
<tr>
<td>10</td>
<td>Middlesex, NJ</td>
<td>0.46</td>
<td>100</td>
<td>Mecklenburg, NC</td>
<td>-0.72</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>
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</thead>
<tbody>
<tr>
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<tr>
<td>3</td>
<td>Hudson, NJ</td>
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<td>Broward, FL</td>
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<tr>
<td>4</td>
<td>Hamilton, OH</td>
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<td>Dist. of Columbia, DC</td>
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<tr>
<td>5</td>
<td>Bergen, NJ</td>
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<td>95</td>
<td>Orange, CA</td>
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<tr>
<td>6</td>
<td>Gwinnett, GA</td>
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<td>San Bernardino, CA</td>
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<tr>
<td>7</td>
<td>Norfolk, MA</td>
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<td>97</td>
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<td>8</td>
<td>Worcester, MA</td>
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<td>Los Angeles, CA</td>
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<td>9</td>
<td>Franklin, OH</td>
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<td>New York, NY</td>
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<tr>
<td>10</td>
<td>Kent, MI</td>
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<td>100</td>
<td>Palm Beach, FL</td>
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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>Rank</th>
<th>County</th>
<th>Annual Exposure Effect (%)</th>
<th>Rank</th>
<th>County</th>
<th>Annual Exposure Effect (%)</th>
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</thead>
<tbody>
<tr>
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<td>Milwaukee, WI</td>
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<td>Bergen, NJ</td>
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<td>New Haven, CT</td>
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</tr>
<tr>
<td>3</td>
<td>Contra Costa, CA</td>
<td>0.72</td>
<td>93</td>
<td>Bronx, NY</td>
<td>-0.76</td>
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<tr>
<td>4</td>
<td>Snohomish, WA</td>
<td>0.70</td>
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<td>Norfolk, MA</td>
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<td>95</td>
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*Exposure effects represent % change in adult earnings per year of childhood spent in county*
<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>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Dupage, IL</td>
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<td>91</td>
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<td>Fulton, GA</td>
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<td>Snohomish, WA</td>
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<td>Suffolk, MA</td>
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<td>4</td>
<td>Montgomery, MD</td>
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<td>Salt Lake, UT</td>
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<tr>
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<td>Contra Costa, CA</td>
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<tr>
<td>10</td>
<td>Middlesex, NJ</td>
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</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)

#### Gender Average vs. Pooled Specification

<table>
<thead>
<tr>
<th>Rank</th>
<th>County</th>
<th>Gender Avg (%)</th>
<th>Pooled (%)</th>
<th>Gender Avg (%)</th>
<th>Pooled (%)</th>
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<tr>
<td>93</td>
<td>Milwaukee, WI</td>
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<td>-0.50</td>
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<td>94</td>
<td>Wayne, MI</td>
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<td>-0.57</td>
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</tr>
<tr>
<td>95</td>
<td>Fresno, CA</td>
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<td>-0.67</td>
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<tr>
<td>96</td>
<td>Cook, IL</td>
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<td>-0.64</td>
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<tr>
<td>97</td>
<td>Orange, FL</td>
<td>-0.67</td>
<td>-0.60</td>
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</tr>
<tr>
<td>98</td>
<td>Hillsborough, FL</td>
<td>-0.67</td>
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<tr>
<td>99</td>
<td>Mecklenburg, NC</td>
<td>-0.69</td>
<td>-0.72</td>
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<tr>
<td>100</td>
<td>Baltimore City, MD</td>
<td>-0.86</td>
<td>-0.70</td>
<td></td>
<td></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
- Poverty Share
- Racial Segregation
- Gini Coef.
- Fraction Single Moms
- Social Capital
- Student-Teacher Ratio

Causal Correlation:
- -0.51
- -0.14
- -0.51
- -0.76
- -0.57
- 0.70
- -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

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

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

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Effect of 1 SD Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction Black Residents</td>
<td>-0.01</td>
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<tr>
<td>Poverty Share</td>
<td>-0.06</td>
</tr>
<tr>
<td>Racial Segregation</td>
<td>-0.16</td>
</tr>
<tr>
<td>Gini Coef.</td>
<td>-0.69</td>
</tr>
<tr>
<td>Fraction Single Moms</td>
<td>-0.11</td>
</tr>
<tr>
<td>Social Capital</td>
<td>0.66</td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>-0.73</td>
</tr>
</tbody>
</table>

Causal Correlation:

-0.01
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
-0.14
-0.02
0.14
-0.06
-0.07
0.00
-0.21
House Prices

- Does it cost more to live in a county that improves children’s outcomes?

- Correlation between causal exposure effect and median rent is negative (-0.3) across CZs
  - Rural areas produce better outcomes

- Across counties within CZ’s, correlation is +0.07 overall

- But significant heterogeneity across CZ’s with low vs. high levels of segregation/sprawl
  - Split sample into CZs based on average commute times
Rents vs. Exposure Effects Across Counties in CZs with High Commute Times

CZs with Populations above 100,000

- Median Monthly Rent ($)
- Annual Exposure Effect (Percentiles)

Slope: $523.2
(92.4)
Rents vs. Exposure Effects Across Counties in CZs with Low Commute Times

CZs with Populations above 100,000

Slope: -61.1
(82.3)
Rents vs. Exposure Effects Across Counties in Small (Rural) CZs
CZs with Populations below 100,000

Slope: -176.3 (41.1)
Why are causal effects on children not fully capitalized in house prices?

- One explanation: causal effects not fully observed

Test by splitting place effects into “observable” and “unobservable” components

- Define observable component as projection of place effect onto observables: poverty rate, commute time, single parent share, test scores, and Gini

- Define unobservable component as residual from this regression, shrunk to adjust for measurement error

Regress median rent on observable and unobservable components

- Roughly one-third of the variance is “observable” and two-thirds is not
Median Rent vs. Observable Component of Place Effect Across Counties
CZs with Populations Above 100,000

Slope: $1,025.6 (83.5)
Median Rent vs. Unobserved Component of Place Effect Across Counties

CZs with Populations Above 100,000

Median Monthly Rent ($)

Slope: $216.8
(123.6)
Main lesson: substantial scope to move to areas that generate greater upward mobility for children without paying much more

- Especially true in cities with low levels of segregation

In segregated cities, places that generate good outcomes without having typical characteristics (better schools, lower poverty rates) provide bargains

- Ex: Hudson County, NJ vs. Bronx in New York metro area

Encouraging for housing-voucher policies that seek to help low-income families move to better areas
Conclusion: Policy Lessons

How can we improve neighborhood environments for disadvantaged youth?

1. Short-term solution: Provide targeted housing vouchers at birth conditional on moving to better (e.g. mixed-income) areas

   MTO experimental vouchers increased tax revenue substantially → taxpayers may ultimately gain from this investment
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**:
  - $841.1$
Conclusion: Policy Lessons

- How can we improve neighborhood environments for disadvantaged youth?

1. Short-term solution: Provide targeted housing vouchers at birth conditional on moving to better (e.g. mixed-income) areas

   - MTO experimental vouchers increased tax revenue substantially → taxpayers may ultimately gain from this investment

2. Long-term solution: improve neighborhoods with poor outcomes, concentrating on factors that affect children

   - Estimates here tell us which areas need improvement, but further work needed to determine which policies can make a difference
Download County-Level Data on Social Mobility in the U.S.
www.equality-of-opportunity.org/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>
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<tbody>
<tr>
<td>Online Data Table 1: Preferred Estimates of Causal Place Effects by Commuting Zone</td>
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<tr>
<td>Online Data Table 2: Preferred Estimates of Causal Place Effects by County</td>
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<tr>
<td>Online Data Table 3: Complete CZ-Level Dataset: Causal Effects and Covariates</td>
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<td>Online Data Table 4: Complete County-Level Dataset: Causal Effects and Covariates</td>
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<td>Online Data Table 5: Pairwise Place Effects by Origin-Destination Pairs of Commuting Zones</td>
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<td>Online Data Table 6: Parent Income Distribution by Child’s Birth Cohort</td>
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