# Neighborhood Effects

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# Midterm Research Outline: Due April 29

Each student should write a “research outline” using the guidelines posted on the website. The outline should be 2-3 pages and is due two weeks from today.

The purpose is just to help you make progress on your final research proposal, which is due at the end of class

The most important part of the outline is a clear discussion of your intended research question, as well as discussion of the existing literature (see guideline document)

Write as much as you can, including discussion of any potential problems with your project. I will provide detailed individual feedback to each student, so the more information I have the more helpful I can (hopefully) be.

“Neighborhood and Network Effects,” Topa and Zenou,
*Handbook of Regional and Urban Economics*, 2015

# Neighborhood Effects as Non-Market Interactions

Important question across the social sciences is how *non-market* social interactions between agents affect economic outcomes

Broad literature encompassing peer effects in education, labor market referrals and networks, social network effects on health behaviors, reviews and expert opinions on products purchases, herding in investment decisions, and many other subjects

One well-studied form of this question asks whether neighborhoods affect the outcomes of residents, and whether it's possible to improve outcomes by moving people to better neighborhoods

Neighborhood effects arise from both social interactions between residents and place-specific effects (ex: local institutions and businesses)

# Common Topics in Neighborhood Effects

Does the neighborhood in which a child grows up affect their lifetime income? Educational attainment? Health?

Relatedly, does childhood neighborhood affect behavior? For example, are children who grew up in a high crime neighborhood more likely to commit a crime themselves?

Do residents recommend each other for jobs (job referrals), or provide notice of new employment positions?

Do job referrals also depend on ethnicity, race, or other demographic characteristics?

Do new immigrants benefit from residing in a neighborhood with co-ethnics (ex: job and housing networks), or does this slow language acquisition and leave them isolated?

# Mechanisms for Neighborhood Effects

Neighborhood effects can come from three different mechanisms:

1. Social interactions among residents (endogenous peer effects)
2. Characterstics of the residents ("contextual effects")
3. Correlated shocks

Example: we want to know whether moving a child to a neighborhood where most children attend college will increase the likelihood of college attendance

It's possible that interactions with studious and motivated children in the neighborhood makes a child work hard to attend college

Another possibility: seeing many college educated adults in the neighborhood changes a child's perspective on college

Lastly, it could be simply all neighborhood children attend the same school or private tutoring center

# Identifying Neighborhood Effects: Reflection Problem

Early literature on neighborhood effects regressed individual outcomes $y_{i,r}$ on average outcomes in the neighborhood $E(y_r)$, average characteristics of residents $E(x_r)$, and individual characteristics $x_{i,r}$

$$y_{i,r} = \phi_2 E(y_r) + \gamma E(x_r) + \beta x_{i,r} + \epsilon_{i,r} \tag{11}$$

Assume that $\epsilon_{i,r}$ is i.i.d., can you see any problems with this approach?

Mean outcomes and characteristics must be collinear: $E(y_r) = \left(\frac{\gamma+\beta}{1-\phi_2}\right) E(x_r)$

Reflection problem (Manski 1993): impossible to distinguish interactions effects $\phi_2$ from contextual effects $\gamma$ by regressing individual outcomes on means

Policy relevant difference: interaction effects have social multipliers.

Ex: helping a neighborhood child to go to college helps the other children through interaction effects. If neighborhood effects are due to contextual effects, then no multiplier

# Identifying Neighborhood Effects: Sorting and Correlated Shocks

Another issue is that neighborhood choice is endogenous

Ex: parents who move to a neighborhood with high achieving students may also provide substantial educational support to their children

A final issue is "correlated shocks": neighborhood outcomes may be similar not due to peer effects, or contextual effects, but simply because people in the same neighborhood are affected by the same neighborhood level shocks

Ex: a high quality tutoring center opens up in the neighborhood

Note that many neighborhood papers are interested in estimating a general neighborhood effect and do not try to separate peer effects, contextual effects, and correlated shocks. (ex: Chetty Hendren papers)

However, these papers must still deal with the sorting issue–what are possible identification strategies?

# Literature on Neighborhood Effects

# Exogenous Assignment to Neighborhoods: Refugee Programs

Many countries have refugee settlement agencies that place new refugees into different locations somewhat independent of the characteristics of the refugees

These settlement policies can be used as a source of exogenous variation in location characteristics

Beaman (ReStud 2012) looks at refugees resettled in US, finds that new refugees are less likely to find a job in a place where many similar refugees were recently located (competition for jobs)

However, also finds that refugees placed into communities with a long history of resettlement (but not many recent refugees) are more likely to find a job

Edin et al. (2003) and Aslund et al. (2011) uses a Swedish refugee program to examine effect of ethnic neighborhood size on earnings and educational attainment, finding effects increasing in ethnic concentration.

Also see Damm (2009, 2014) for evidence using a refugee program in Denmark

# Random Assignment at Very Small Spatial Level

Bayer, Ross, and Topa (JPE 2008) study whether neighbors recommend each other for jobs

Authors argue that while location choice is endogenous, at a very granular spatial level it is random

Ex: people may choose overall neighborhoods but the exact street or block is random due to limited availability of housing, thus neighbors are random

Specifically, they compare the likelihood of two residents of the same block to work at the same location, compared to two residents in the same *block group*, but not the same block

Clever strategy and easy to implement with good data. Influenced many subsequent papers on job referrals, including Hellerstein et. al. (2011), Hellerstein et al. (2014), and Schmutte (2014).

Also see Bayer, Mangum, Roberts (AER 2021) investigating neighborhood effects on housing investment.

# Experimental Variation from Moving Programs

Some countries have policies that try to help residents in poor or high crime neighborhoods move to better neighborhoods

Most famous is “Moving to Opportunity” program in US

Participants in high-poverty neighborhoods volunteered and were randomly assigned to three treatments: i) no new assistance ii) housing vouchers with no geographical restrictions iii) housing vouchers that could only be used in low-poverty neighborhoods

Program studied in multiple papers (Kling et al. QJE 2005, Kling et al. ECMA 2007) and found no effects on economic outcomes, but some evidence for positive effects on mental health

Recent paper by Chetty and Hendren (AER 2015) do find positive effects that depend on exposure time in new neighborhood

"The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects," Chetty, Raj and Hendren, Nathaniel, *Quarterly Journal of Economics*, 2018

# Chetty and Hendren Neighborhood Work

A series of papers by Chetty, Hendren, and co-authors have demonstrated that neighborhoods have important effects on children that vary with their exposure (how young were they when moved to new neighborhood)

These papers have launched a resurgence of interest in neighborhood effects

Chetty Hendren (QJE 2018, part 1) use administrative data (tax records) to look at earnings and other outcomes of adults who moved to new neighborhoods as children

They compare the outcomes of individuals who moved with the outcomes of those who never moved ("permanent residents"), in both the origin and destination locations

Find that earnings change in the direction of the move at a rate of 4% per year of exposure: children who move to better neighborhoods have higher earnings, children who moved to worse neighborhoods have lower earnings

# Data: Federal Income Tax Records, 1996-2012

Authors obtain tax data (with personal identifiers removed) from US Internal Revenue Service

In US, children are designated as ”dependents” (necessary to receive tax deductions), allowing authors to observe age of children for each filing adult

Authors focus on children born between 1980-1988, who were US citizens in 2013; note that 1980 cohort is already 16 in first year of their data, while 1988 is 8

Location defined by “commuting zones” (CZs): cluster of counties where residents live and work (economic areas, not political). Observable in tax data (ZIP code)

Divide sample into permanent residents (parents who stayed in one CZ throughout 1996-2012) and movers

Main sample is 24.6 million children living in CZs with populations of at least 250,000: 19.5m are permanent residents, 5.1m are movers

# Summary Statistics for Permanent Residents

| Variable | Mean (1) | Std. dev. (2) | Median (3) | Num. of obs. (4) |
|---|---|---|---|---|
| Panel A: Permanent residents: Families who do not move across CZs | | | | |
| Parent family income | 89,909 | 357,194 | 61,300 | 19,499,662 |
| Child family income at 24 | 24,731 | 140,200 | 19,600 | 19,499,662 |
| Child family income at 26 | 33,723 | 161,423 | 26,100 | 14,894,662 |
| Child family income at 30 | 48,912 | 138,512 | 35,600 | 6,081,738 |
| Child individual income at 24 | 20,331 | 139,697 | 17,200 | 19,499,662 |
| Child married at 26 | 0.25 | 0.43 | 0.00 | 12,997,702 |
| Child married at 30 | 0.39 | 0.49 | 0.00 | 6,081,738 |
| Child attends college between 18–23 | 0.70 | 0.46 | 1.00 | 17,602,702 |
| Child has teen birth (females only) | 0.11 | 0.32 | 0.00 | 9,670,225 |
| Child working at age 16 | 0.41 | 0.49 | 0.00 | 13,417,924 |

# Stats for Movers (only 1 move, at least 100mi)

Mean, Std. dev, Median, Obs

| Panel C: Primary analysis sample: families who move exactly once across CZs | | | | |
|---|---|---|---|---|
| Parent family income | 97,064 | 369,971 | 58,700 | 1,553,021 |
| Child family income at 24 | 23,867 | 56,564 | 18,600 | 1,553,021 |
| Child family income at 26 | 32,419 | 108,431 | 24,500 | 1,160,278 |
| Child family income at 30 | 47,882 | 117,450 | 33,600 | 460,457 |
| Child individual income at 24 | 19,462 | 48,452 | 16,000 | 1,553,021 |
| Child married at 26 | 0.25 | 0.43 | 0.00 | 1,016,264 |
| Child married at 30 | 0.38 | 0.49 | 0.00 | 460,457 |
| Child attends college between 18–23 | 0.69 | 0.46 | 1.00 | 1,409,007 |
| Child has teen birth (females only) | 0.11 | 0.32 | 0.00 | 769,717 |
| Child working at age 16 | 0.39 | 0.49 | 0.00 | 1,092,564 |

# Child Outcomes by Parental Income and Location

Authors are interested in how childhood exposure to a location affects adult outcomes, conditional on parental income

Measure incomes using percentile ranks within a birth cohort ($y_i$), following earlier work. Parental income ($p_i$) is also ranked based on child birth cohort (ex: rank among all parents with kid born in 1985)

$\bar{y}_{pcs}$: mean rank of children in cohort $s$ with parents at income percentile $p$ in CZ $c$

Authors first show $\bar{y}_{pcs}$ is linear in parent rank (example for Chicago next slide)

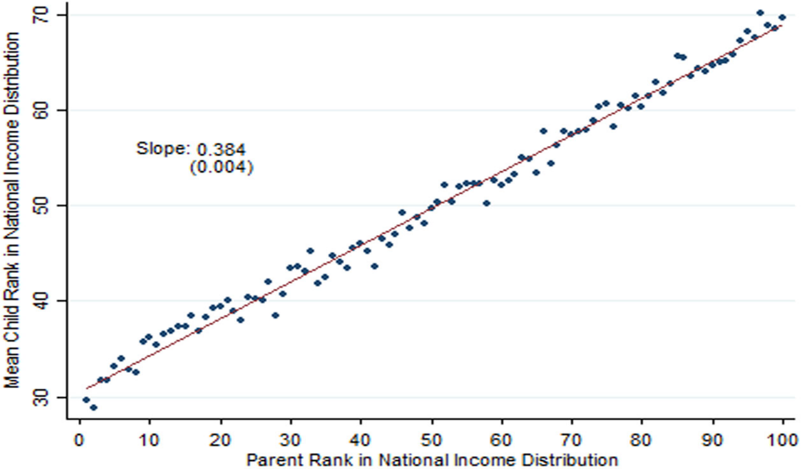
Given linearity, estimate $\bar{y}_{pcs}$ with regression: $y_i = \alpha_{cs} + \phi_{cs} p_i + \epsilon_i$

Then predict $\bar{y}_{pcs}$ as $\bar{y}_{pcs} = \hat{\alpha}_{cs} + \hat{\phi}_{cs} p$

(I assume this helps for cases where the data is too sparse to simply calculate the mean)

# Child Income Rank vs Parents' Rank, 1980 Cohort, Chicago

Parents are permanent residents of Chicago CZ; child income at 30



# Geography of Intergenerational Mobility (Chetty et al. 2014)

Earlier paper found large variation in mobility (child rank conditional on parental rank) across locations in US

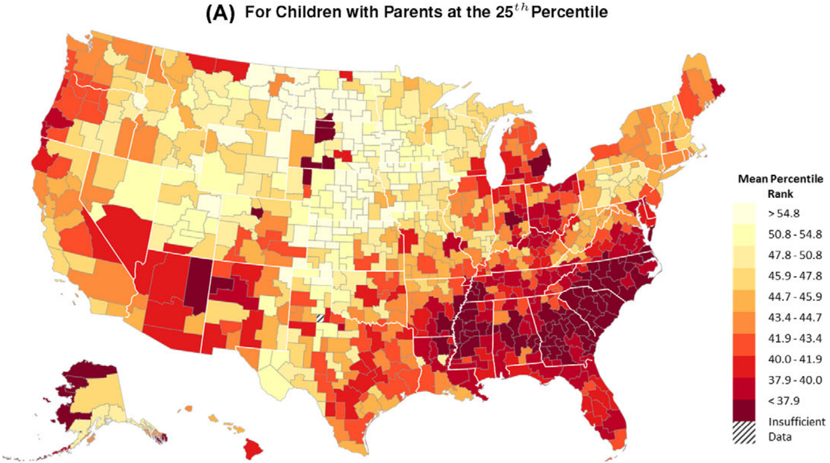
Ex: prob a child reaches top quintile, given parents in bottom quintile, is 4.4% in Charlotte, NC, 10.8% in Salt Lake City, UT, and 12.9% in San Jose, CA

This descriptive paper led to lots of follow-up work, including extensive work on causal effects of neighborhoods: https://opportunityinsights.org/neighborhoods/

Opportunity Atlas Interactive Maps: https://www.opportunityatlas.org/

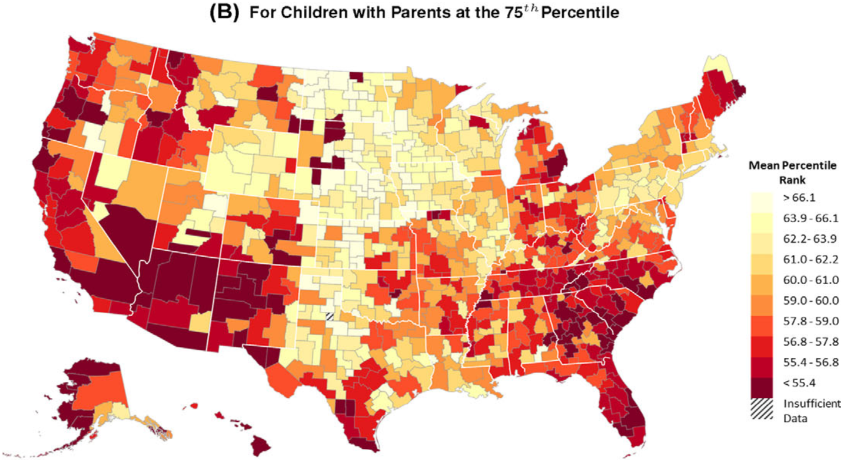
# Mean Child Rank by CZ with Parents at **25th** Ptile

Income at age 30 for 1980 cohort; parent HH income 25pt: $30,000



# Mean Child Rank by CZ with Parents at **75th** Ptile

Income at age 30 for 1980 cohort; parent HH income 75pt: $97,000



# Estimating Exposure Effects from Ideal Experiment

"Our objective is to determine how much a child's potential outcomes would improve on average if he were to grow up in an area where the permanent residents' outcomes ar 1 percentile point higher."

Exposure effect at age $m$: effect of child spending year $m$ in area where permanent residents' outcomes are 1 percentile point higher

If children are *randomly* assigned to new neighborhoods (CZs) $d$ age at $m$, then can predict adult outcome $y_i$ with outcomes of residents in $d$, $\bar{y}_{pds}$, where $p$ is parent percentile and $s$ is child birth cohort:

$$y_i = \alpha_m + \beta_m \bar{y}_{pds} + \theta_i \tag{3}$$

Exposure effect is then $\gamma_m = \beta_m - \beta_{m+1}$ (since $\beta_m$ captures effect of multiple years)

Random assignment implies $E[\theta_i \bar{y}_{pds} = 0]$, but not (likely) true in observational data

# Estimating Exposure Effects from Observational Data

$$y_i = \alpha_m + \beta_m \bar{y}_{pds} + \theta_i \tag{3}$$

Without random assignment, regressing child outcomes on CZ PR outcomes yields a coefficient:

$$b_m = \beta_m + \delta_m \quad \text{where } \delta_m = \frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})}$$

Can we identify the exposure effect $\gamma_m = \beta_m - \beta_{m+1}$ if $\delta_m \neq 0$?

Yes! If we assume that the selection effect does not vary with the age at move: $\delta_m = \delta, \forall m$

Then $\gamma_m = \beta_m - \beta_{m+1} = (b_m - \delta) - (b_{m+1} - \delta)$

Restating key assumption: families may select into new neighborhoods, but age of child when family moves is uncorrelated with anything affecting outcomes

# Estimating Exposure Effects with $\delta_m = \delta$

Authors look at outcomes at age $T$ (ex: $T = 24$), exposure effect must be zero for any move after $T$ since outcome already realized before move: $\beta_m = 0$ if $m > T$

Implies that authors can estimate selection effect $\delta$ by regressing outcomes at $T$ on moves $m$ *after* $T$

Estimate $y_i = \alpha_m + b_m \bar{y}_{pds} + \theta_i$ when $m > T$, then $b_m = \beta_m + \delta = 0 + \delta$

Ex: maybe well-educated parents (conditional on income) are more likely to move to places with other well-educated people, even after children have left home

With an estimate of $\delta$, authors can calculate $\beta_m = b_m - \hat{\delta}$.

Aggregating all $\gamma_m = \beta_m - \beta_{m+1}$ estimates yields $\beta_0 = \sum_0^T \gamma_m$

Interpret $\beta_0$ as causal effect of growing up *from birth* in an area with 1 percentile better outcomes

# Implementation

Specification (3) for ideal random assignment: $y_i = \alpha_m + \beta_m \bar{y}_{pds} + \theta_i$

Specification for actual observational data:

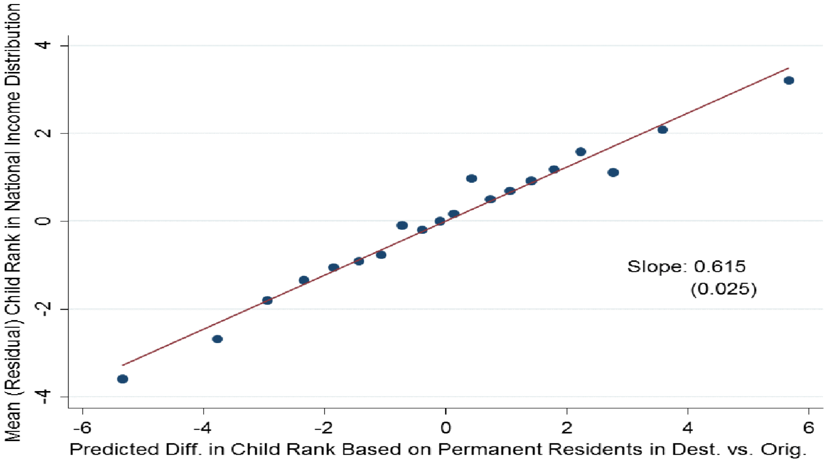
$$y_i = \alpha_{qos} + b_m \Delta_{odps} + \epsilon_{1i}, \quad \text{where } \Delta_{odps} = \bar{y}_{pds} - \bar{y}_{pos} \tag{4}$$

Term $\alpha_{qos}$ is fixed effect for parental income decile $q$ (not percentile to reduce FEs), origin $o$, and birth cohort $s$

$\Delta_{odps}$ is difference in predicted income rank (at age 24) of permanent residents in destination versus origin, for parental income rank $p$ in birth cohort $s$

Ex: a child born in $s = 1985$ to parents in 30th income percentile moves at age $m = 13$. In origin, the 1985 cohort for $30th$ percentile has income percentile 35 at age 24; in destination this cohort parent group has income percentile 40 at age 24. If $b_m = 0.1$ then we predict mover income rank at 24 to increase by 0.5 percentile points.

# Residuals Plot: Movers' vs Permanent Residents in $d$, $m = 13$




V. axis: $y_i^r = y_i - E[y_i|q, o, s]$; H. axis: $\Delta_{odps}^r = \Delta_{odps} - E[\Delta_{odps}|q, o, s]$

# Full Non-parametric Specification

Previous slide showed effect for $m = 13$; authors then run for all ages:

$$y_i = \alpha_{qosm} + \sum_{m=9}^{30} b_m I(m_i = m)\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s I(s_i = s)\Delta_{odps} + \epsilon_{2i} \tag{5}$$

Notice that $\alpha_{qosm}$ now also captures age at move

The second summation term allows for move effects to vary by cohort, which helps to deal with greater measurement error for earlier cohorts (since data starts in 1996, observe 1980 cohort from age 16, but 1988 cohort from age 8)

Next slide: authors plot estimates of $b_m$; exposure effect is $\gamma_m = b_m - b_{m+1}$

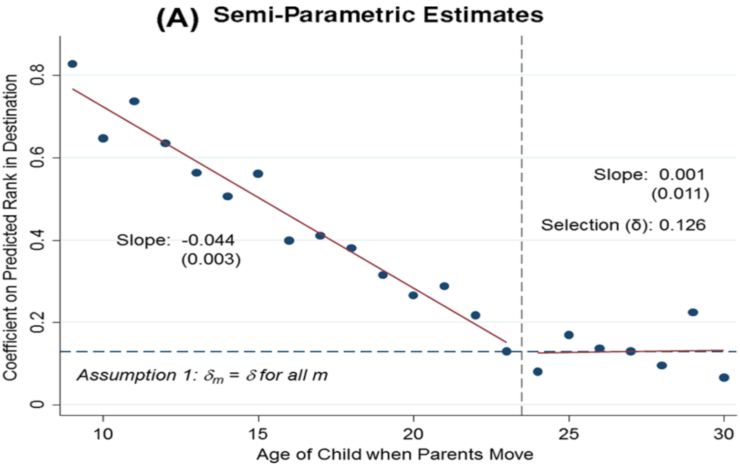
Also show estimates of $\delta$ by running (5) for $m > 24$ (e.g., parents move when child is 24+)

Note: sample in main estimates restricted to families observed to move only once (not multiple moves)

# Estimates of $b_m$

For each year of exposure, income rank at 24 changes by $0.044 \times \Delta_{odps}$

Selection is positive $\delta_m > 0$ but unchanging $\delta_{25} = \delta_{26} = \delta_{m>24} = \delta$



# Mechanisms: Critical Age vs Exposure

Critical age models: effect of exposure to new neighborhood depends on age when child is exposed (ex: early exposure has larger effect on language acquisition than later)

Critical age models (where early matters more) and exposure models both suggest that effect of moving to a new neighborhood will decline with age at move (later age and fewer years of exposure are collinear)

Ex: children who move to a better neighborhood earlier have better outcomes: consistent with earlier age more important and longer exposure more important

To distinguish these two effects, authors look at families that move *multiple* times. Ex: child moves from bad to good, and then back to bad; critical age model would suggest more of an impact than exposure model (the final bad period should be less important if there are critical age effects)

Authors find similar exposure effect when controlling for age at each move—argue no evidence for critical age effects

# Robustness: Family Fixed Effects

Key assumption that selection is uncorrelated with age at move ($\delta_m = \delta$) may be too strong

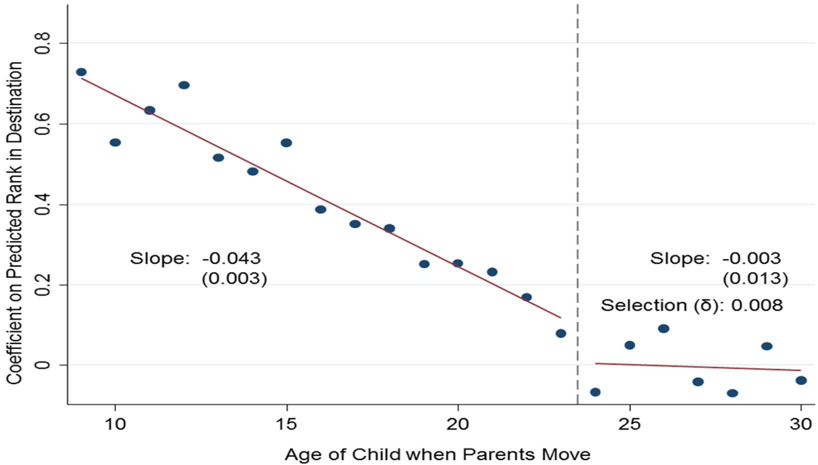
Ex: families who value education more may purposefully move to a better neighborhood when child is younger (学区房)

Authors add family fixed effects to regression, thus comparing siblings who move to new neighborhood at same time, but have different exposure due to age difference

Find similar exposure effect, but now estimate zero selection effect $\delta = 0$

Authors argue this is consistent with selection that doesn't vary with age at move: families where children would have better outcomes move to better areas, but this family effect would be differenced out across siblings

# Family Fixed Effects Plot



# Robustness: Other Checks

Examine exposure effect when looking at moves caused by “displacement shocks,” or arguably exogenous events that cause a large number of people to move out of a CZ (ex: natural disasters)

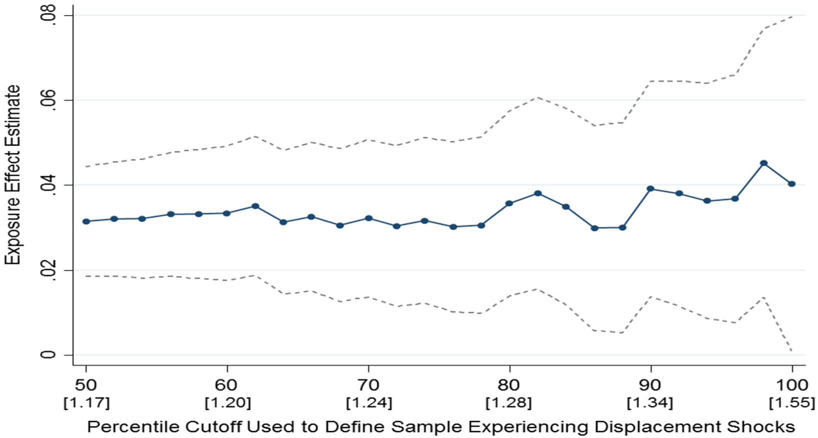
Define displacement shock statistically (not based only on observable events) as outflow in a given year divided by average annual outflow over entire sample; when this measure is significantly greater than 1, it captures unusually large outflows

Then compare exposure effects estimated at different levels of displacement, find similar exposure estimates for cases with moderate and high shocks

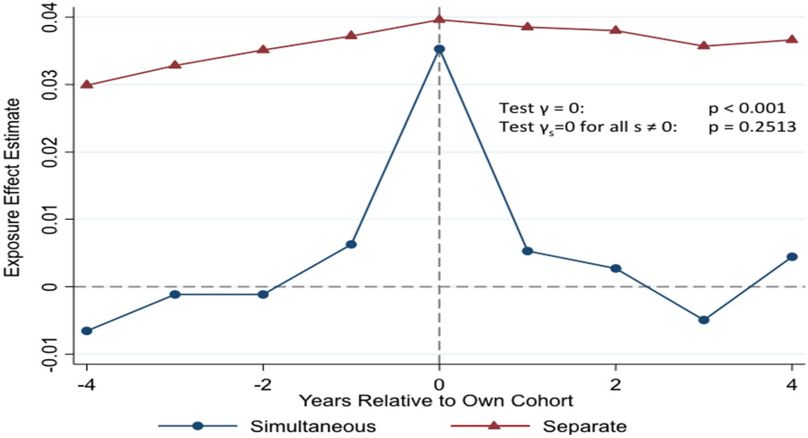
Additional check: use permanent resident predictions based on other cohorts; idea is that difference with other cohorts should have a weaker effect than own cohort

Ex: outcomes may change for different cohorts within a location (ex: school quality increases), but effect should be strongest for same cohort (ex: if school quality increases after a student has graduated it should not affect income rank)

# Exposure Effects using Displacement Shocks



# Exposure Effects Placebo Test: Other Cohorts



# Other Outcomes

Authors examine college attendance, marriage age, teenage birth, and employment at 16 using a slight modification of their main design

For college attendance, they replace $\Delta_{odps}$ with $\Delta^{C}_{odps} = C_{pds} - C_{pos}$: the difference in fraction of children 18-23 attending college in the origin and destination neighborhoods

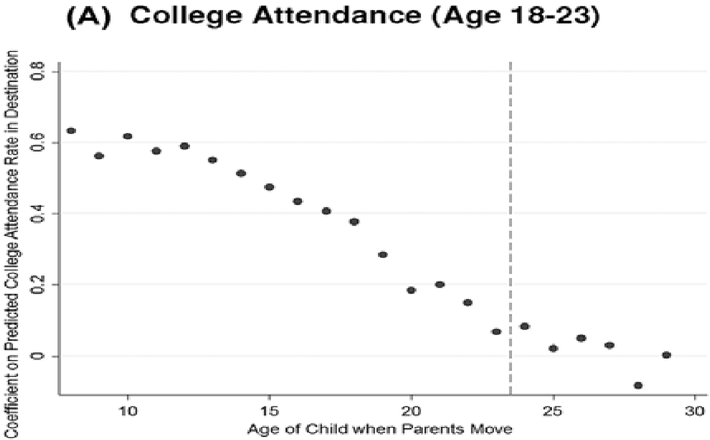
For marriage, replace $\Delta_{odps}$ with $\Delta^{M}_{odps} = M_{pds} - M_{pos}$: difference in fraction of children married at age 26 between origin and destination

Find exposure effect for college is $\gamma = 0.037$ and for marriage $\gamma = 0.025$

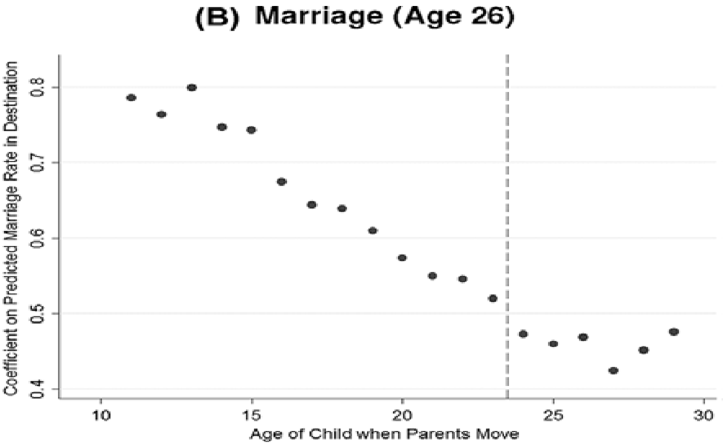
For teenage birth, find sharp effects for girls between age 13 and 18

For employment at age X: find sharp discontinuity right before X—moving to a place before age X could have a large effect, but not at X+1, suggests environment around age X is important (Ex: availability of summer jobs)

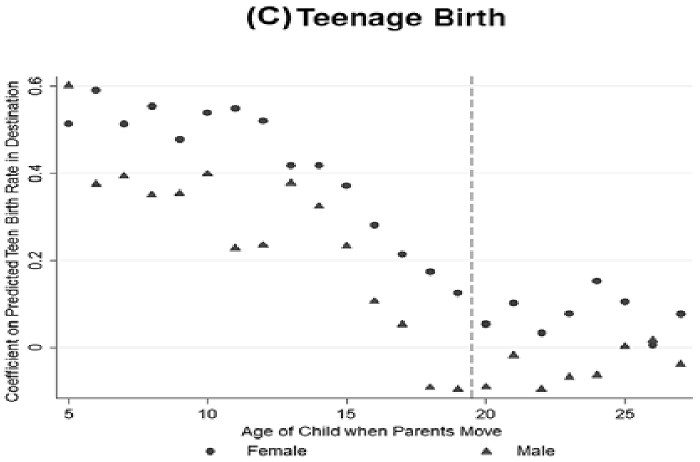
# College Attendance



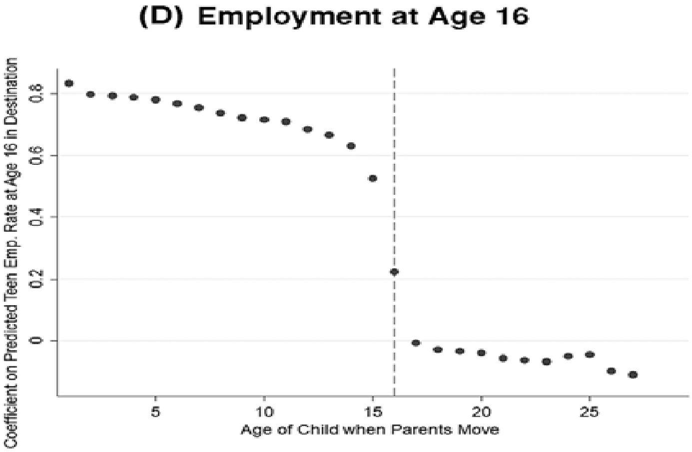
# Marriage Age



# Teenage Birth



# Employment at Age 16



# Conclusion

Very impressive paper, lots to learn

If you find this subject interesting, see follow-up work on opportunity insights website

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