Neighborhood Effects and Child Outcomes: Evaluating the Recent Empirical Literature

Michael Galperin

Econ 350, Spring 2022

February 26, 2020

Table of Contents

Reminder: Chetty and Hendren (2018a) Estimation Strategy

- Given birth cohort s and CZ c, let p be the *parents'* percentile in the *national* income distribution.
- Let y_i denote the child's national income rank in adulthood.
- Authors assume linearity and estimate the following regression on the sample of children with permanent resident parents:

$$y_i = \alpha_{cs} + \psi_{cs} p_i + \varepsilon_i$$

  where p_i is the percentile rank of child i's parent in the national income distribution.

- Then, predict mean percentile ranks given c, s, and parent rank p:

$$\bar{y}_{pcs} = \hat{\alpha}_{cs} + \hat{\psi}_{cs} p$$

- $\bar{y}_{pcs}$ is the measure of neighborhood quality.

CH 2018: Definition of Exposure Effects

- Thought experiment: randomly assign child of parental income rank p, to new neighborhood d, starting at age m, for remainder of childhood. Estimate:

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

  where θ_i captures unobservable determinants of y_i (e.g., family inputs).

- Given random assignment at age m, and conditional on spending all years of childhood after m in destination d, β_m is the impact of a 1 percentile increase in the adult outcomes of permanent-d-resident children on i's adult outcome rank.
- *Exposure effect* at age m is $\gamma_m = \beta_m - \beta_{m+1}$, the effect on y_i of spending the year from age m to age $m+1$ in the destination.
- $\beta_0 = \sum_{t=0}^{T} \gamma_m$ is the impact on y_i from random assignment to d at birth.

CH 2018: Key Identifying Assumption

- Obviously, migration is not random, and estimating the above equation using observational data will yield estimates:

$$b_m = \beta_m + \underbrace{\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})}}_{\text{Selection Bias}}$$

- This will bias estimated age-based exposure effects γ_m since:

$$b_m - b_{m+1} = \underbrace{\beta_m - \beta_{m+1}}_{\gamma_m} + \left(\left[\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})} \right]_m - \left[\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})} \right]_{m+1} \right)$$

- The authors solve this problem by assuming that the term $cov(\theta_i, \bar{y}_{pds})/var(\bar{y}_{pds})$ is constant across ages. In other words, it is assumed that selection effects do not vary with the child's age at move.
- This rules out, e.g., differential preferences among parents by age of child for local amenities, such as school quality, that are not fully captured in adult income percentile rank $\bar{y}_{pds}$.

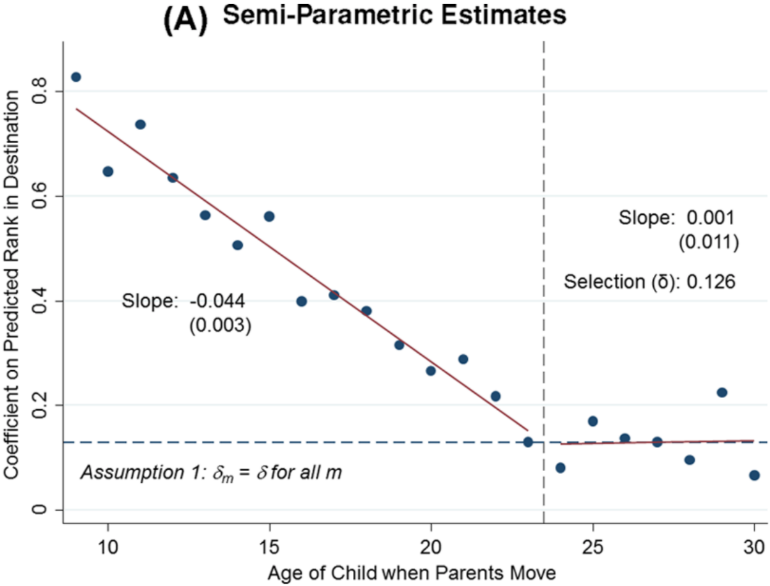
Estimation using Observational Data

- Define $\Delta_{odps} = \bar{y}_{pds} - \bar{y}_{pos}$ as the difference in mean income rank (at age 24) of permanent residents in the destination (d) location versus origin (o).
- The authors estimate:

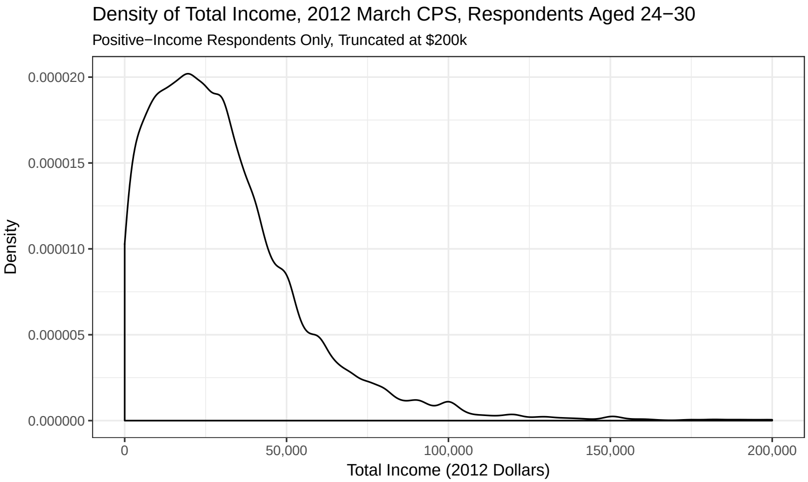
$$y_i = \alpha_{qosm} + \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\}\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s \mathbf{1}\{s_i = s\}\Delta_{odps} + \varepsilon$$

  where α_{qosm} is an (origin $\times$ parent income decile $\times$ birth cohort $\times$ age) fixed effect.
- $\hat{b}_m$ is the average effect on age-24 income rank y_i, conditional on moving from o to d at age m, of a 1 percentile increase in Δ_{odps}.
  - Assumed that within parent income deciles q, changes in this spread are driven entirely by $\bar{y}_{pds}$, not $\bar{y}_{ods}$.

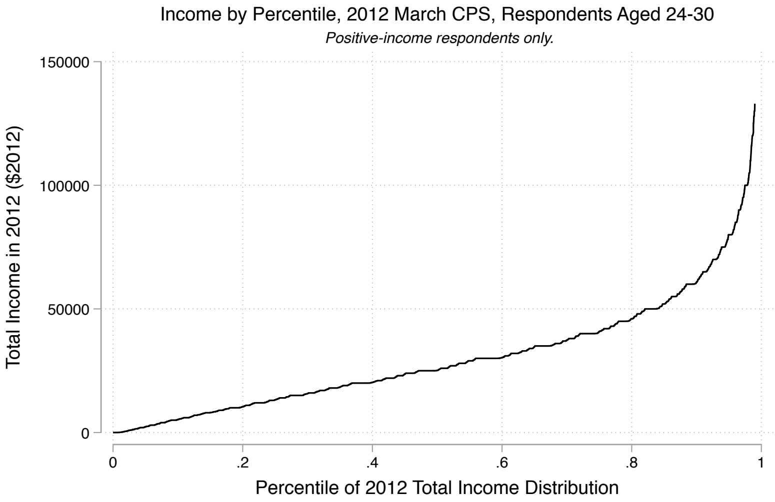
Results: $\hat{b}_m$ as function of age m



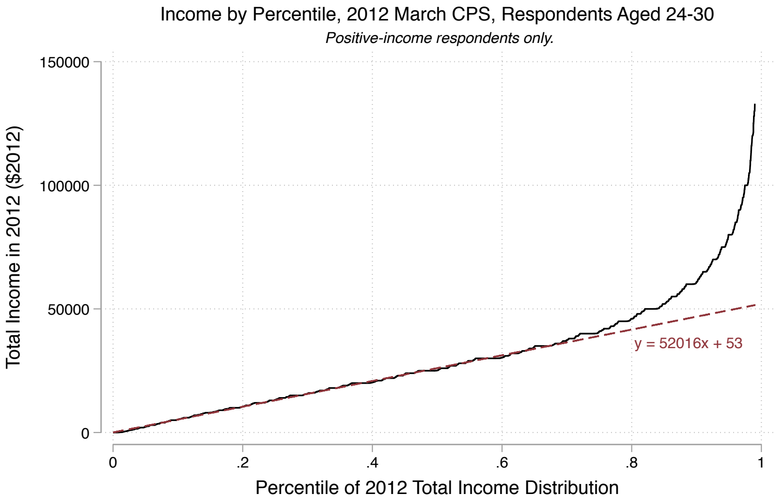
Mapping Ranks to Dollars



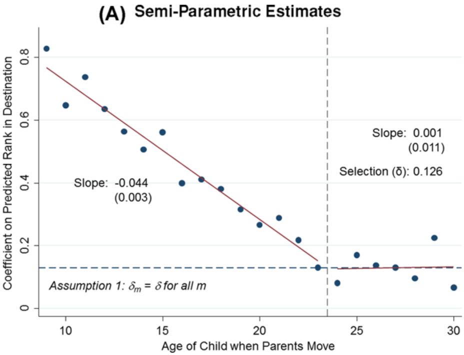
Mapping Ranks to Dollars



Mapping Ranks to Dollars

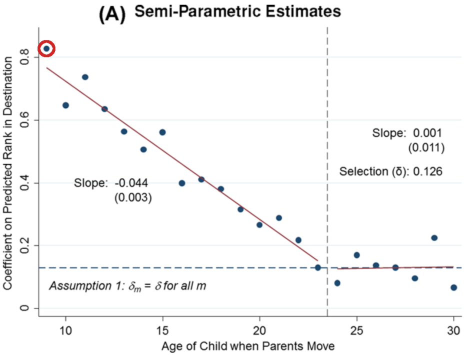


Mapping Neighborhood Effects to Dollars



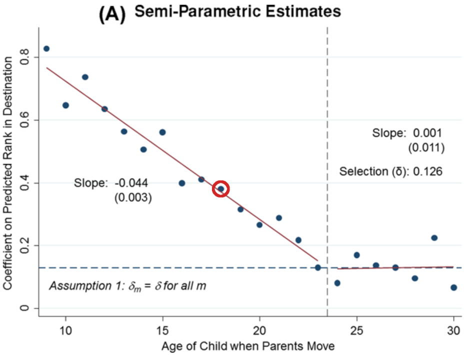
- Answering Jack's question: How big are the effects of moving to destination with 1 pctile better outcomes?

Mapping Neighborhood Effects to Dollars



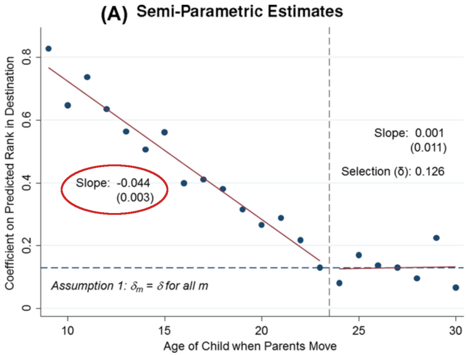
- Answering Jack's question: How big are the effects of moving to destination with 1 pctile better outcomes?
- Move age 8: $\hat{b}_8 \approx 0.82$ $\approx$ \$427/year in income.

Mapping Neighborhood Effects to Dollars



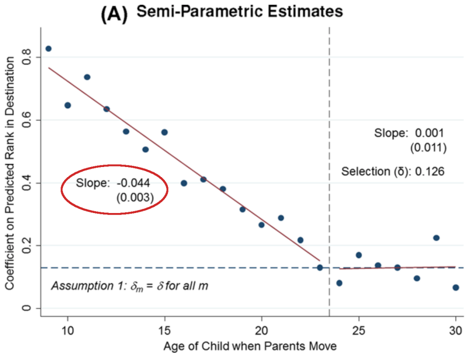
- Answering Jack's question: How big are the effects of moving to destination with 1 pctile better outcomes?
- Move age 8: $\hat{b}_8 \approx 0.82$ $\approx$ \$427/year in income.
- Move age 18: $\hat{b}_{18} \approx 0.39$ $\approx$ \$203/year in income.

Mapping Neighborhood Effects to Dollars



- Answering Jack's question: How big are the effects of moving to destination with 1 pctile better outcomes?
- Move age 8: $\hat{b}_8 \approx 0.82$ $\approx$ \$427/year in income.
- Move age 18: $\hat{b}_{18} \approx 0.39$ $\approx$ \$203/year in income.
- Every year in 1 pctile better destination $\approx$ \$23 in yearly adult income.

Mapping Neighborhood Effects to Dollars



- Answering Jack's question: How big are the effects of moving to destination with 1 pctile better outcomes?
- Move age 8: $\hat{b}_8 \approx 0.82$ $\approx$ \$427/year in income.
- Move age 18: $\hat{b}_{18} \approx 0.39$ $\approx$ \$203/year in income.
- Every year in 1 pctile better destination $\approx$ \$23 in yearly adult income.

- Move age 0, assuming constant age effects (linearly decreasing b_m)?

$$\underbrace{(0.126 + 0.044(23.5))}_{=1.16 \text{ percentiles}} \times \frac{52,016}{100} \approx \$604/\text{year}$$

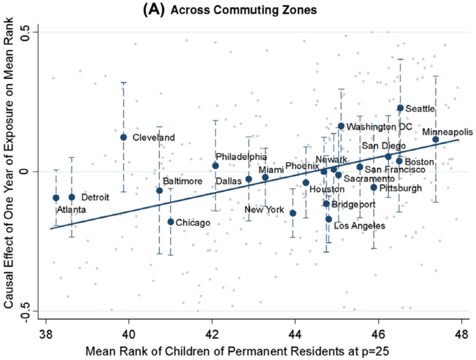
Mapping of Percentiles to Incomes in Chetty et al. (2018b)

- To map percentiles to dollars, Chetty et al. (2018b) estimate:

$$\bar{y}^{\$}_{pc} = \alpha + \beta_p \bar{y}_{pc} + \varepsilon$$

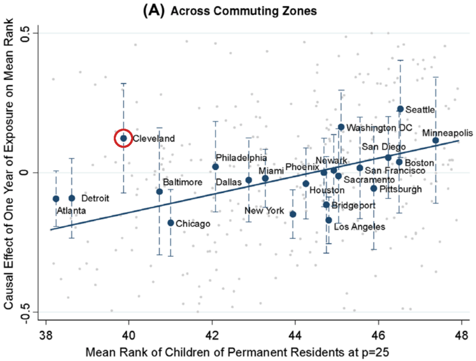
  - $\bar{y}^{\$}_{pc}$: Mean income of children of permanent residents in CZ c.
  - $\bar{y}_{pc}$: Mean income rank of children of permanent residents in CZ c
  - Estimated across CZs in sample of children of permanent residents, separately by *parent* income rank p.
- $\hat{\beta}_{25} = \$818$
  - "A 1 percentile increase in income [rank] translates to an additional \$818 at age 26 on average."
- "The mean income of children with below–median income parents is \$26,091; therefore, a 1 percentile increase corresponds to approximately a $\frac{818}{26{,}091} = 3.14\%$ increase in income."

CZ–level analogue in Chetty et al. (2018b)



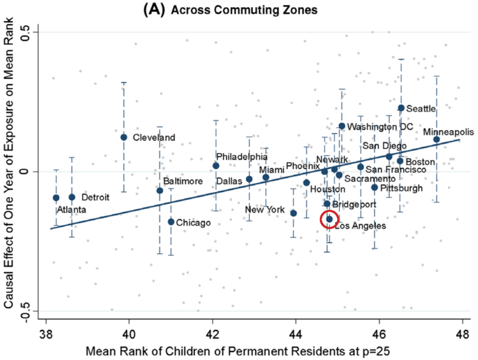
- This plot: CZ–level one–year exposure effects, against $\bar{y}_{25,c}$.

CZ–level analogue in Chetty et al. (2018b)



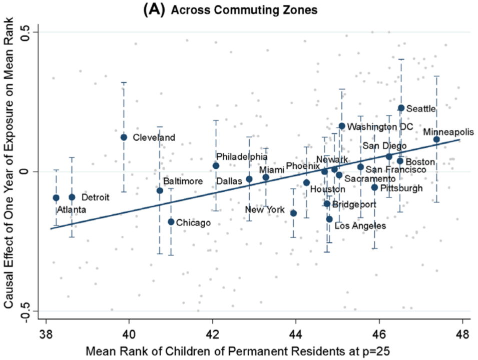
- This plot: CZ–level one–year exposure effects, against $\bar{y}_{25,c}$.
- "One year of exposure to Cleveland instead of average CZ raises child's income by $0.12 \times 3.14\% = 0.38\%$."

CZ–level analogue in Chetty et al. (2018b)



- This plot: CZ–level one–year exposure effects, against $\bar{y}_{25,c}$.
- "One year of exposure to Cleveland instead of average CZ raises child's income by $0.12 \times 3.14\% = 0.38\%$."
- For Los Angeles: $-0.17 \times 3.14\% = -0.53\%$.

CZ–level analogue in Chetty et al. (2018b)



- This plot: CZ–level one–year exposure effects, against $\bar{y}_{25,c}$.
- "One year of exposure to Cleveland instead of average CZ raises child's income by $0.12 \times 3.14\% = 0.38\%$."
- For Los Angeles: $-0.17 \times 3.14\% = -0.53\%$.

- Then, extrapolate to presence in CZ since birth.
  - 20 yrs. exposure to Cleveland: $20 \times 0.38\% = 7.5\%$ increase in adult income.
  - 20 yrs. exposure to L.A.: $20 \times -0.53\% = 10.7\%$ decrease.

Estimation: Parametric Model

- Original model has more than 200,000 fixed effects α_{qosm}.
- Authors also estimate a "more tractable" alternative: a parametric model estimating cohort– and age–specific slopes instead of fixed effects.

$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\} \left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\} \left(\zeta_m^1 + \zeta_m^2 p_i\right)$$
$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\} \Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\} \Delta_{odps} + \varepsilon_i$$

Discussion: Parametric Model

What is being controlled for here?

$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\}\left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\}\left(\zeta_m^1 + \zeta_m^2 p_i\right)$$

$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\}\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\}\Delta_{odps} + \varepsilon_i$$

Discussion: Parametric Model

What is being controlled for here?

$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\}\left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\}\left(\zeta_m^1 + \zeta_m^2 p_i\right)$$
$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\}\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\}\Delta_{odps} + \varepsilon_i$$

- A separate slope and intercept for $\bar{y}_{pos}$ within each birth cohort.
  - Intended to control for origin.

Discussion: Parametric Model

What is being controlled for here?

$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\} \left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\} \left(\zeta_m^1 + \zeta_m^2 p_i\right)$$

$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\} \Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\} \Delta_{odps} + \varepsilon_i$$

- A separate slope and intercept for $\bar{y}_{pos}$ within each birth cohort.
  - Intended to control for origin.
- A separate slope and intercept for p_i within each moving age.
  - Intended to control for disruption from moving (maybe varies with p_i).

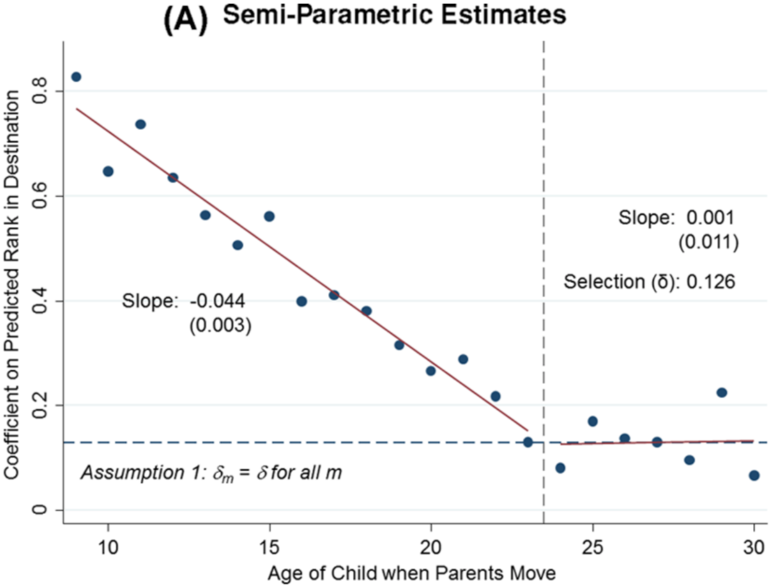
Discussion: Parametric Model

What is being controlled for here?

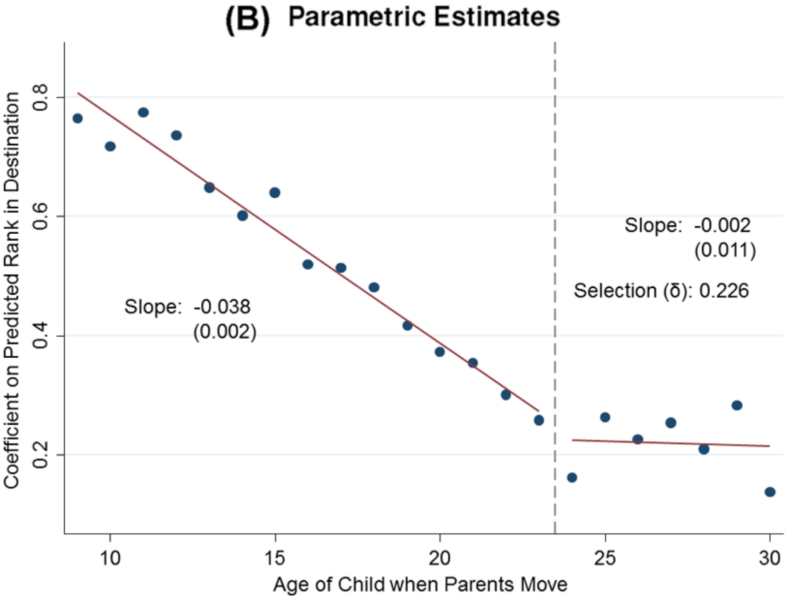
$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\} \left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\} \left(\zeta_m^1 + \zeta_m^2 p_i\right)$$
$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\}\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\}\Delta_{odps} + \varepsilon_i$$

- A separate slope and intercept for $\bar{y}_{pos}$ within each birth cohort.
  - Intended to control for origin.
- A separate slope and intercept for p_i within each moving age.
  - Intended to control for disruption from moving (maybe varies with p_i).
- Assumed that remaining variation in y_i is due to changes in destination quality.

Results: Original Model (for comparison)



Results: Parametric Model



Discussion: Parametric Model with Family Fixed Effects

- Authors address time-varying selection possibility by adding family fixed effect:

$$y_i = \sum_{s=1980}^{1988} \mathbf{1}\{s_i = s\} \left(\alpha_s^1 + \alpha_s^2 \bar{y}_{pos}\right) + \sum_{m=9}^{30} \mathbf{1}\{m_i = m\} \left(\zeta_m^1 + \zeta_m^2 p_i\right)$$
$$+ \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\} \Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s^d \mathbf{1}\{s_i = s\} \Delta_{odps} + \bar{\theta}_{fam} + \varepsilon_i$$

- Regression is now estimated entirely on sample of families with ≥ 2 children. Intuitively, family–level mean effects are taken out.

Discussion: What do Family Fixed Effects Capture?

- Suppose we can write $\varepsilon_i = \bar{\theta}_{fam} + e_i$
  - $\bar{\theta}_{fam} i$: fixed family inputs (e.g., culture, parents' human capital, etc.)
  - e_i: variable inputs (e.g., wealth shocks, noise)
- The selection assumption is that $\frac{cov(\varepsilon_i, \Delta_{odps})}{var(\Delta_{odps})}$ is constant in age.
- Including family fixed effects controls for $\bar{\theta}_{fam}$, e.g., if higher-skill families choose better neighborhoods at earlier ages.
- To interpret results as "no selection" still need $\frac{cov(e_i, \Delta_{odps})}{var(\Delta_{odps})}$ constant in age.
  - This can be violated, e.g., if shocks to wealth are correlated with child age.
  - One such wealth shock correlated with first child's age: the birth of a second child!
  - E.g., could be meaningful differences between families where kids are 4 years vs. 8 years apart.

Results: Parametric with Family Fixed Effects

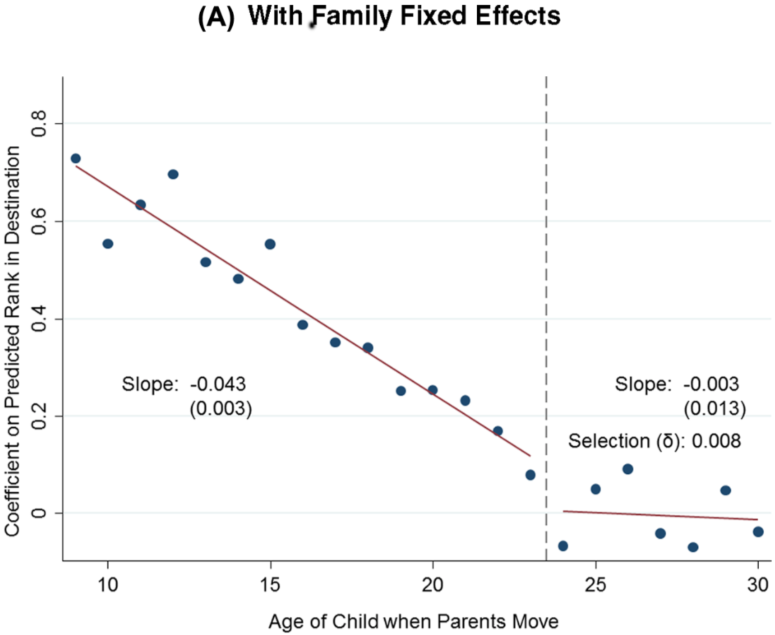


Table of Contents

Chetty et al. (2016) — the MTO study

- Chetty et al. (2016) study the role of exposure to better neighborhoods on children in the context of the Moving to Opportunity (MTO) experiment.
- MTO offered randomly selected families housing vouchers to move from high–poverty housing projects to lower–poverty neighborhoods. Low–income, low–human capital sample.
- Previous work (e.g., Ludwig et al. 2013) showed MTO improved adult mental and physical health, but had no consistent effects on adult economic self–sufficiency.
  - Effects on educational attainment and earnings also previously estimated to be small (Sanbonmatsu et al., 2011).

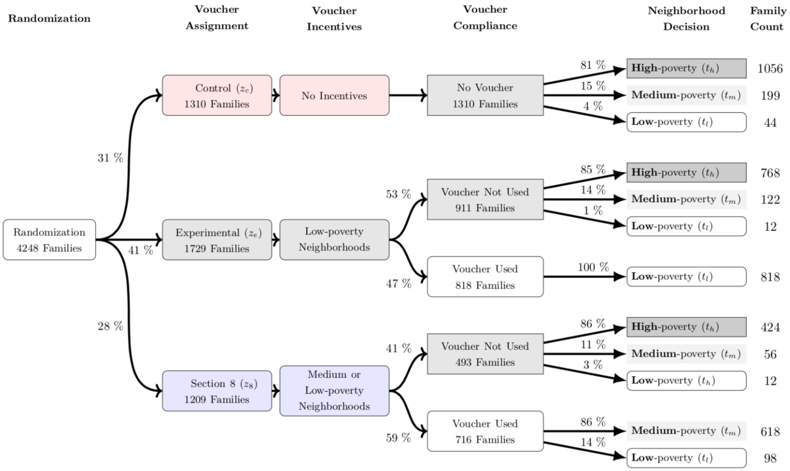
Results of Chetty et al. (2016)

Chetty et al. (2016) find:

- Moving when young (before age 13) increases college attendance and earnings in adulthood.
  - ITT estimate: $1,624 higher annual incomes (experimental vs. control).
- Moving as an adolescent has slightly negative impacts on these life outcomes (though imprecise estimates).
- Substantial noncompliance among voucher recipients (roughly 50% takeup) ⇒ most results presented are reduced–form "Intent to Treat" (ITT) estimates.
- Treatment–on–Treated (TOT) use voucher takeup as instrument for neighborhood effects among sample of movers, and are for this reason roughly twice as large ($3,477).
  - Pinto (2019) treats this noncompliance as reflective of rational choice among voucher recipients, and uses this framework to identify neighborhood effects (instead of voucher effects) for adult labor market outcomes of MTO.

Patterns of Noncompliance in MTO (Pinto, 2019)

Figure 1: **Neighborhood Relocation by Voucher Assignment and Compliance**



Estimation Details: Chetty et al. (2016)

- ITT regression in Chetty et al. (2016):

$$y_i = \alpha + \beta_E^{ITT} Exp_i + \beta_S^{ITT} S8_i + \delta \boldsymbol{s}_i + \varepsilon_i$$

  - $Exp_i = \mathbf{1}\{\text{randomly assgn. experimental voucher}\}$
  - $S8_i = \mathbf{1}\{\text{randomly assgn. Section 8 voucher}\}$
  - $\boldsymbol{s}_i =$ randomization site fixed effect.

- 2SLS regression for TOT effects:

$$y_i = \alpha_T + \beta_E^{TOT} \widehat{TakeExp}_i + \beta_S^{TOT} \widehat{TakeS8}_i + \delta_T \boldsymbol{s}_i + \varepsilon_i^T e$$

where Exp_i and $S8_i$ instrument for $TakeExp_i$ and $TakeS8_i$, respectively.

What does the estimated effect measure?

- Consider a simplified case where randomization is not site-specific and there is only an experimental treatment. Let Y denote the outcome.
- Let D denote treatment (using a voucher), and Z denote the instrument (random assignment to the voucher).
- Assume standard Imbens and Angrist (1996) "monotonicity" assumptions:
  - Exogeneity: $Z \perp (Y_0, Y_1, D_0, D_1)$
  - Relevance: $\text{Cov}(D, Z) \neq 0$
  - Monotonicity: $D_1 \geq D_0$
- Then:

$$\beta_{IV} \equiv \frac{\text{Cov}(Y, Z)}{\text{Cov}(D, Z)} = \frac{\mathbb{E}[Y \mid Z = 1] - \mathbb{E}[Y \mid Z = 0]}{\mathbb{E}[D \mid Z = 1] - \mathbb{E}[D \mid Z = 0]}$$

- Can show:

$$\beta_{IV} = \mathbb{E}[Y_1 - Y_0 \mid D_1 = 1, D_0 = 0] = \text{LATE}$$

- "Treatment on the Treated" in Chetty et al. (2016) is LATE for voucher *compliers.*
- Relevant for policy interpretation to understand who is the complier group.

How are Compliers Different? (Pinto, 2019)

Variable	Full Sample					Experimental Group			Section 8 Group		
	Control Group	Experimental vs. Control		Section 8 vs. Control		Experimental Compliers	Comparison Compliers vs. Not		Section 8 Compliers	Comparison Compliers vs. Not	
	Mean	*Diff*	*p-val*	*Diff*	*p-val*	*Mean*	*Diff*	*p-val*	*Mean*	*Diff*	*p-val*
	2	3	4	5	6	7	8	9	10	11	12
Family											
Disable Household Member	0.15	0.01	0.31	0.00	0.82	0.15	-0.04	0.34	0.13	-0.06	0.23
No teens (ages 13-17) at baseline	0.63	-0.03	0.12	-0.01	0.55	0.65	0.10	**0.00**	0.66	0.11	**0.00**
Household size is 2 or smaller	0.21	0.01	0.48	0.01	0.39	0.26	0.08	**0.04**	0.23	0.03	0.56
Sociability											
No family in the neighborhood	0.65	-0.02	0.35	0.00	1.00	0.65	0.03	**0.06**	0.65	0.01	0.57
Respondent reported no friends	0.41	-0.00	0.78	-0.01	0.56	0.44	0.06	**0.02**	0.41	0.02	0.48
Chat with neighbor	0.53	-0.01	0.60	-0.03	0.19	0.50	-0.05	**0.04**	0.51	0.01	0.77
Watch for neighbor children	0.57	-0.02	0.31	-0.03	0.16	0.51	-0.07	**0.00**	0.55	0.03	0.36
Neighborhood											
Victim last 6 months (baseline)	0.41	0.01	0.41	0.01	0.45	0.45	0.05	**0.08**	0.45	0.06	**0.09**
Living in neighborhood > 5 yrs.	0.60	0.00	0.97	0.02	0.28	0.59	-0.03	0.17	0.59	-0.08	**0.00**
Unsafe at night (baseline)	0.50	-0.02	0.27	-0.00	1.00	0.52	0.08	**0.00**	0.54	0.10	**0.00**
Moved due to gangs	0.78	-0.01	0.52	-0.02	0.24	0.79	0.04	**0.00**	0.78	0.04	**0.00**
Schooling											
Has a GED (baseline)	0.20	-0.03	**0.04**	0.00	0.81	0.18	0.03	0.46	0.20	0.00	0.98
Completed high school	0.35	0.04	**0.01**	0.01	0.47	0.41	0.02	0.57	0.39	0.06	0.10
Enrolled in school (baseline)	0.16	0.00	0.95	0.02	0.22	0.19	0.07	0.10	0.19	0.04	0.45
Never married (baseline)	0.62	-0.00	0.97	-0.02	0.36	0.66	0.06	**0.00**	0.63	0.05	**0.02**
Teen pregnancy	0.25	0.01	0.41	0.01	0.69	0.27	0.02	0.49	0.29	-0.09	**0.05**
Missing GED and H.S. diploma	0.07	-0.01	0.12	-0.01	0.54	0.04	-0.03	0.50	0.06	-0.01	0.80
Welfare/economics											
AFDC/TANF Recipient	0.74	0.02	0.34	0.00	0.85	0.78	0.04	**0.00**	0.78	0.08	**0.00**
Car Owner	0.17	-0.01	0.65	-0.01	0.43	0.19	0.04	0.26	0.17	0.04	0.48
Adult Employed (baseline)	0.25	0.02	0.28	0.01	0.75	0.26	-0.01	0.84	0.27	0.03	0.51

2SLS Case: What does $\hat{\beta}_E^{TOT}$ identify?

- Now consider the following 2SLS specification, accounting for site-specific randomization using fixed effects $\boldsymbol{S}_i$:

$$Y_i = \alpha + \beta_E^{TOT} \widehat{D}_i + \delta \boldsymbol{S}_i + \varepsilon_i$$
$$D_i = \pi + \gamma Z_i + \xi \boldsymbol{S}_i + \nu_i$$

- Adjust assumptions to be conditional on X:
  - Exogeneity: $(Y_0, Y_1, D_0, D_1) \perp Z \mid \boldsymbol{S}$
  - Relevance: $\mathbb{P}[D = 1 \mid Z = 1] \neq \mathbb{P}[D = 1 \mid Z = 0]$
  - Monotonicity: $\mathbb{P}[D_1 \geq D_0 \mid \boldsymbol{S}] = 1$
  - Overlap: $\mathbb{P}[Z = 1 \mid \boldsymbol{S}] \in (0, 1)$ (obviously satisfied here).
- Can point identify conditional LATE by within-site β_{IV}:

$$\mathbb{E}[Y_1 - Y_0 \mid T = c, \boldsymbol{S} = s] \equiv \text{LATE}(s)$$

2SLS Case: What does $\hat{\beta}_E^{TOT}$ identify?

- Can show that aggregated *LATE* is:

$$\mathbb{E}[Y_1 - Y_0 \mid T = c] = \mathbb{E}\left[\frac{\text{LATE}(\boldsymbol{S}) \cdot \mathbb{P}[T = c \mid \boldsymbol{S}]}{\mathbb{P}[T = c]}\right]$$

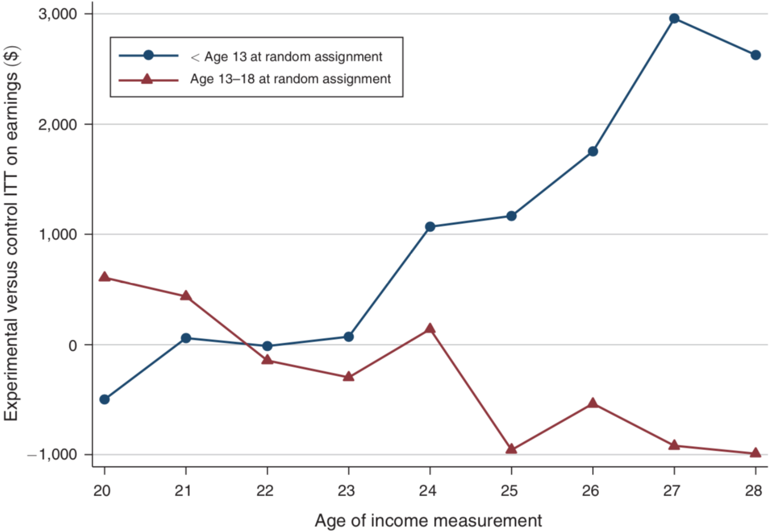
- A weighted average of effects on compliers across locations, where the weights are the share of compliers in each location.
- Compliance varies widely across sites (Pinto, 2019):

Table 5: Compliance Rates by Site

Site	All Sites	Baltimore	Boston	Chicago	Los Angeles	New York
Experimental Compliance Rate	47 %	58 %	46 %	34 %	67 %	45%
Section 8 Compliance Rate	59 %	72 %	48 %	66 %	77 %	49%

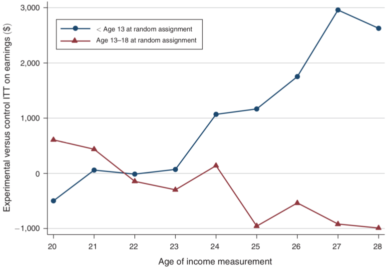
This tables presents the fraction of voucher recipients that used the voucher (compliance rate) to relocate by site.

Results of Chetty et al. (2016)

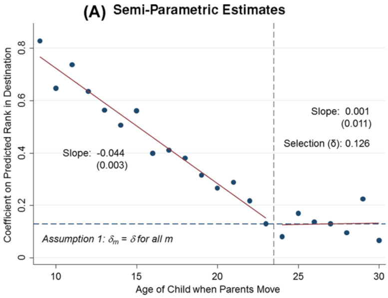


How to Reconcile these Results?

MTO study



Observational Study



- MTO study finds that moving after age 13 harmful to children, while observational study finds that moving to a better neighborhood is valuable at least until age 23.
- Treatment–control comparison is different between the two groups.
  - MTO study: compares voucher–receipt groups to no–voucher control group.
    - Although, substantial (∼19%) rates of movers in control group (Pinto, 2019).
  - Observational study: comparisons *only* within sample of movers.

Implications for Disruption Effects of Moving

- One way to reconcile these results is to say the disruption cost of moving is constant in age, i.e. $\kappa_a = \kappa$ for all a.
  - Chetty et al. (2016): *"The MTO experimental design cannot be used to conclusively establish that childhood exposure to a better environment has a causal effect on long–term outcomes because the ages at which children move are perfectly correlated with their length of exposure ... as a result, we cannot distinguish differences in disruption effects by age at the time of a move from an age-invariant disruption cost coupled with an exposure effect."* (pg. 858)
  - In this statement, possibilities in between also possible: For example, weak causal effect of exposure combined with slightly increasing exposure effect.
- Constant κ seems implausible — e.g., hard to imagine significant social disruption effects for infants. Plausible that effects of social disruption during adolescence are large.
- Could also have κ_a increasing in a. Then regressions with age–at–move fixed effects would "net out" the effect.

Implications for Disruption Effects of Moving

- Both situations still challenge the interpretation of estimates from the second CH study (2018b) as the causal effect of a county; at best they are causal effects *conditional on moving away from home*.
- Adds an important caveat for interpreting the county–level estimates and identification of "opportunity bargains" in Chetty and Hendren (2018b).
- The MTO study suggests that such moves could actually be harmful for adolescents; comparisons conditional on moving are not the relevant question for a family deciding *whether* to move.
- Interpreting the effects presented in CH (2018b) as "the effect of growing up in each county" requires extrapolating estimates estimated on sample of older children to apply equally since birth.

Summary – Empirical Work

- Rather than being purely a criticism, the point of these slides is to say that the Chetty work does not address and leaves open some of the most interesting questions about the impacts of neighborhoods on child outcomes.
    1. Evaluated in dollars (not ranks), what is the shape of γ_m across moving-age profiles? Is it concave, as a theory of dynamic complementarity would suggest?
    2. What are the interactions between the decision of migration destination, the age of children, local amenities, and shocks to parental income?

Appendix

Appendix: Slides covered Last Week

Included for reference.

Motivation: Unanswered questions about the role of neighborhoods in intergenerational mobility.

- What are estimated neighborhood effects really measuring?
  - Characteristics of neighborhood (schools, safety, housing stock, air quality, etc.)
  - Characteristics of the child (e.g., age) in interaction with the above.
- Choices in measurement can influence estimated effects
  - Evolution of incomes over life cycle $\Rightarrow$ timing of measurement matters.
  - Ability to observe children at early moving ages.
  - Averaging due to missing data in some years might also prevent studying influence of shocks.
  - Mapping of income rank to welfare.

Motivation: Unanswered questions about the role of neighborhoods in intergenerational mobility.

- Recent work by Chetty, Hendren, and coauthors has demonstrated importance of neighborhoods in determining intergenerational mobility in incomes.
- The results, though important, leave unanswered several crucial questions in the study of intergenerational mobility:
    1. What is the role of neighborhood *characteristics* (e.g., crime, education, HH size, etc.) in shaping their impact on mobility?
    2. What do the results tell us about the timing of investment in children?
- This presentation will focus on (2). I will discuss the identification strategy of the Chetty studies, and isolate some questions they leave open.
- After discussing the Chetty et al., work, I present a model sketch attempting to integrate neighborhood effects with the theory of dynamic complementarity in childhood skill formation.

Motivation: Effects of Place on Lifetime Outcomes

$$y_i = \sum_{a=1}^{A} \left[\mu_{c(i,a)} - \kappa_a \mathbf{1}\left\{ c(i,a) \neq c(i,a-1) \right\} \right] + \theta_i$$

- y_i: child i's outcome (e.g., income) in adulthood.
- $c(i,a)$: place c in which child i lives at age $a = 1, \ldots, A$ of childhood.
  - $\mu_{c(i,a)}$: Effect of living in c at age a.
- κ_a: one-time disruption cost of moving at age a.
- θ_i: Effect of other factors (e.g., family inputs) on y_i.

Reduced–form framework can give us mean effects, but leaves several crucial questions unanswered:

1. How does κ_a vary with age and location? Will discuss the implications/plausibility of what the Chetty studies, taken together, imply about disruption effects.
2. How could measurement error in y_i, or in parent incomes, affect the results? What assumptions are required for this not to matter?
3. Assumption of no complementarities of neighborhood effects across years.

C&H 2018: Measure of Neighborhood Quality

- Typically, studies of intergenerational mobility attempt to estimate the elasticity between child income and parent income (the IGE), β_n, in:

$$Y_{in}^c = \alpha_n + \beta_n Y_{in}^p + \varepsilon_{in}$$

- This study (Chetty and Hendren, QJE 2018a) instead aims to estimate the effects of "better" neighborhoods on the IGE. It therefore requires a measure of neighborhood quality.
- This measure is calculated using children of "permanent residents," defined as parents who stay in the same commuting zone (CZ) over the sample period (1996 to 2012).

C&H 2018: Measuring Neighborhood Quality

- Given birth cohort s and CZ c, let p be the *parents'* percentile in the *national* income distribution.
- Let y_i denote the child's national income rank in adulthood.
- Authors assume linearity and estimate the following regression on the sample of children with permanent resident parents:

$$y_i = \alpha_{cs} + \psi_{cs} p_i + \varepsilon_i$$

  where p_i is the percentile rank of child i's parent in the national income distribution.

- Then, predict mean percentile ranks given c, s, and parent rank p:

$$\bar{y}_{pcs} = \hat{\alpha}_{cs} + \hat{\psi}_{cs} p$$

- $\bar{y}_{pcs}$ is the measure of neighborhood quality.

CH 2018: Motivation of Linearity Assumption

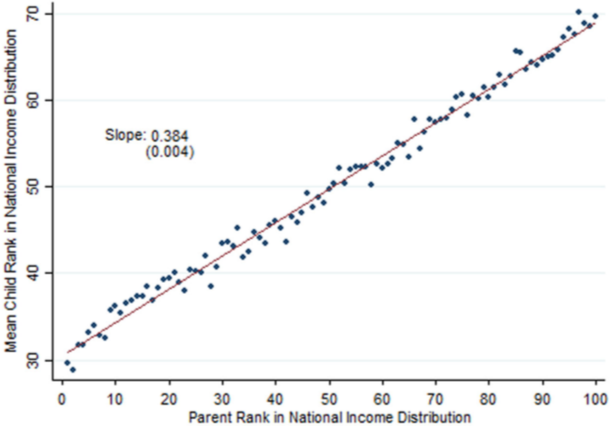
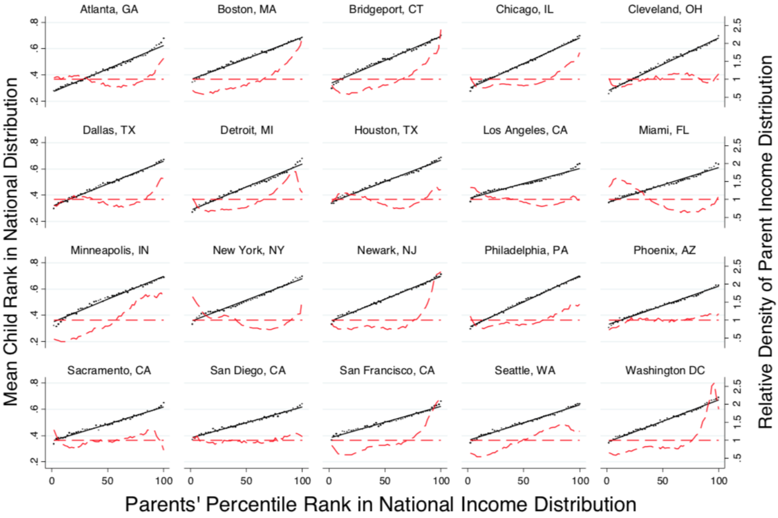


FIGURE I

Mean Child Income Rank versus Parent Income Rank for Children Raised in Chicago

CH 2018: Motivation of Linearity Assumption



CH 2018: Definition of Exposure Effects

- Consider thought experiment: randomly assign child of parental income rank p, to new neighborhood d, starting at age m, for remainder of childhood.
- Linear regression of child's adult national income distribution rank y_i on permanent resident mean outcome rank $\bar{y}_{pds}$:

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

  where θ_i captures unobservable determinants of y_i (e.g., family inputs).
- Given random assignment at age m, and conditional on spending all years of childhood after m in destination d, β_m is the impact of a 1 percentile increase in the adult outcomes of permanent-d-resident children on i's adult outcome rank.
- *Exposure effect* at age m is $\gamma_m = \beta_m - \beta_{m+1}$, the effect on y_i of spending the year from age m to age $m+1$ in the destination.
- $\beta_0 = \sum_{t=0}^{T} \gamma_m$ is the impact on y_i from random assignment to d at birth.

CH 2018: Key Identifying Assumption

- Obviously, migration is not random, and estimating the above equation using observational data will yield estimates:

$$b_m = \beta_m + \underbrace{\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})}}_{\text{Selection Bias}}$$

- This will bias estimated age-based exposure effects γ_m since:

$$b_m - b_{m+1} = \underbrace{\beta_m - \beta_{m+1}}_{\gamma_m} + \left(\left[\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})} \right]_m - \left[\frac{cov(\theta_i, \bar{y}_{pds})}{var(\bar{y}_{pds})} \right]_{m+1} \right)$$

- The authors solve this problem by assuming that the term $cov(\theta_i, \bar{y}_{pds})/var(\bar{y}_{pds})$ is constant across ages. In other words, it is assumed that selection effects do not vary with the child's age at move.
- This rules out, e.g., differential preferences among parents by age of child for local amenities, such as school quality, that are not fully captured in adult income percentile rank $\bar{y}_{pds}$.

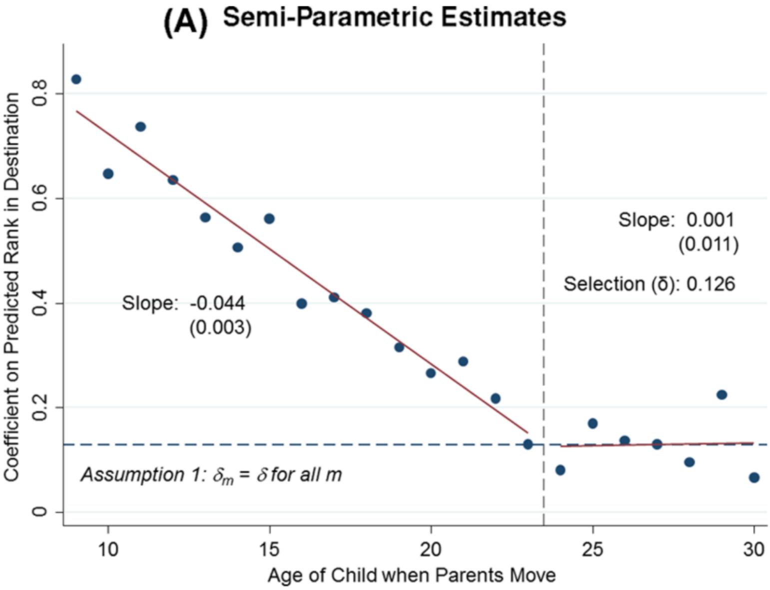
Estimation using Observational Data

- Consider a family that moves from origin o to destination d. Define $\Delta_{odps} = \bar{y}_{pds} - \bar{y}_{pos}$ as the difference in mean income rank (at age 24) of permanent residents in the destination location versus origin.
- The authors estimate:

$$y_i = \alpha_{qosm} + \sum_{m=9}^{30} b_m \mathbf{1}\{m_i = m\}\Delta_{odps} + \sum_{s=1980}^{1987} \kappa_s \mathbf{1}\{s_i = s\}\Delta_{odps} + \varepsilon$$

  where α_{qosm} is an (origin $\times$ parent income decile $\times$ birth cohort $\times$ age) fixed effect.
- $\hat{b}_m$ is the average effect on age-24 income rank y_i, conditional on moving from o to d at age m, of a 1 percentile increase in Δ_{odps}.
  - Assumed that within parent income deciles q, changes in this spread are driven entirely by $\bar{y}_{pds}$, not $\bar{y}_{ods}$.

Results



(A) Semi-Parametric Estimates
Coefficient on Predicted Rank in Destination
0
0.2
0.4
0.6
0.8
10
15
20
25
30
Age of Child when Parents Move
Slope: -0.044
(0.003)
Slope: 0.001
(0.011)
Selection (δ): 0.126
Assumption 1: $\delta_m = \delta$ for all m

Are the Results Interpretable?

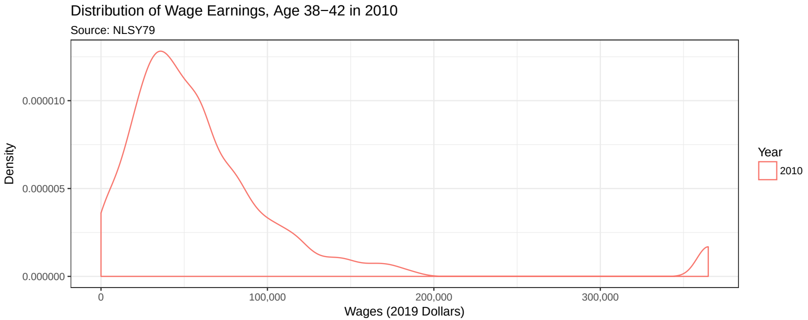
Set aside the selection assumption. What do the results imply?

- Linear relationship between b_m and age at move m implies exposure effect $\gamma_m = b_{m+1} - b_m$ is roughly constant with respect to age at move.
  - This seems inconsistent at first glance with the notion of dynamic complementarity, which would imply convexity in the relationship and declining γ_m with age.
- Interpretation of constant γ depends on the mapping of a one-percentile change in income rank to *actual* (dollar-valued) changes in adult income.
  - For example: income distrbutions are skewed rightward (Neal and Rosen 2000), so the magnitude of a 1 percentile change is much larger at high incomes.
- Move from $p10$ to $p11$ neighborhood and move from $p90$ to $p91$ neighborhood (based on $\bar{y}_{pcs}$) have same Δ_{odps}, so would produce same rank shift in y_i. Much larger in dollar terms for children of the rich.
- Authors address this question in Chetty and Hendren (2018b) by estimating:

$$\bar{y}_{pc}^{\$} = \lambda_0 + \lambda_1 \bar{y}_{pc} + \varepsilon$$

Estimate $\hat{\lambda}_1$ is dollar value of 1 percentile increase in $\bar{y}_{pc}$. Cross–county regression estimated separately within percentiles.

Income Distribution – Ranks to Levels



What does the selection assumption imply for behavior?

- One implication is that parents' preferences over local amenities that are (a.) heterogeneous across locations, and (b.) not perfectly collinear with $\bar{y}_{pcs}$, do not change with the age of children. Many local factors could violate this assumption: school quality, safety, etc.
- In particular, this assumption could be violated for parents of very young children, who may be more likely to be concerned about school quality or local safety. Earliest age at which moves are observed in this study is 8 (third grade).

Possibility of interaction between selection and measurement error.

- Incomes are measured with error in the study. Sample and variable definitions:
  - Sample of children: those born between 1980-1988.
  - Measure of parent income: average of tax records from 1996-2000.
- Children are therefore between 8 and 12 years old at youngest when parent incomes are measured. They are between 16 and 20 at oldest.
- Large literature suggesting that the birth of a first child is a significant shock to incomes (recently: Larrimore, Mortenson, and Splinter 2016, Splinter 2019, Kleven et al. 2018).
- Migration shown to be substantially influenced by income prospects (Kennan and Walker, 2011).
- My point: if fluctuations in income (a.) vary systematically with child age in early years of childhood, and (b.) influence the choice of migration destination, then the Chetty assumption does not hold in general for early years, and the use of average parental incomes at later ages of childhood masks important variation in early years of childhood.

Justification of Constant-in-Age Selection Assumption

- The authors perform several tests to justify this assumption. Suppose we can write selection as:

  $$\theta_i = \bar{\theta}_i + \tilde{\theta}_i$$

  where $\bar{\theta}_i$ represents fixed family inputs (e.g., genetics) and $\tilde{\theta}_i$ is a residual.
- To address age-varying selection due to $\bar{\theta}_i$, the authors use two strategies. Both leave the estimates qualitatively unchanged:
  - Add family fixed effects (identifying off of siblings)
  - Control for changes in parents' income and marital status.