Comparable Rank-Based Measures of Intergenerational Educational Mobility

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March 5, 2020

Outline

Preview

Methods for IEM Estimation

Results: India

Results: United States

Preview of Presentation

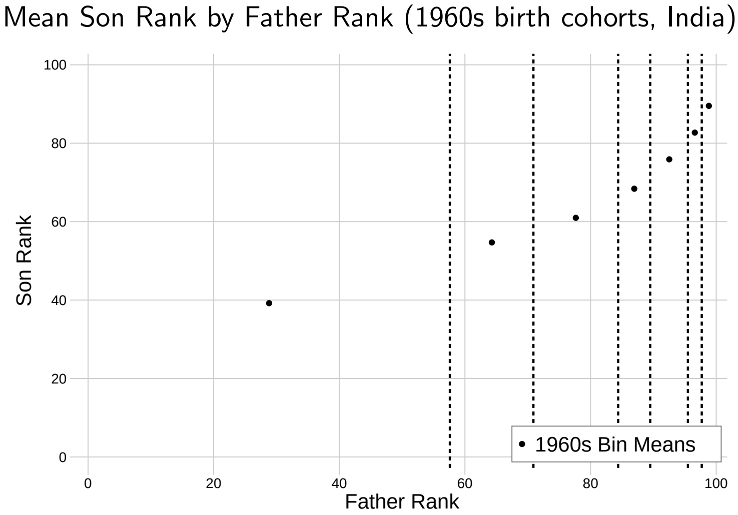
Broad Goal: Estimate upward mobility for population subgroups in contexts with poor or absent income data.

- Focus on educational mobility
- Propose a measure analogous to Chetty et al. (2014) absolute upward mobility (p_{25}) that works well with education data.

Narrow Goals:

- Generate a measure of educational mobility for the U.S. that is comparable to p_{25}; compare with income mobility p_{25}.
- Measure upward mobility in India, comparing Scheduled Castes, Muslims, and non-minority groups over time.
- Compare upward educational mobility of minority groups across countries and contexts.

The Challenge: Coarse Education Bins



Preview of Methods

- Upward mobility can at best be partially identified, given binned education data.

- We propose **Bottom Half Mobility** (μ_0^{50}), which is an analog to p_{25}, but can be bounded much more tightly than p_{25} with binned data.

- BHM is the expected outcome of a child born to a parent in the bottom half of the parent education distribution.

Preview of Results

In the United States:

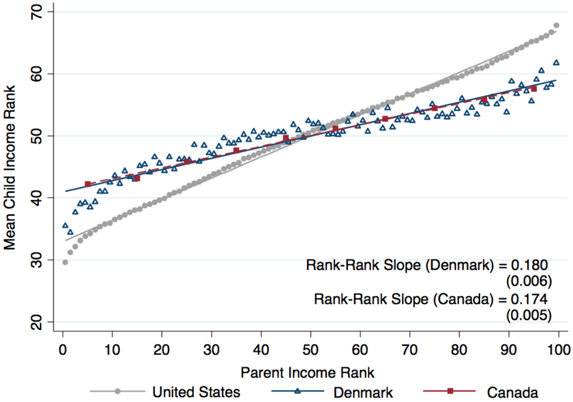
- Educational mobility (41.5) is almost identical to income mobility (42).
- Compared with income mobility, black-white gap in ed mobility is smaller for men; larger for women

In India:

- Low overall mobility
- Secular growth among SCs; comparable decline among Muslims
- Among men, Muslim mobility (29) is considerably lower than U.S. black mobility (38.5); Scheduled Caste mobility is similar (38)

Outline

Measurement of Mobility (Chetty et al. 2014)



- I will refer to this function as $E(Y|X)$
- Some common mobility measures: Absolute Upward Mobility (p_{25}); Rank-Rank Gradient (β)

Educational Mobility is Sometimes a Desirable Measure

- When matched parent-child income data is unavailable
  - Or unavailable at comparable ages $\rightarrow$ life cycle bias
- When matched parent-child income data is unreliable
  - e.g. How to attribute household income to coresident parents/children?
  - Very low formal female LFP / unremunerated work in India
- Education is a good proxy for lifetime income
  - Data on linked parent-child education are more widely available
  - Educational mobility may be independently of interest

Limitations of Conventional IEM Measures

Standard approach:

- Linear estimation of child education (rank) on father education (rank)
- High coefficient $\rightarrow$ Low mobility

Some weaknesses of this measure:

1. Pools information from top and bottom of rank distribution

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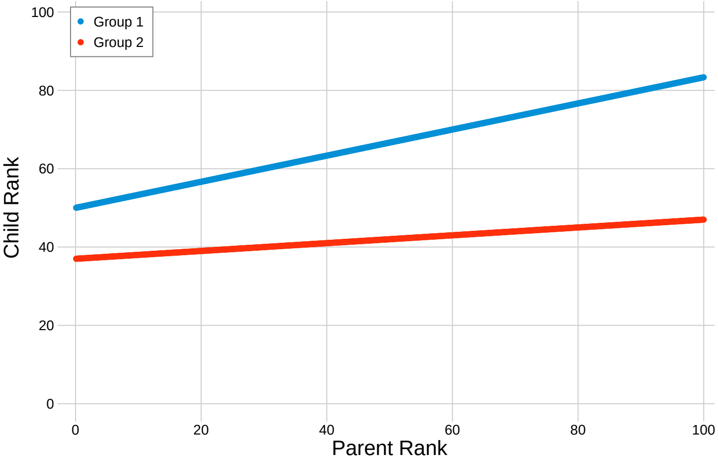
Gradient Not Useful for Subgroup Analysis



Group 2 has a lower rank-rank gradient $\rightarrow$ more mobile?

Limitations of Conventional Method for IM Estimation

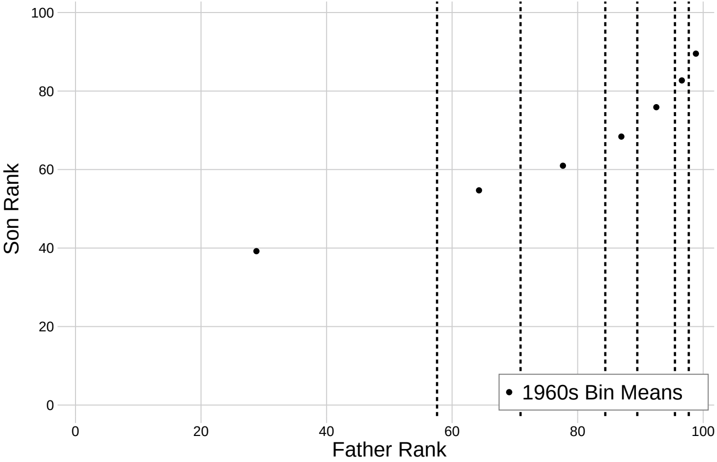
Standard approach:

- Linear estimation of child education (rank) on father education (rank)
- High coefficient $\rightarrow$ Low mobility

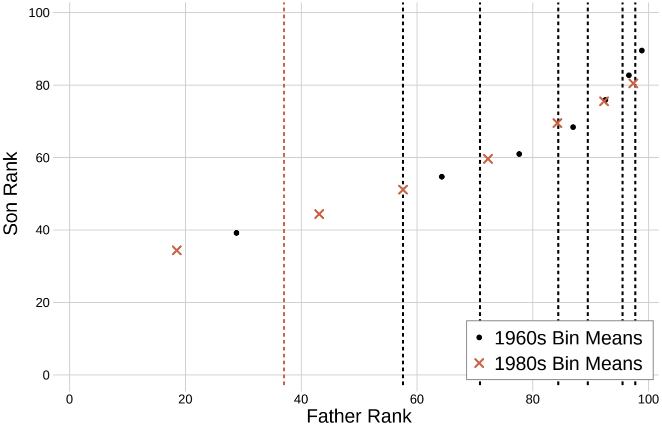
Some weaknesses of this measure:

1. Pools information from top and bottom of rank distribution
2. Not useful for subgroup analysis
3. Education is observed coarsely
    - In 1960s India, 57% of fathers, 82% of mothers report bottom-coded education
    - Internationally comparable datasets (e.g. IPUMS) use $\leq$5 ed bins

Mean Son Rank by Father Rank (1960s birth cohorts, India)

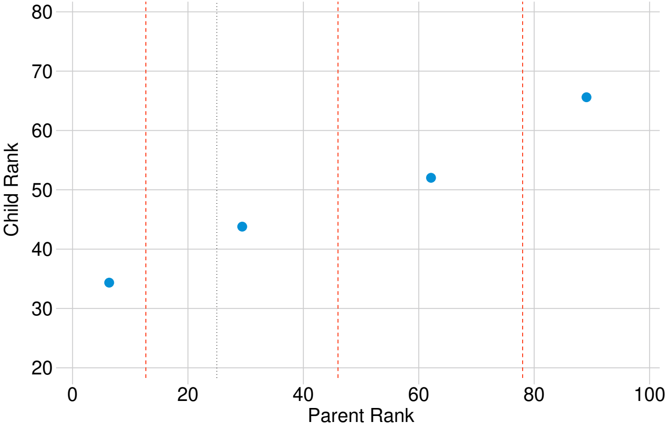


Comparing CEFs across time: India 1960s vs. 1980s



How should we compare the 1980 and 1960 birth cohorts?

U.S. Father-Child Mobility CEF



Other Approaches in the Recent Literature

- Card et al. (2018) on educational mobility (IEM) in the 1920s, also used by Derenoncourt (2019)
  - Definition: the 9th grade completion rate of children whose parents have 5–8 years of school
    - This is approximately $E(y > 50|x \in [30, 70])$
  - Both compare this in 1980s with Chetty et al. measure $E(y|x = 25)$

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    - ... and $E(y > 18 | x \in [0, 42])$ in South Africa

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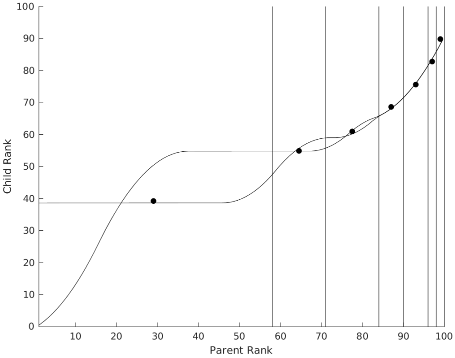
- Our goal: calculate $E(y|x \in [a, b])$ for any a and b

Our Strategy: A Partial Identification Approach

- **Key Idea**: Under minimal assumptions, we can *bound* the set of feasible mobility functions
- **Goal**: Conditional expectation function of child rank given parent *education percentile rank*
  - Call this $E(y|x = i)$
  - From this function, we can calculate p_{25}, p_{75}, β, and other measures of mobility
- **Problem**: Education rank X is interval censored — only observed in coarse bins
- **Solution**: Build on Manski and Tamer (2002)

Two Candidate Father-Son CEFs: India (1960s birth cohort)



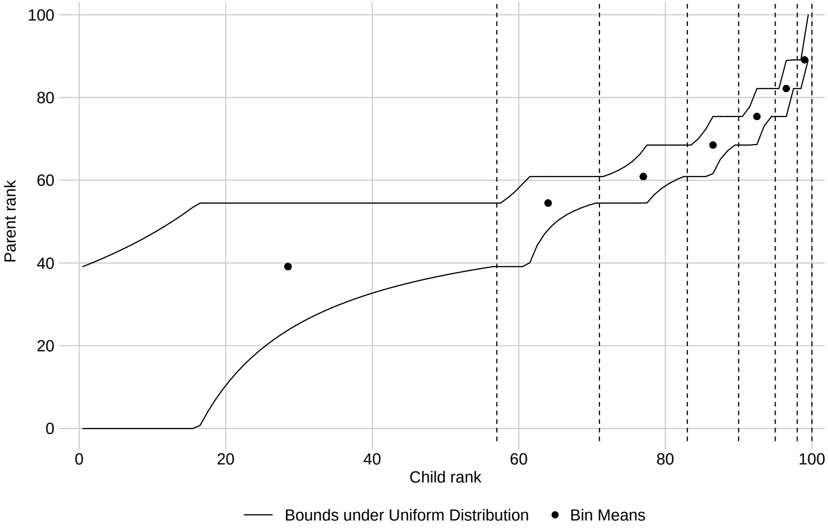
Key question: What can we say about the latent conditional expectation function?

- Both of these CEFs $Y(i)$ fit the data with zero MSE

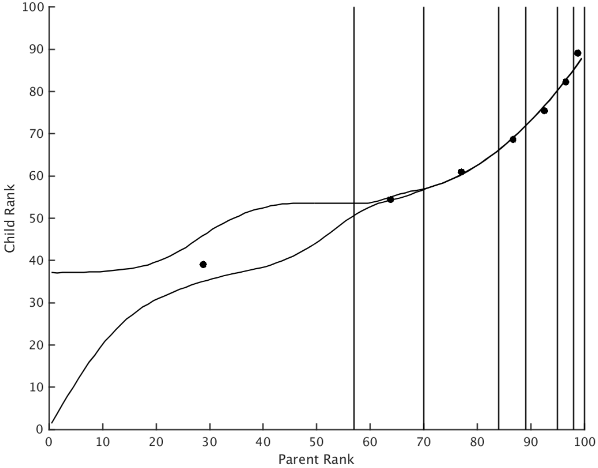
Overview of Methods

- Assume:
  1. There exists a latent education rank, observed in coarse intervals Latent
  2. Monotonicity: Expected child rank is weakly increasing in parent rank (Dardanoni 2012)
  3. Child CEF has discrete jumps or kinks at major education boundaries only (if at all)
  4. Child rank directly observed (loosened in paper)

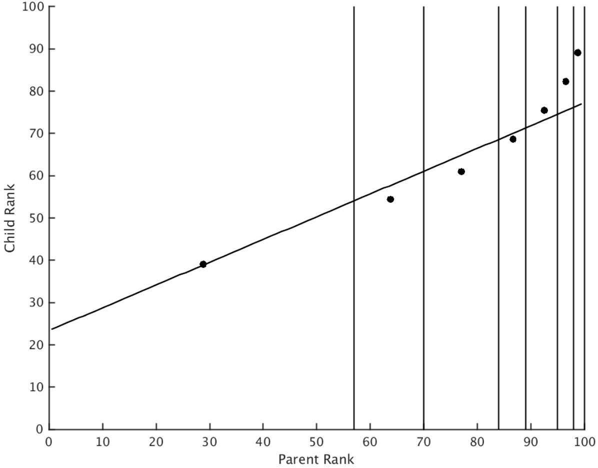
Bounds on E(Parent Rank — Child Rank), India 1960s



Constrained Curvature Bounds on E(Parent Rank — Child Rank), India 1960s



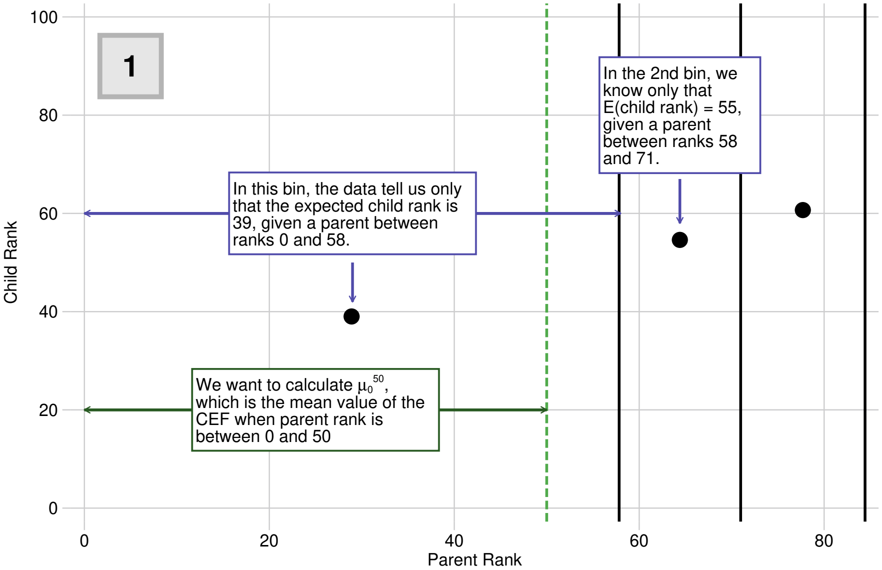
CEF Bounds under Interval Data: $\overline{C} = 0$



Our Measure: μ_a^b and Bottom Half Mobility

- The CEFs above show that $E(Y|x = 25)$ has bounds that are too wide to be informative.
- We propose an alternate function of the CEF: $\mu_a^b = E(Y|x \in (a, b))$
  - We can estimate this in arbitrary $[a, b]$
  - μ_0^{50}: expected child rank, given a parent in the bottom 50%
  - This is a close analog of p_{25} from Chetty et al.
    - p_{25} is the expected rank of a child born to the median parent in the bottom half
    - μ_0^{50} is the expected rank of a child born to any parent in the bottom half
  - If the CEF is linear, $\mu_0^{50} = p_{25}$

Example: Intuition for Tight Bounds on μ_0^{50}



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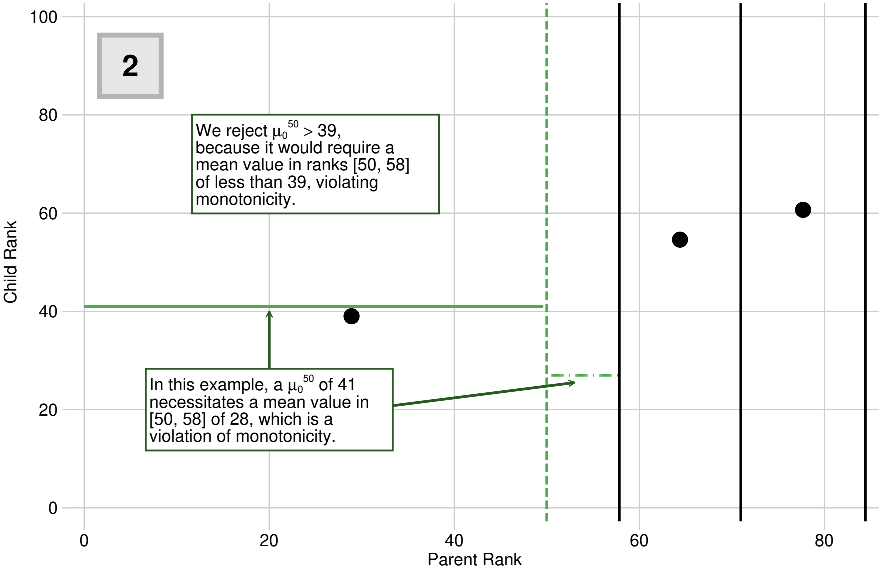

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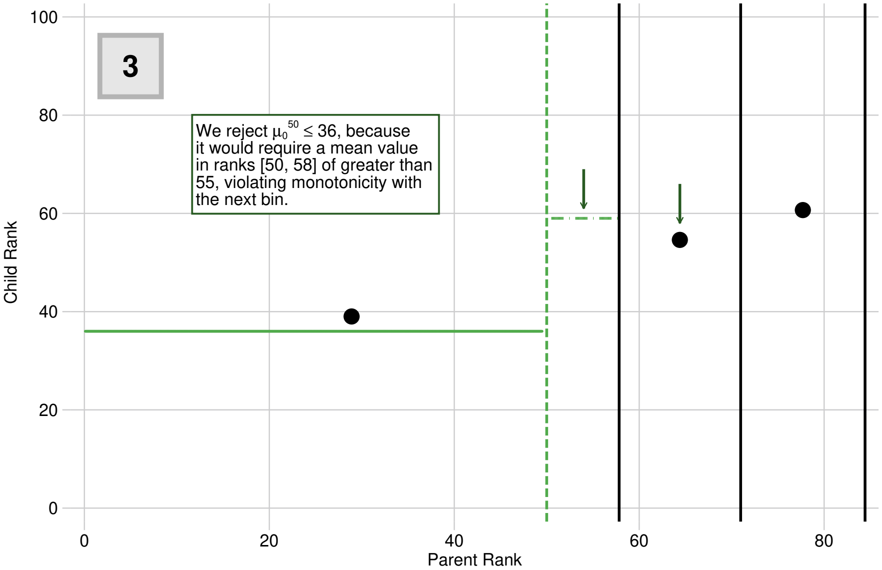

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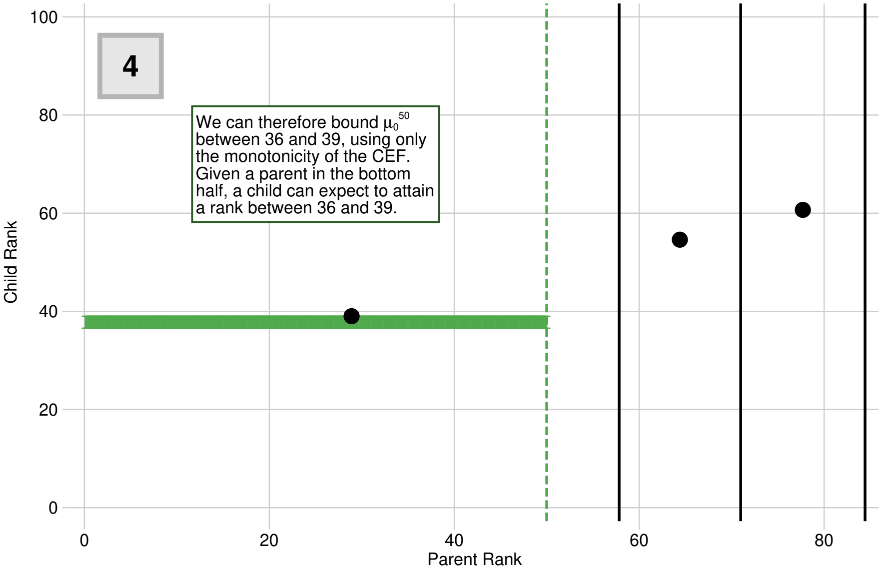
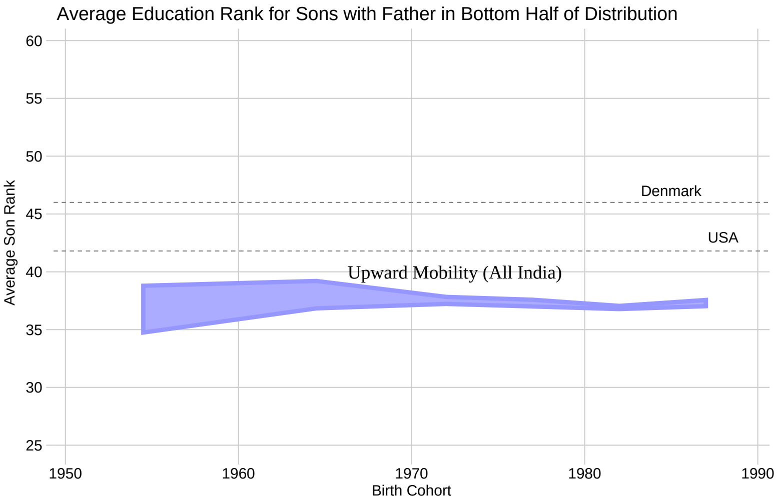
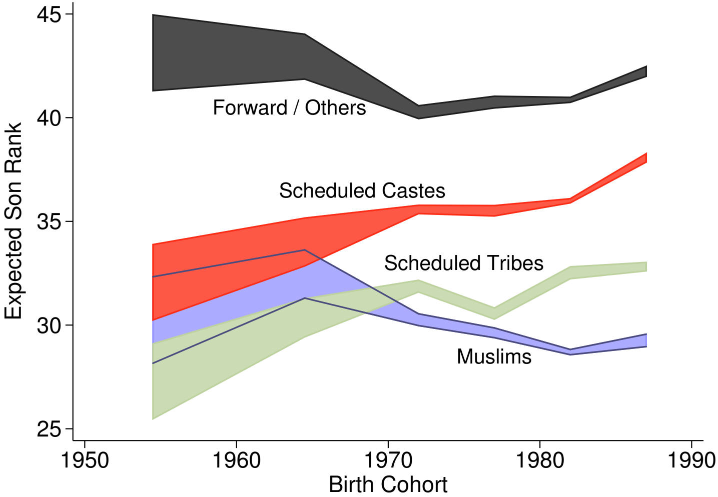


Outline

Upward Mobility over Time: All India



Upward Mobility: By Subgroup

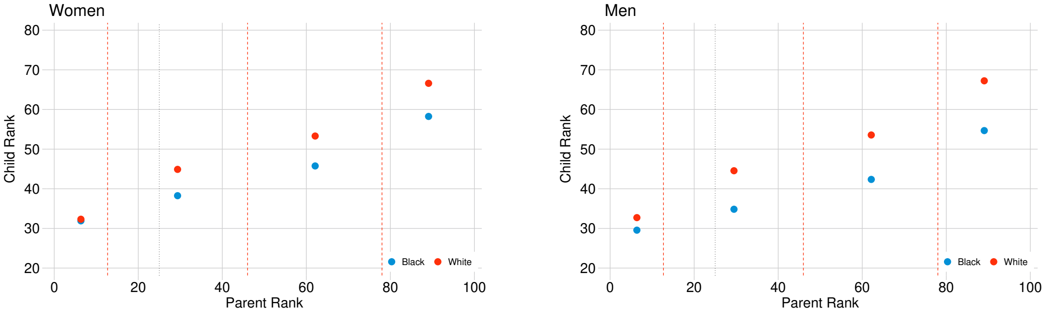


Outline

Data

- Data from Chetty, Hendren, Jones and Porter (2018)
- Source: Census 2000 and ACS 2005–2015
- Sample: Children age > 24
- Ed attainment in four categories:
  - Less than High School
  - High School
  - Some College
  - B.A. or Higher
- Focus here on black/white levels and gaps

Father-Child Education Rank CEFs (U.S. 2000–2015)



Cannot Tightly Bound p_{25} Without Significant Shape Assumptions

Bounds on p_{25}, U.S. Black women:

p_{25}	
Monotonicity only	[32, 42]
Conservative Curvature Constraint	[32.5, 39.7]
Aggressive Curvature Constraint	[34.9, 38.8]
Linear Fit	[36.4, 36.4]
μ_0^{50}	
Monotonicity only	[36.6, 37.2]
Conservative Curvature Constraint	[36.6, 37.2]
Aggressive Curvature Constraint	[36.7, 37.1]
Linear Fit	[36.4, 36.4]

Bounds on Bottom Half Mobility (μ_0^{50}): U.S. 2000–2015

Midpoint of μ_0^{50} bounds (all of which have width < 0.5)

	Father-Daughter	Father-Son
U.S. Black	36.9	33.7
U.S. White	42.0	41.9

Compare with income p_{25} (Chetty et al. 2018):

	Father-Daughter	Father-Son
U.S. Black	41.1	38.6
U.S. White	39.6	48.6

Some Conclusions on Educational Mobility

- Using a measure directly comparable to Chetty et al. 2014's p_{25}, U.S. intergenerational education mobility is the same on average as intergenerational income mobility...
- ... but subgroup differences are substantial.
  - Relative to income mobility, educational mobility is higher for white women, and lower for men and black women
- International comparisons can be made:
  - Indian Muslim male mobility much lower than U.S. Black; comparable to Native Americans
  - Indian SC male mobility higher than U.S. Black

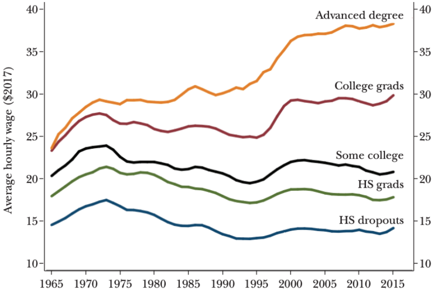
Other Applications of the Method: Less Educated Americans

Marriage Rates at Ages 40 to 44, 1980 to 2017

	Share of men married at ages 40 to 44			
Group	*1980*	*2000*	*2017*	*Change 1980–2000 (percentage points)*
By Education				
<HS	80%	65%	60%	–16
HS graduate	82%	62%	59%	–19
Some college	82%	67%	64%	–16
College	85%	77%	79%	–8

Coile and Duggan (JEP 2019)

Figure 1
Real Hourly Earnings by Education Status, Men Aged 25–54, 1965–2016



Binder and Bound (JEP 2019)

Conclusions: Widely Applicable Methods

- Our mobility measure is valid for comparison across subgroups, countries, and time
- Our partial identification approach may be useful in other contexts:
  - Changing fertility, marriage patterns by education
  - Expectation of Y given income when income is top-coded
  - Expectation of default given bond rating
  - CEFs with Likert Scales or other survey data
  - Monotonicity not required, but it will help

Public Stata/Matlab packages: `https://github.com/paulnov/nra-bounds`

THANK YOU!

Appendix

Comparison with Other Approaches

Other approaches to dealing with coarse data

- Focus on groups for whom education has not changed very much
- Assume linearity of CEF
  - Canonical approach, but:
  - Many fully supported CEFs are concave at bottom
  - Doesn't distinguish change at top from change at bottom
  - Identical to our approach with $\overline{C} = 0$
- Randomly reassign people across bins to get same bin sizes
  - Very widely used
  - Used in World Bank's 2018 flagship report on intergenerational mobility
    - Concludes Ethiopia has almost perfect upward mobility
  - Equivalent to assuming CEF is a function with zero slope and large steps right at education boundaries

Overview of Methods

- Assumption 1: There exists a latent education rank, observed in coarse intervals
- Arises out of the most standard human capital investment model (e.g. Card 1999, Card et al. 2018)
  - Schooling choice determined by heterogeneous cost and benefit shifters
  - Model suggests a continuous optimal level of schooling E for each individual
  - Individuals complete the last year with positive expected value
- High ranked individuals within bin would advance to next level if marginal cost/benefit shifted only a little
- Note: this is a descriptive exercise
  - We are not trying to estimate causal effects of parent education

Back

Why are mu-bounds tighter?

Bounds on key mobility statistics $\overline{C} = 3$:

Gradient β:	[0.45, 0.63]
Abs. Mobility p_{25}:	[31.0, 46.0]
Interval Mobility μ_0^{50}:	[36.5, 38.5]

Why are μ_0^{50} bounds so much tighter?

- Bin 1 has fathers in ranks 1-57:
  - μ_0^{57} is point identified – we observe it in the data
- μ_0^X is mean of $\mu_0^1, \mu_1^2, ..., \mu_{X-1}^X$
- Given μ_0^{57} and monotonicity, narrow set of possible values of μ_0^{50}.
- In paper: proof of analytical bounds for μ_a^b given interval data

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