Child Poverty and Income Mobility

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Child Poverty and Intergenerational Mobility in the U.S.

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Motivation

- Chetty et al. (2016) and Chyn et al. (2016) find a linear effect of exposure to better neighborhoods on children's income.
- Earlier childhood development suggests very early childhood is most important, suggesting nonlinearity in timing.
- Apparent conflict, combined with limited definition of poverty, creates puzzle we hope to solve.

Hypotheses

We set out to test two hypotheses that can explain this tension:

1. Both *intensity* and *duration* of childhood poverty have distinct impacts on economic status of individuals in adulthood.
2. *Intensity* and the *duration* affect adulthood economic outcomes nonlinearly in their timing.

Data and Measures

- Data come from Panel Study of Income Dynamics (PSID).
  - Attractive because of large number of parent/child pairs.
  - Includes wide selection of covariates in both adulthood and childhood.
- Need to select sample, however. We use following rules, following recommendations from mobility literature:
  - Five or more childhood observations
  - Three or more adulthood observations
  - Maximum one period of poverty (i.e. no switching in and out; made for convenience)
- We use some measurements and definitions frequently:
  - Following Chetty et al., use rank measures of income, built from empirical distribution of household incomes (from IPUMS).
  - Use two rank measures: 'net rank' is difference between rank in adulthood and parents rank during childhood, 'raw rank' is rank during adulthood.
  - Define poverty in multiple dimensions:
    - Timing: age at which household first entered poverty (simplified by one period restriction).
    - Intensity: mean shortfall from poverty line in childhood years when household was poor, in percentage points.
    - Duration: percent of childhood years when household was poor.

Table 1: Selected Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Adulthood Rank	1,692	0.314	0.176	0.014	0.957
Childhood Rank	1,692	0.388	0.238	0.010	1.000
Net Rank	1,692	−0.074	0.221	−0.850	0.729
Intensity	1,692	0.295	0.358	0.000	1.000
Duration	1,692	0.272	0.355	0.000	1.000

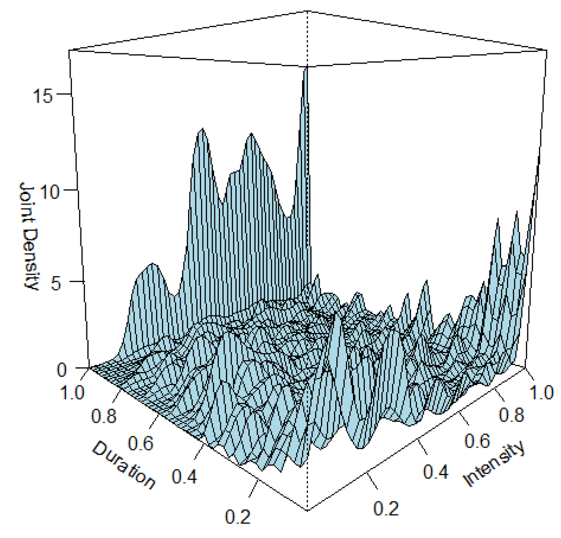
Method

- Use Generalized Propensity Score (GPS) estimator, which includes three steps, following Hirano and Imbens (2004):
  1. Selection Equation:
     - $R_{ij} = T_{ij} = \beta_0 + \beta_{1j} X_{ij} + \epsilon$
  2. Outcome Function:
     - $Y_i = \alpha_0 + \alpha_{1j} T_{ij} + \alpha_{2j} \widehat{R}_{ij} + \alpha_3 T_{ij} * \widehat{R}_{ij} + \epsilon_i$
  3. Dose Response Function:
     - $\widehat{E[Y(t)]} = \frac{1}{N} \sum_{i=1}^{N} \left(\widehat{\alpha}_0 + \widehat{\alpha}_{1j} t_j + \widehat{\alpha}_{2j} \widehat{R}_{ij}(t, X_{ij}) + \alpha_3 t_j \widehat{R}_{ij}(t, X_{ij}) \right)$
- Noteworthy features:
  - Removes bias from selection on observables, comparing like individuals with varied treatment.
  - More flexible than matching or regression.
  - Note that this **is not** matching, does not claim to remove bias from unobservables.

Selection Equation

- Estimate treatment values as functions of demographics, and parental education, labor market participation, and marital status.
- Use non-parametric estimates to account for potential interactions; produces better fits ($\sim$ **20** percentage point improvements in R^2) compared to linear LS specification.
- Non-standard density (Fig. 1) means we can't make distributional assumptions that make GPS more straightforward.

Figure 1: Nonparametric Joint Treatment Density



Preliminary Results

- Outcome function needs to have several features to allow hypothesis tests:
  - Interaction between intensity, duration, and timing
  - Nonlinearity in all three
  - Interactions specified to allow nonlinear cross-partial derivatives (e.g effect of intensity depends on timing.)

Figure 2: Treatment Surfaces

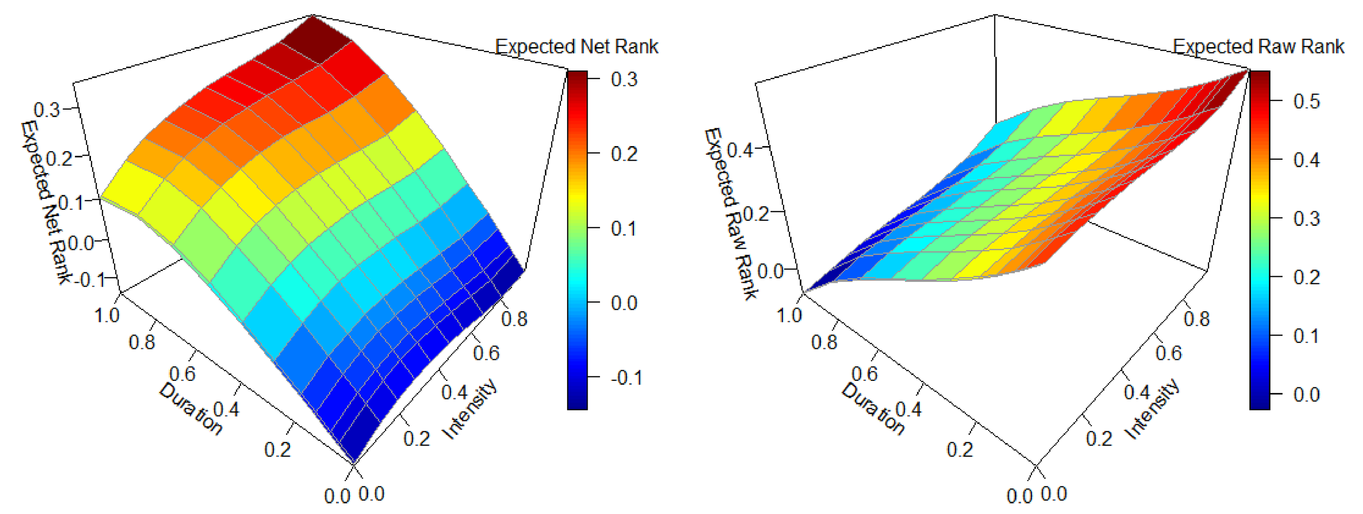
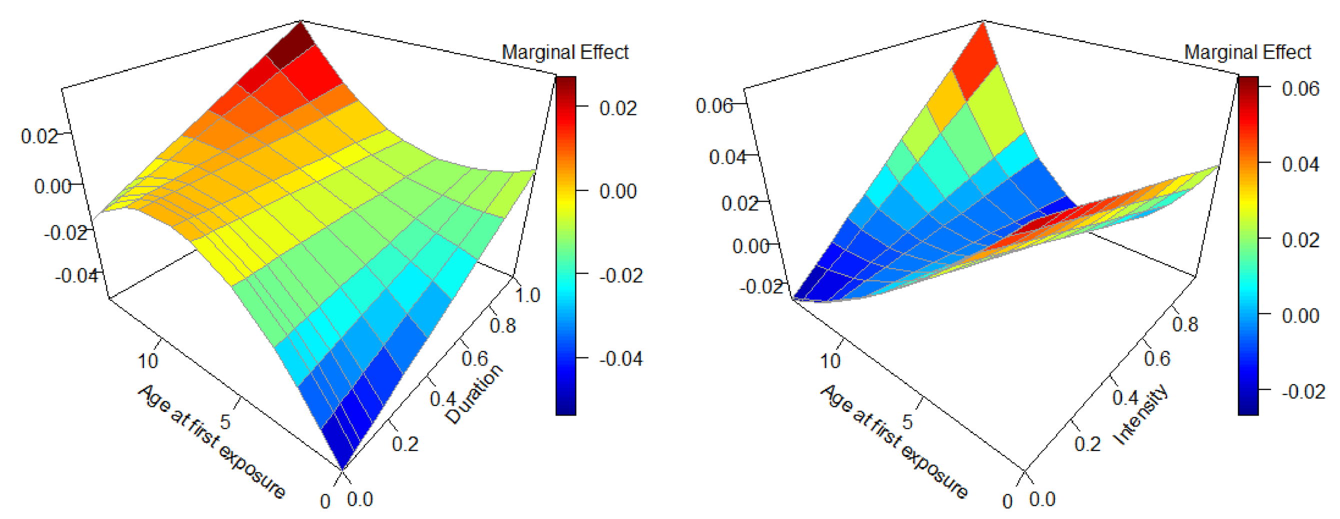


Figure 3: Marginal Effects of Intensity and Duration (from Raw Rank model)



Conclusions

- Raw rank results partially consistent with hypotheses:
  - Duration has the more substantial effect, as expected value changes little across intensity given duration.
  - Fairly steep duration gradient in expected rank, however.
  - Marginals behave somewhat as expected: intensity effect more negative if exposed at younger ages, although saddle shaped duration surface suggest higher ages are worse.
- Childhood rank and treatments are closely correlated, weakening distinction between our story and standard mobility literature.
- Due in part to this relationship, more poverty predicts more upward mobility (left panel, Figure 1), perhaps due to mean reversion.

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