SES-Based Effect Modification and Intergenerational Educational Stratification

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This study brings new light to familiar questions about intergenerational educational stratification—that is, why children of more educated parents have higher educational attainment than children of less educated parents, and what we can do about the resulting inequality. We usually approach these problems from the status attainment perspective, tracing the causal paths linking social origins to destinations through mediating factors (Blau and Duncan 1967, Sewell, Haller and Portes 1969). Disparate backgrounds yield disparate experiences, resources, and skills, which translate into disparate outcomes.

Despite its unmistakable contributions to stratification research, this approach makes the implausible assumption that the effects of mediating factors are homogenous across social backgrounds. Problems with this assumption may help explain the persistence of intergenerational educational stratification despite vast policy changes expected to improve the education of disadvantaged children (Hout and Janus 2011). If we are to better understand intergenerational inequality and design interventions to address it, we must understand how children’s backgrounds alter the nature of the attainment process.

Background

Scholars taking a mobility perspective have long suspected that certain factors are more important to the upward mobility of disadvantaged children than to the attainment of their more advantaged peers, as the former must overcome more obstacles to achieve the same outcomes (Crockett 1962, Lundberg 2013). Resilience research in developmental psychology takes similar interest in skills and circumstances that are especially important to the healthy development of at-risk children (Masten 2001). In other words, certain skills may be more important to the educational success of disadvantaged youth.

Sociological, psychological, and economic theories central to educational attainment also imply social background-based effect heterogeneity. Rational choice models assume that the preferences, costs and constraints, and perceived probability of success that determine educational decisions have joint, interactive effects (Gambetta 1987). Similarly, models of child development and human capital formation share the notion that external influences (or investments) and child skills have reciprocal and interactive effects on each other throughout childhood (Becker and Tomes 1986, Bronfenbrenner and Ceci 1994, Cunha, Heckman and Schennach 2010, Freese 2008). In both cases, interactions imply that the influence of any particular factor depends on the levels of others. Given socioeconomic disparities in many of these factors, we should expect them to have differential impacts on educational attainment across socioeconomic backgrounds.

Hence, a missing link in our logic, and a key aspect of stratification processes, is the way social background modifies the process of educational attainment. Social background not only affects children’s attainment by influencing levels of the skills and circumstances
that affect their educational outcomes, but also by altering the effects of these factors. This challenges our efforts to understand and address educational stratification, as it muddles the consequences of efforts to improve the plight of disadvantaged youth. It is no longer only disparities in the skills and circumstances of different groups of children that matter, but also how these factors affect the children of different groups.

**Data and Methods**

I address this problem with data from the Child and Young Adult cohorts of the National Longitudinal Survey of Youth 1979. I stratify children by their mothers’ educational attainment and use flexible decomposition techniques to quantify the importance of disparities in the levels and effects of family characteristics, parental investments, and child skill development at particular childhood stages to later educational disparities.

For simplicity, I compare children of mothers without a high school diploma (low-SES, N=2,796) to those of mothers with at least a bachelor’s degree (high-SES, N=2,065). I examine inequality between these groups in high school GPA and educational aspirations, high school graduation, college attendance, and bachelor’s degree attainment.

I classify explanatory factors temporally and theoretically. First are antecedents set prior to birth that influence parental SES and subsequent child outcomes (race and maternal skills, attitudes, and behaviors). Next are factors that become important at birth, including gender, the number of older siblings, and child birth weight and length. After birth, I distinguish seven stages of childhood: ages 0-2, 3-4, 5-6, 7-8, 9-10, 11-12, 13-14. Each includes measures of family background (log of family income, family structure, number of children in the household), parental investments (cognitive stimulation and emotional support), and child skills (intellectual skills, behavior problems, delinquency, etc.).

I use decompositions to quantify the importance of SES differences in the levels and effects of these explanatory factors. Each is based on the counterfactual in which low-SES youth are given the attributes of high-SES youth. This aligns with policies aiming to improve the plight of disadvantaged youth, which seem more practical and politically palatable than efforts to worsen the circumstances of advantaged youth.

The decomposition methods combine the benefits of inverse probability weighting (IPW) and regression modeling (Fortin, Lemieux and Firpo 2011). I use IPW to reweight the low-SES group to resemble the high-SES group on explanatory factors. IPW alone permits “aggregate” decompositions that partition composition effects (differences in the distribution of all covariates) and structure effects (differences in the effects of all covariates) with no functional form assumptions. This is advantageous because the “technologies” of learning and educational decision-making are poorly understood.

However, this approach does not describe how specific factors contribute to inequality, and it requires conditional ignorability—IPW weights derived from observed covariates must make groups identical in the distribution of factors that influence outcomes. Sequential IPW decompositions use a sequence of IPW analyses in steps that reflect the
causal ordering—here ordered temporally—to identify composition effects of particular groups of variables (Altonji, Bharadwaj and Lange 2012). They capture the total effect of SES disparities in one group of covariates, net of disparities in all prior stages.

Regression models allow a more detailed decomposition by estimating ceteris paribus effects of each variable simultaneously. They also replace the ignorability assumption with the weaker assumption of mean independence. This is at the cost of functional form assumptions, however, and misspecification of the outcome model may bias regression coefficients and thus the estimated composition and structure effects. Combining IPW and regression allows regression decompositions where both groups have similar covariate distributions (Fortin, Lemieux and Firpo 2011). This reduces bias from omitted nonlinearities and isolates the misspecification error. This method also partitions out reweighting errors in the IPW analyses, better isolating the true contributions of disparities in the levels and effects of explanatory factors.

**Preliminary Findings and Implications**

The IPW decompositions attribute most inequality in high school GPA (83%), aspirations (101%), high school graduation (78%), and college attendance (87%) to composition effects, which correspond to the adverse skills and circumstances of low-SES youth (see Table 1). These components also represent the reduction in inequality we might expect from improving low-SES attributes to resemble those of high-SES youth. The composition effect is substantially smaller (51%) for bachelor’s degree attainment.

The residual gaps for all outcomes except aspirations indicate that structure effects also contribute to intergenerational educational inequality. That is, the differential returns to skills and circumstances among high-SES youth increase inequality because they gain more from these factors than low-SES youth. These structure effects also represent the shortfall of efforts to address inequality by improving the attributes of low-SES youth. The structure effects are substantial for bachelor’s degree attainment (49%).

Sequential IPW decompositions trace these composition effects to antecedent background factors (mainly maternal skills and attributes) set prior to birth. Net of these antecedents, disparities in skill development increase inequality in most outcomes, although disparities in family attributes and resources increase inequality in bachelor’s degree attainment.

The IPW regression decompositions will provide more detailed information on the composition and structure effects of specific factors, holding others constant. For instance, these analyses will help determine which particular factors mediate the total effects of antecedent factors, and at which states these disparities materialize.

Overall, preliminary findings indicate that efforts to improve the skills and circumstances of low-SES youth will be insufficient to eliminate many aspects of intergenerational educational inequality, especially college completion. High-SES youth not only have more of what it takes to succeed educationally, but also reap greater returns to what they
have. We must better understand the sources of these differences to make further progress addressing educational stratification.

### Table 1. Summary of IPW Decompositions: Counterfactual 1

<table>
<thead>
<tr>
<th>Raw Gap (in means)</th>
<th>HS GPA</th>
<th>Aspirations</th>
<th>HS Dipl.</th>
<th>Coll. Att.</th>
<th>BA Degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.71</td>
<td>0.84</td>
<td>0.32</td>
<td>0.44</td>
<td>0.50</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aggregated components</th>
<th>Composition</th>
<th>Structure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>83.31</td>
<td>16.69</td>
</tr>
<tr>
<td></td>
<td>100.60</td>
<td>-0.60</td>
</tr>
<tr>
<td></td>
<td>77.96</td>
<td>22.04</td>
</tr>
<tr>
<td></td>
<td>87.03</td>
<td>12.97</td>
</tr>
<tr>
<td></td>
<td>51.16</td>
<td>48.84</td>
</tr>
</tbody>
</table>

**Sequential:**

**Composition by category**

- Antecedents: 97.29, 104.38, 51.89, 87.29, 64.79
- Skills and attributes: 11.41, -5.70, 41.40, 12.43, -29.67
- Family background: -25.90, -8.58, -2.08, -12.18, 21.76
- Parenting: 0.51, 10.50, -13.24, -0.52, -5.72

**Sequential:**

**Composition by stage**

| Pre-birth | 97.29 | 104.38 | 51.89 | 87.29 | 64.79 |
| Birth    | -4.48 | -12.09 | 13.20 | -0.34 | -24.67 |
| 0-2      | -4.89 | -1.10  | -5.01 | -3.23 | 3.94  |
| 3-4      | -1.68 | 4.54   | 4.17  | -2.73 | 17.55 |
| 5-6      | -15.49| -3.95  | -7.16 | -8.44 | -11.30|
| 7-8      | 1.67  | 6.21   | 5.55  | 3.32  | 8.93  |
| 9-10     | -2.34 | -1.63  | -1.52 | 2.66  | -7.64 |
| 11-12    | 7.69  | 0.70   | -2.03 | 2.50  | 7.72  |
| 13-14    | 5.55  | 3.54   | 18.88 | 5.99  | -8.18 |

Each cell represents the total percentage reduction in inequality that results from equalizing the distribution of the set of covariates (giving low-SES youth high-SES covariates). Estimates are based on analyses of multiply imputed data (m=25, separately by group), with inverse probability weights to adjust for attrition.
References


