Schooling, Statistics and Poverty: Measuring School Improvement and Improving Schools

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Outline of Talk

• Controversy Over No Child Left Behind
• Statistical Issues Central
• Some Surprising Findings
• Relationship to the New Committee on Education at Chicago
Background

• High Stakes Testing Under NCLB
• Key Aim: Improve schooling for poor children.
From NCLB, 2001

• This law is intended to close “the achievement gap between high- and low-performing children, especially the achievement gaps between minority and non-minority students, and between disadvantaged students and their more advantaged peers”
Theory of Action

• Hold schools accountable for outcomes

• Allow flexibility in achieving these outcomes

• Key role of statistical evidence
Debate over re-authorization

• There is considerable support for accountability
• Some strong opposition
• A controversy over statistics
The Controversy

• How to Measure School Quality
• How to Measure School Improvement

• Quality of Statistical Evidence is Key to the Theory of Action!
Dominant Approach

• School mean proficiency = quality
• Change in proficiency between cohorts = improvement

• But
  – student proficiency = cumulative effects of prior experience
  – School-mean proficiency reflects student intake
  – Change in school mean reflects change in intake
High Failure Rates of High-Poverty Schools

• In 2004, 66% of all Illinois schools found to be “in need of improvement” were in Chicago.

• Indeed, over 60% of Chicago schools were so classified.

• Similarly, 69% of those schools found to be in need of in the state of New York were in New York City.
Are High-Poverty Schools Failing?

• Sociological theory predicts this:
  – Deprivation of resources (Pfeffer and Salancik, 1978)
  – Role models, collective socialization, peers (Jencks and Mayer, 1989)
  – Cohesion and informal social control (Sampson, Raudenbush, and Earls, 1997)
  – Social Capital (Coleman, 1989)
  – Academic Pacing (Barr and Dreeben, 1983)
Supporting perceptions of failure

• Past empirical evidence on “contextual effects”
  – Neighborhood effects (Garner and Raudenbush (1991)

• Accounts in the popular literature (Kozol’s “Savage Inequalities”)
However…

Likely bias of NCLB results

Importance of public perception

(Lowry, 2002)
An Alternative: “Value Added”

- Hold Schools Accountable for Kids’ Growth Not Status
- School Improvement = Change in Value Added
- Intuitive Appeal
- Creates an “even playing field” for high poverty schools
Objections to Value Added

- Annual testing
- Must track students over time
- Need equated tests
- Challenging data analysis
  - Problem of transparency
  - School district capacity
Inferential Issues

Reliability of “change in change”

Potential bias of controlling for prior school effects
Figure 1. Average reading achievement trajectories of two hypothetical schools
• Moreover, school differences in growth could reflect differences in intake
• Or differences in summer learning.
My Investigation

• Analyze Four Data Sets Spanning K-12
• Compare effectiveness indicators based on mean proficiency \((a\ la\ NCLB)\) versus value added

• Examine how high and low poverty schools fare on these
Comparisons

• Grades k-1 (Early Childhood Longitudinal Study)
• Grades 1-3 (Sustaining Effects Study)
• Grades 1-5 (DC accountability data)
• Grades 8-12 (National Educational Longitudinal Study)
Finding 1

Mean Proficiency and Value Added Give Quite Different Results
Table 4: Correlations between Mean Proficiency and Value Added, Grades 2-5 (Washington D.C. data)

<table>
<thead>
<tr>
<th>Sample</th>
<th>Grade</th>
<th>Reading</th>
<th>Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting in 98</td>
<td>2</td>
<td>.40</td>
<td>.62</td>
</tr>
<tr>
<td>Starting in 98</td>
<td>3</td>
<td>.34</td>
<td>.45</td>
</tr>
<tr>
<td>Starting in 98</td>
<td>4</td>
<td>.49</td>
<td>.35</td>
</tr>
<tr>
<td>Starting in 98</td>
<td>5</td>
<td>.44</td>
<td>.47</td>
</tr>
<tr>
<td>Starting in 99</td>
<td>3</td>
<td>.33</td>
<td>.47</td>
</tr>
<tr>
<td>Starting in 00</td>
<td>4</td>
<td>.30</td>
<td>.33</td>
</tr>
<tr>
<td>Starting in 01</td>
<td>5</td>
<td>.35</td>
<td>.40</td>
</tr>
</tbody>
</table>
Finding 2

Mean Proficiency Strongly Biased Against High Poverty Schools
## Design of Early Childhood Longitudinal Study (ECLS)

<table>
<thead>
<tr>
<th>Age</th>
<th>60 months</th>
<th>69.5 months</th>
<th>72.5 months</th>
<th>82 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade</td>
<td>Fall K</td>
<td>Spring K</td>
<td>Fall 1</td>
<td>Spring 1</td>
</tr>
</tbody>
</table>
Model for individual growth

\[ \pi_{ij} = \text{kindergarten learning rate/month} \]
\[ \pi_{2ij} = \text{summer learning rate/month} \]
\[ \pi_{3ij} = \text{first-grade learning rate/month} \]
Model for Individual Differences in Learning

\[ \pi_{0ij} = \gamma_{00} + \gamma_{01} (High\ Poverty)_{ij} + u_{0j} + r_{0ij} \]
\[ \pi_{1ij} = \gamma_{10} + \gamma_{11} (High\ Poverty)_{ij} + u_{1j} + r_{1ij} \]
\[ \pi_{2ij} = \gamma_{00} + \gamma_{01} (High\ Poverty)_{ij} + u_{2j} \]
\[ \pi_{3ij} = \gamma_{30} + \gamma_{31} (High\ Poverty)_{ij} + u_{3j} + r_{3ij} \]

\[
\begin{pmatrix}
  u_{0j} \\
  u_{1j} \\
  u_{2j} \\
  u_{3j}
\end{pmatrix}
\sim N(0, \Omega),
\begin{pmatrix}
  r_{0j} \\
  r_{1j} \\
  r_{2j}
\end{pmatrix}
\sim N(0, \tau)\]
Under Our Model,

• **Mean Proficiency in grade 1**
  \[ = \text{E}(\text{fall k status} + \text{k learning} + \text{summer learning} + \text{grade 1 learning}) \]

• **Value Added in grade 1**
  \[ = \text{E}(\text{summer learning} + \text{grade 1 learning}) \]
Early Childhood Longitudinal Study (ECLS)

(a) Reading

Reading Score vs. Age (months)

- Low poverty
- High poverty
Comparing Indicators

School Pov associated with Fall k status, summer loss, First grade growth

NCLB indicators WOULD be quite strongly correlated with School Poverty

Grade-1 Value Added indicators:

- Would be weakly associated with School Pov, for two reasons:
  1. Summer loss is greater in high pov schools
  2. Modestly lower growth during grade 1 in high pov schools
Figure 3. Mean trajectories, high and low poverty schools (ECLS)

(b) Math
Comparing Indicators

• School Poverty associated only with Fall K entry status. No association with summer loss or academic year growth.

• So NCLB indicators WOULD be quite strongly correlated with School Poverty

• Value Added indicators would NOT be so associated
Figure 5. Average trajectories, Grades 1-3, high and low poverty schools (Sustaining Effects Study)

(a) Reading
Comparing Indicators

- School Poverty associated only with entry status (spring grade 1) and summer growth.

- So NCLB indicators WOULD be quite strongly correlated with School Poverty

- Value Added indicators would be WEAKLY correlated with School Pov
  - and then only because summer growth is less in high poverty schools!
Figure 5. Average trajectories, Grades 1-3, high and low poverty schools (Sustaining Effects Study)

(b) Math

Age (months) vs. Math Score, showing trends for Low poverty and High poverty schools.
Comparing Indicators

• School Poverty associated with entry status (spring 1) only.

• So NCLB indicators WOULD be quite strongly correlated with School Poverty

• Value Added indicators would NOT.
Figure 6. Average achievement trajectories, Grades 8-12 (NELS 88).

(a) Science

![Graph showing average achievement trajectories for Science grades 8 to 12, comparing low and high poverty levels.](image-url)
Comparing Indicators

• School Poverty negatively associated with 8th grade status and average growth;
• NCLB indicators strongly associated with School Pov
• Value-added indicators also associated.
• But….
  – Corr (school mean status and school mean growth)=.68
  – Corr (student status and growth)=.68
Figure 6. Average achievement trajectories, Grades 8-12 (NELS 88).
Comparing Indicators

• Story nearly identical to that in the case of Science
Finding 3: Value Added is Not a Gold Standard!

Affected by summer learning

Growth rates are correlated with status of kids prior to entry to school

Open to several interpretations
Finding 4

• Surprisingly weak association between school poverty and academic learning rates
  – Especially in early years
  – Especially in math
Emerging Questions

• Do poor students in high-poverty schools learn much less than the poor students in low-poverty schools?
• Let’s take a look at social inequality in ECLS
Growth as a function of student social background: ECLS

(a) Reading

![Graph showing growth in reading score as a function of age, with two lines representing high (Hi) and low (Low) SES.](image-url)
Growth as a function of school poverty for low SES students

(a) Reading

![Graph showing the relationship between age (months) and reading score for low poverty (Low Pov) and high poverty (Hi Pov) groups. The graph indicates a trend where reading scores generally increase with age, with some variability in the low poverty group.](image_url)
Growth as a function of student social background: ECLS

(b) Math

![Math Growth Graph]

- Hi SES
- Low SES

Math Score vs. Age (months)
Growth as a Function of School Poverty for low SES kids

(b) Math

Math Score

Age (months)
Growth as a Function of Student Poverty: Sustaining Effects Data

(a) Reading

- Not poor
- Poor
Growth as a Function of School Poverty for Poor Children: Sustaining Effects Data

(a) Reading

![Graph showing growth in reading scores as a function of age and poverty level. The graph compares low poverty and high poverty conditions.](image-url)
Growth as a Function of Student Poverty: Sustaining Effects Data

(b) Math

![Graph showing growth as a function of student poverty in math scores over age (months). The graph compares data for students who are not poor and those who are poor, with math scores plotted against age in months. The graph indicates a trend where students from poor backgrounds have lower math scores compared to those from non-poor backgrounds.](image)
Growth as a Function of School Poverty for Poor Children: Sustaining Effects Data

(b) Math

![Graph showing the math score over age (months) for low poverty and high poverty children. The graph indicates a higher math score for children in low poverty compared to those in high poverty.]
Conclusions

• “Mean proficiency” seriously biased against high poverty schools
• “Value added” biased more subtly
• Growth rates in high- and low-poverty schools are quite similar.
• Accountability may motivate educators, but how can it overcome social inequality?
Hypotheses

• School and neighborhood social context are “weak forces” in shaping cognitive skill in the early years

• Making high poverty schools “look like” low poverty schools will not eliminate social disparities
So What Are the “Strong Forces?”

• Interactions with caregivers prior to K
  – Shape language
  – General knowledge
  – Concept Development
    (Goldin-Meadow, Huttenlocher, Levine)

• Interventions and Policy Options
  (Raver; Keels; Heckman, Neal)
Strong Forces (cont’d)

• Ambitious instruction in literacy and math during the early years
  – Nicole Woodard-Iliev, Tim Knowles
  – Stein in Science
  – Sally, Usiskin in Math

• Integrating social services with instruction
  – (Roderick, Courtney)
“The Chicago Model for Urban Schooling”

• Explicating and practicing our theory
  – (Yowell, Knowles)
  – Preparing teachers (Stodolsky)

• Testing the Theory: 7 experiments
  – (Schanzenbach, Easton)
Final Prediction

• The University of Chicago is positioned to make seminal contributions to understanding and reducing social inequality in cognitive skills
• We are attuned to the “strong forces!”
• Keys
  – Interdisciplinary interchange
  – Testing the ideas we practice