Parsing Achievement Gaps: The Influence of Individual, Family, and School Factors on the Evolution of Hispanic-White Achievement Differences in Mathematics the Elementary Grades

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Overview

Study uses data from the Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K) to examine children's trajectories of mathematics learning from Kindergarten until the fifth grade. Explores factors that help account for Hispanic-White achievement differences at school entry and in achievement growth over time.

Study Background / Literature Review

- Achievement gap = difference between *average* achievement of Hispanic and White students
- Achievement gaps are large (about 1 SD) and persistent
- Most research to date focuses on Black-White achievement differences
- Gaps have narrowed over past 30 years but progress may have stalled
- Gaps already evident before children enter Kindergarten
- No single factor fully explains gaps; achievement associated with diverse factors across multiple domains
- Cumulative effect of small differences in home, school educational inputs a possible explanation for expanding gaps
- Educational "inputs" may have heterogeneous effects
- Inherited ability an important but elusive influence on achievement
- Genetic contribution to gaps remains uncertain and controversial
- Individual characteristics (e.g., LBW, first born, poor health) may exert long-lasting influence on achievement
- "Noncognitive" traits and learning behaviors also important; possibly influenced by prior experiences of educational failure, success
- Family SES strongly correlated with achievement; parental ability an important moderator
- Differences in family structure (e.g., single/teen parent) and "conduciveness to learning" of home environment may help explain achievement gaps
- School factors generally less important in explaining differences in achievement than individual, family characteristics
- Debate about whether gaps widen or remain about the same after students enter school
- Differences in early education may help explain gaps at school entry; effects may fade over time
- Few reliable signals of school, teacher "quality" (e.g., novice teachers, % minority students, overall student mobility, class sizes)

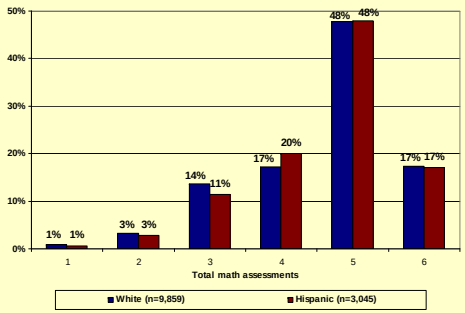
Data: The ECLS-K

- Sponsored by U.S. Department of Education, National Center for Education Statistics
- Longitudinal follow-up (through grade 12) of nationally representative sample of about 20,000 children entering Kindergarten (public and private) in 1998-99
- Five (5) "waves" of data collected to-date: K-fall, K-spring, Gr1-fall, Gr1-spring, Gr3-spring, Gr5-spring
- Various modes of data collection: direct child assessments, parent interviews, school/principal/ teacher data, student record abstracts

Analysis Sample

- 12,904 children with DOB, school identification, and Mathematics test scores at *any* assessment point
- Include children who change schools (movers)
- About 24 percent Hispanic
- About 60,000 person-period data points
- Almost two-thirds of sample have 5 or 6 data points

Figure 1. Sample distribution by number of assessments available



Outcome Measure

- IRT scale score in mathematics developed by NCES
- Theoretical range from 0 (at Kindergarten entry) to 153 (in spring of fifth grade)
- Results will be reported in scale score units, as effect sizes and as grade equivalent scores

Figure 2. Evolution of mathematics scores in the ECLS-K study sample

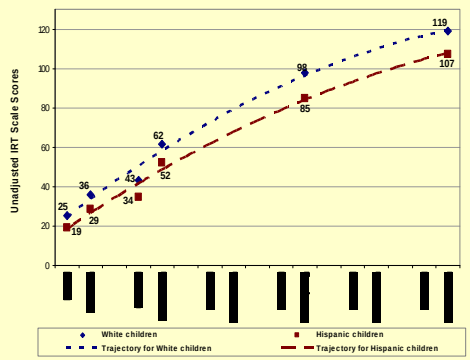
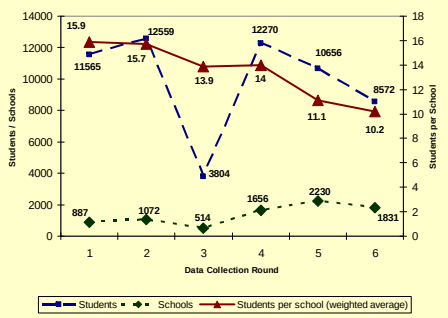


Figure 3. Students and Schools in ECLS-K Study Sample



Analytic Strategy

- 3-level hierarchical growth curve model (HGCM) of mathematics achievement
  - Level 1: Time
  - Level 2: Individuals
  - Level 3: Schools
- Bayesian MCMC/Gibbs sampling methods (MLwiN) for estimation of HGCM with crossed random effects
- Normalized, base-year sampling weights

Empirical Model

$$Y_{tis(t)} = \gamma_{000} + u_{00s(t)} + r_{0is(t)} + \Sigma\gamma_{00k}(X_{ik}) +$$

$$(\gamma_{100} + \Sigma\gamma_{00k}(X_{ik}) + \Sigma\gamma_{10m}(Z_{ti}^{m}) + \Sigma\gamma_{1p0}(S_{ts(t)}^{p}) + u_{10s(t)} + r_{1is(t)})$$

$$\text{X AGE}_{tis(t)} + e_{tis(t)}$$

where:

- $Y_{tis(t)}$ is the test score at time *t* for child *i* in school *s(t)*;
- γ_{000} is the grand mean of mathematics achievement at Kindergarten entry;
- $u_{00s(t)}$ is the deviation from γ_{000} for students attending school *s(t)*, assumed to be a random effect;
- $r_{0is(t)}$ is the deviation, for student *i*, from school *s(t)*'s mean achievement ($\gamma_{000} + u_{00s(t)}$);
- γ_{100} is the overall mean slope across all students and schools;
- $u_{10s(t)}$ is the deviation from γ_{100} for students in school *s(t)*, also assumed to be a random effect;
- $r_{1is(t)}$ is the deviation for student *i* from mean slope for school *s(t)* ($\gamma_{100} + u_{10s(t)}$), also a random effect;
- X_i^k is k-dimensional vector of time-invariant child characteristics and cumulative family-determined educational inputs, observed at Kindergarten entry;
- Z_{ti}^{m} is m-dimensional vector of time-varying, family-chosen cumulative inputs experienced by child *i* through time ***t*****;** and,
- $S_{tis(t)}^{p}$ is p-dimensional vector of time-varying, school-determined inputs experienced by child *i* at school *s(t)*

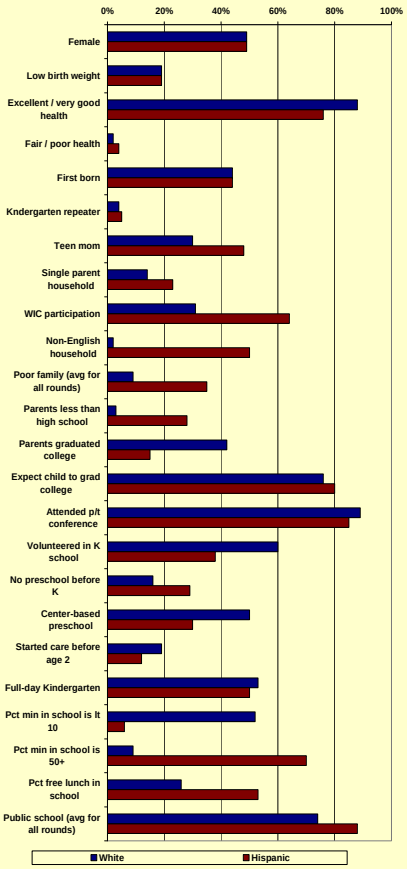
Study Contributions

- Address important gap in literature on Hispanic-White achievement differences and identify promising "policy levers"
- Use best-available ECLS-K data (restricted-use files)
- Application of state-of-the-art HGCM estimation techniques (Bayesian MCMC/Gibbs sampling)
- More generalizable results since include children who move/change schools
- Attention to effects of cumulative inputs on achievement growth over time
- Explore heterogeneous effects (poor children, ELLs, contextual effects)

Study Limitations

- Correlational analysis
- Retrospective data on experiences before K entry
- No data on schooling experiences in grades 2 or 4
- Sample attrition
- Movers are subsampled (possible selection bias)

Figure 4: Selected Sample Characteristics



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