Research Report

Assessing Cognitive Achievement Growth During the Kindergarten and First Grade Years

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Abstract

This study attempts to identify different patterns of cognitive growth in kindergarten and first grade associated with selected subpopulations. The results are based upon a nationally representative sample of fall kindergartners who were retested in the spring of their kindergarten year and then again in the fall and spring of their first grade year. Of special interest here is the estimation of the growth rates of subpopulations of children that are often considered to be at risk, educationally and/or economically. This study also investigates whether or not the absence of formal schooling during the summer differentially impacts subpopulations who are "at risk" because they may lack a strong educational support system in the home.

Key words: Longitudinal, kindergarteners, cognitive, growth, multilevel, summer effect, at-risk

The research discussed here attempts to identify different patterns of growth in reading and mathematics achievement associated with selected subpopulations in kindergarten and first grade. Longitudinal data was collected at four time points: fall kindergarten, spring kindergarten, fall first grade, and spring first grade. Of special interest here is the estimation of the growth rates of subpopulations of children that are often considered to be at risk, educationally and/or economically. In addition to estimating the amount of growth, this study will investigate how the subpopulations may differ with respect to the quality of their growth. That is, we will also use a criterion-referenced approach to measuring change that looks at how the subpopulations differ with respect to where on the scale their growth is taking place. More specifically, this study investigates how the growth patterns in reading and mathematics may differ by: (a) the highest educational level achieved by a parent, (b) gender of the child, (c) ethnicity, and (d) school sector.

This study will also investigate the summer effect and whether or not the relative absence of formal schooling during the summer may have a differential negative impact on the cognitive growth of particular subpopulations who are at risk because they lack a strong educational support system in the home. The literature on summer learning is rather extensive. However, most if not all of the literature deals with the absence or presence of the summer effect from grades 1 on up. This study will be able to fill in the gap with respect to potential differential summer learning decline using the spring kindergarten to fall first grade year time points. Heyns (1998) found that pupils in Atlanta schools gained more during the school year than during the summer, and that summer learning was inversely related to parents' educational level. Entwisle, Alexander, and Olson (1997) found that school year learning was unrelated to socioeconomic status while summer learning was negatively related to socioeconomic status in both reading and mathematics. Entwisle and Alexander (1992, 1994) also investigated the relationship of ethnicity with summer learning compared with in-school learning. Cooper, Nye, Charlton, Lindsey, and Greathouse (1996) conducted a meta-analysis of summer learning studies and concluded that achievement test scores decline when schools are not in session. Many of the earlier studies did not use vertically equated tests with a common scale spanning grades of interest, which theoretically would be more sensitive to change as well as minimize both floor and ceiling effects. To our knowledge, no other study used a vertically equated adaptive test. It is possible that the finding of a summer loss as opposed to a de-acceleration in growth may be due to a lack of sensitivity to growth and/or floor and ceiling effects that may characterize the repetition of the same or a parallel form on successive testings. The potential floor and ceiling effects of nonadaptive measurement instruments could seriously distort gain comparisons between disadvantaged and advantaged children, who tend to occupy the opposite tails of ability distributions.

The data for this study comes from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K) sponsored by the U. S. Department of Education, National Center for Education Statistics. The ECLS-K base year sample was a national probability sample of approximately 20,000 children who entered kindergarten in fall 1998. The ECLS-K longitudinal study is designed to follow children’s progress in a number of cognitive areas from kindergarten entry to the spring of fifth grade. The study described here focuses on changes in early reading and mathematics skills taking place during the first 2 years of schooling. This study used mathematics and reading scores gathered at four points in time: fall kindergarten, spring kindergarten, fall first grade, and spring first grade. The reading and mathematics scale scores gathered at the four time points were based on individually administered adaptive tests.

Sample

The analysis sample was restricted to those children who had both reading and mathematics scores in the fall (Time Point 1) and spring (Time Point 2) of their kindergarten year *and* remained in the same school during their kindergarten and first grade years. They also had to have complete information on: (a) gender, (b) parental education, (c) ethnicity, and (d) school sector. This reduced sample numbered 14,707 children. At Time Point 3 (fall first grade) a probability subsample of the base year sample numbering about 5,000 was retested, of whom 3,032 children met the requirements described above. Estimates of summer gains were based on this subsample, targeting the growth occurring between spring kindergarten (Time Point 2) and fall first grade (Time Point 3). The assessment at the fourth time point (spring first grade) included 10,406 children who matched the children meeting the requirements for inclusion in the longitudinal sample being analyzed here.

Method

Multilevel modeling (Bryk & Raudenbush, 1992; Goldstein, 1995; Snijders & Bosker, 1999) was used to investigate variation in growth curves at both the school and child levels. Multilevel software programs are particularly appropriate when the data have a hierarchical organization where units at one level are nested within units at one or more higher levels. The data organization for longitudinal studies is inherently hierarchical with occasions nested under individuals. In addition, the ECLS-K sampling design was a two-stage design that sampled schools and then children within schools, leading to a more complex three-level hierarchy. The ability of multilevel software to automatically correct the standard errors for the clustering effects associated with having children from the same school, along with the ability to handle missing data at the different time points, makes the methodology particularly attractive for large scale longitudinal studies. Rival procedures such as the multivariate analysis of covariance (MANCOVA), which can relax assumptions about the error structure, are not typically able to efficiently handle missing data on the repeated occasions or to compensate for the clustering effects. Therefore the multilevel approach was applied here using MlwiN software (Goldstein et al., 1998) with the school sample being Level 3 in the model; the child sample, Level 2, and the four testing occasions within the child sample, Level 1. Panel sampling weights were used in all analyses. The panel sample weights are longitudinal weights that apply to children who participated in the data collection at all time points (excluding the fall first grade subsample) and weight up to the population of kindergarteners in fall 1998. Children who joined the ECLS-K sample after the base year (fall kindergarten) would have a panel weight of 0 regardless of whether they were assessed or not.

The dependent measures for each of the four occasions for each child were scale scores in reading and mathematics. These scale scores were obtained from longitudinally equated adaptive tests in each subject. On each testing occasion, a child received first stage routing tests in reading and mathematics, which were designed to assess the child's approximate ability level. Depending on the routing test score, each child was then administered one of three second-stage tests in each subject. Children who achieved high scores on the routing test received a difficult second stage form, while those with low scores received the easiest second stage form. Children in the middle range on the routing test received the middle difficulty second stage form. The resulting targeting of item difficulties to the child's ability level maximized measurement precision while minimizing the potential for floor and ceiling effects. Item response theory (IRT) scaling (Lord, 1980) was carried out, using items shared across forms to arrive at a common vertically equated scale.

The scale scores are just one of the family of IRT-based measures available on the ECLS public use data file (National Center for Education Statistics, 2002). The scale scores are particularly appropriate as overall outcome measures for multilevel analysis because of their continuous nature and relatively normal distribution. The theoretical range of the reading scale scores is 0 to 92, while the comparable range for the mathematics scale scores is 0 to 64. The reading scale score is an IRT-based estimate of the number of items a child would have answered correctly if the whole pool of 92 items that appeared in all forms of the tests had been administered. Similarly, the mathematics scale scores are estimates of number-correct scores based on the pool of 64 unique mathematics items. The actual reading scores ranged from a low of 10.5 to 89.0, while the comparable range in mathematics was 7.0 to 60.5. The reading scale was defined to have five criterion-referenced points, marking an ascending order of reading and prereading skills. The lower end of the hierarchical set of skills dealt with letter recognition and then moved up through beginning sounds, ending sounds, simple sight words, and finally comprehension of words in context at the upper end of the scale. The set of mathematics scores also included criterion-referenced markers, but these are not addressed in this paper.

In order to explain the variation in intercepts and slopes at both the child and school levels, age, school sector, individual demographic variables, and their interactions with age at time of testing were added to the multilevel models. The regression weights associated with subgroup variables (e.g., ethnicity, gender) provided estimates of the difference in subgroup intercepts as well as significance tests. The regression weights associated with the interaction terms provide estimates of the different rates of growth and their significance tests for the subgroups.

In the multilevel analysis, a sequence of models of increasing complexity were fit to the data beginning with a simple regression of reading (or mathematics) scores on four occasions based on the child's age at time of testing, measured in months. In this simple model (Model 0), only the intercept was considered random at both Level 3 (school) and Level 2 (child). This linear growth curve model allows both schools and children to have different intercepts for their regression lines. In this and all succeeding models, age is a time-covarying explanatory variable, which is key to defining and interpreting the growth curves at both the school and child levels. Age at time of testing is very important because the time lapse between testings varies among occasions and to a certain extent across children within the same occasion. Since age is a carrier for both maturation and accumulated formal and informal learning, age is a critical control/explanatory variable. The equation for Model 0 is as follows:

$$\begin{aligned} y_{ijk=} &= \beta_{0ijk} + \beta_1 x_{1ijk} \\ \beta_{0ijk} &= \beta_0 + v_{0k} + u_{0jk} + e_{0ijk} \end{aligned} \tag{1}$$

Where $y_{ijk} =$ the reading (or math) score for the ith test administration for the jth child in the kth school, and

$x_{1ijk} =$ age of the child at the ith testing occasion measured as deviations in months from the overall mean age at the time of the initial assessment (Time 1), and

$\beta_1 =$ regression of reading (or math) on age at time of testing, assumed in this model to be fixed, meaning that the regression slopes are constant across children and schools, and

$\beta_0 =$ overall average intercept, which is assumed to be a random effect in this base model, and thus we also have

$v_{0k} =$ estimate of the deviation of the kth school's intercept from the average intercept, and

$u_{0jk} =$ estimate of the deviation of the jth child's intercept from the average within school intercept, and

$e_{0ijk} =$ residual variation in reading (or math) scores unexplained by the model.

The next, more complex model (Model 1) is the same as the above model with the exception that the slopes are also assumed to be a random effect, and thus we estimate variation due to schools and children having different slopes associated with their growth curves. That is, the next model, Model 1, allows the slopes of reading scores on ages as well as their intercepts to vary by school and child. Model 2 simply adds age squared as a fixed effect to Model 1 in order to investigate whether the growth curves have a significant nonlinear component. Model 3 introduces the dummy-coded main effects of the explanatory variables (gender, parental education, school sector, and ethnicity) as fixed effects. The addition of the fixed main effects would be expected to explain some of the variation in the intercepts at both the school and child level. In addition, the regression weights associated with the main effects reflect differences among subgroups in their reading and mathematics scores at entry to kindergarten. Model 4 adds the interactions of the explanatory variables with age to the main effects from Model 3. The introduction of the interactions is primarily an attempt to explain the variability in the slopes of the growth curves at both the school and individual level. The regression weights in the fixed part of model associated with specific age by explanatory variable interactions will address the question of how growth rates differ for populations considered to be at risk, compared with those considered to be advantaged.

After completing the multilevel analysis, a series of regressions were run in an attempt to pinpoint the presence or absence of a differential impact associated with summer learning.

While gains in scale scores tell us how much the child has gained, they do not tell us where on the scale the gains are being made. Two children may have each gained 6 score points on the overall reading scale, but one child is gaining in his/her proficiency in ending sounds (located in the middle of the scale) while the other child is gaining in beginning reading for comprehension (the upper end of the scale). In this example, the quantitative gains in terms of scale score points are equivalent, but there is a *qualitative* difference that is at least as important in understanding children's gain scores. The adaptive tests used here were designed to be both norm-referenced and criterion-referenced. The criterion-referenced scale points were designed to mark milestones in the development of early reading skills. In this study, one particular criterion-referenced milestone was used to aid in the interpretation of the overall gains. That is, in addition to knowing how much a child has gained, we would like to know if he/she is gaining on that part of the scale where one of the critical reading behavior milestones is located. For the purposes of this study, the criterion-referenced point of interest chosen was related to the child's progress in mastering Level 5 skills (i.e., comprehension of words in context). This particular milestone was chosen because it was deemed to be especially important that children make gains in this area rather than in just prereading mechanics skills by the end of the first grade. Using IRT procedures, the first graders were separated into two groups: One group was making their maximum gains in the neighborhood of the scale that references this milestone, while the remainder of the sample was making their maximum gains on the scale points dealing with lower level prereading mechanics. While the mathematics scale was also criterion-referenced, no one learning milestone was identified as being particularly critical for future performance. See Rock and Pollack (2002) for additional examples of analysis using the criterion-referenced scores on the Early Childhood Longitudinal Study public use data file.

Results

Table 1 presents a summary of the incremental fit in terms of the reduction of the overall chi-squares associated with each increasingly more complex growth model. Inspection of Table 1's marginal reduction in chi-square when going from the linear growth model (Model 1) to the nonlinear growth (Model 2) indicates that an accelerated growth curve is much more characteristic of the growth in reading than growth in mathematics. The marginal reduction in chi-square when going from a simpler to a more complex model is computed by taking the difference in chi-square between the simpler model and the more complex model divided by the difference in degrees of freedom. That is, the marginal reduction in chi-square from Table 1 is (242,972-241,548)/4 = 1,424 when we add the squared age term to the linear growth model in reading, while the comparable reduction in chi-square for mathematics is 37. This indicates that the addition of a quadratic term to the linear reading model leads to a much better fit comparatively than is the case when the quadratic term is added to the linear mathematics model. The marginal reduction in the overall chi-square when going from Model 2 to Model 3 is quite similar in reading (92.18) and mathematics (109.36) suggesting that introducing the dummy variables indicating group membership in the gender, school sector, parental education, and ethnicity groups had similar impacts on the goodness of fit of the respective growth curves.

Table 1

Summary of Changes in Goodness of Fit as Increasingly More Complex Growth Models Are Estimated

Growth models	Reading				Math			
	Chi-sq.	DF	Marginal reduction in chi-sq./ change in DF	Prob. of marginal reduction in chi-sq.	Chi-sq.	DF	Marginal reduction in chi-sq./ change in DF	Prob. of marginal reduction in chi-sq.
Model 0 Linear in age: intercept random Lev. 2 & 3	247,839	4	--------	-------	221,887	4	-------	------
Model 1 Linear in age: intercept & slope random Lev. 2 & 3	242,972	8	1,217.00	0.00	219,639	8	562.00	0.00
Model 2 Age as fixed effect added to Model 1 above	241,548	9	1,424.00	0.00	219,602	9	37.00	0.00
Model 3 Model 2 plus covar. main effects	240,534	20	92.18	0.00	218,399	20	109.36	0.00
Model 4 Model 3 plus age by covar. interactions	240,210	31	29.45	0.00	218,225	31	15.82	0.00

Table 2 provides a summary of the reduction in the between school and between child variation in reading as the main effects of the covariates (explanatory variables) and their interactions with age at time of testing are added to the models. Table 3 presents the parallel results for the mathematics scores. As expected, adding the main effects associated with the demographic group memberships (covariates) primarily explained the residual variance in the school level intercepts and to a lesser extent the child level variance in intercepts. For example, using the variance estimates from Table 2 suggests that adding the subgroup main effects to Reading Model 2 led to a 51% marginal reduction (17.277-8.406)/17.277 in the school level variation in intercepts. Similarly, the addition of the main effects to Model 2 led to a 9% marginal reduction (68.629-62.329)/68.629 in the student level variation in intercepts.

Table 2

Reduction in the Variance of Intercepts and Slopes in Reading Scores at the School and Child Level as the Explanatory Variables (Covariates) and Their Interactions Are Introduced

Growth model	Variance of intercepts with standard errors ( )		Variance of slopes with standard errors( )	
	School	Child	School	Child
Model 2	17.277	68.629	0.043	0.176
Linear and quadratic in age at testing; intercepts and linear slopes random	(1.230)	(1.229)	(0.003)	(0.005)
Model 3	8.406	62.329	0.043	0.176
Model 2 above plus main effects of covariates	(0.744)	(1.124)	(0.003)	(0.005)
Model 4	8.274	61.791	0.033	0.169
Model 3 above plus age at testing by covarariate interaction	(0.735)	(1.124)	(0.003)	(0.005)

The comparable numbers from Table 3 in mathematics were 66% reduction in school level intercepts and 8% in the child level intercept variance. As expected, adding the interactions had very little effect on the intercepts. However, the addition of the interaction terms to the main effects model in reading led to a 23% marginal reduction in the residual variation in slopes at the school level. In terms of residual variation in the reading slopes at the child level, the marginal reduction was 4%. In mathematics, the comparable numbers were 23% at the school level and 0 % at the child level. Undoubtedly part of the better prediction of both intercepts and slopes at the school level than at the child level from the background explanatory variables is due to the fact that both slopes and intercepts are more reliable at the school level.

Table 3

Reduction in the Variance of Intercepts and Slopes in Mathematics Scores at the School and Child Level as the Explanatory Variables (Covariates) and Their Interactions Are Introduced

Growth model	Variance of intercepts with standard errors ( )		Variance of slopes with standard errors( )	
	School	Child	School	Child
Model 2 Linear and quadratic in age at testing; intercepts and linear slopes random	10.884 (0.768)	42.090 (0.746)	0.013 (0.001)	0.041 (0.002)
Model 3 Model 2 above plus main effects of covariates	3.673 (0.379)	38.596 (0.695)	0.013 (0.001)	0.041 (0.002)
Model 4 Model 3 above plus age at testing by covarariate interaction	3.703 (0.380)	38.614 (0.695)	0.010 (0.001)	0.041 (0.002)

Figure 1 presents the regression weights and their standard errors (in parenthesis) for the fixed part of Model 4 as well as the variances and covariances of the random intercepts and slopes for the full model (Model 4) in reading. Figure 2 presents the comparable model for the mathematics scores. All explanatory variables in the model with the exception of age at time of testing are considered categorical and are dummy- coded. For example, girls are coded 1 and boys are coded 0. The contrast group (i.e., the 0-coded group) for the gender comparison does not appear in the equation. The regression weight associated with girls in the reading model is 2.3139, indicating that when controlling for all other variables in the model, girls start school, on average, at 2.3139 scale points higher than boys. Similarly, based on the regression weight in the reading model, children who are enrolled in Catholic schools start kindergarten at 1.3183 reading scale points higher than the 0-coded contrast group, children attending public schools. This interpretation of the main effects regression weights is possible because of the way the age variable is scaled. The age variable is measured as deviations from the mean age at Time Point 1 (kindergarten entry). The interaction terms of age with the dummies for the main effect variables have a similar interpretation. For example, the regression weight for the age by gender interaction, agedxgirl equals .0957, indicating that the regression slope of reading on age at time of testing for girls is .0957 scale points steeper than that for boys. This increment in slope for girls over that of the boys is statistically significant as shown by the regression weight divided by its standard error (.0957/.0109) giving a t-statistic of 8.78.

$$\text{read}_{ijk} \sim \text{N}(XB,\ \Omega)$$

$$\begin{aligned}\text{read}_{ijk} = {} & \beta_{0ijk}\text{cons2}_{jk} + \beta_{1jk}\text{agedevl}_{ijk} + 2.3139(0.1770)\text{girls}_{jk} + 1.3183(0.4120)\text{cathol}_{jk} + 7.7901(0.8317)\text{pvtnrc}_{jk} + \\ & 2.5648(0.3838)\text{hsgrd}_{jk} + 4.4044(0.3960)\text{ltcolgrd}_{jk} + 6.5493(0.4194)\text{colgrd}_{jk} + 9.6554(0.4651)\text{gtcolgd}_{jk} + \\ & 1.0662(0.3029)\text{white}_{jk} + {-0.1723}(0.4195)\text{hisp}_{jk} + 4.2063(0.4524)\text{asian}_{jk} + {-0.0200}(0.7227)\text{othrmn}_{jk} + \\ & 0.0957(0.0109)\text{agedxgirl}_{ijk} + {-0.0140}(0.0258)\text{agedxcth}_{ijk} + {-0.1490}(0.0524)\text{agedxpvt}_{ijk} \\ & + 0.1197(0.0188)\text{agedxwht}_{ijk} + \\ & 0.1306(0.0261)\text{agedxhisp}_{ijk} + 0.2337(0.0282)\text{agedxasn}_{ijk} + 0.0590(0.0447)\text{agedxothr}_{ijk} \\ & + 0.1358(0.0236)\text{agedxhsgd}_{ijk} + \\ & 0.2331(0.0244)\text{agedxltcl}_{ijk} + 0.2629(0.0259)\text{agedxclgd}_{ijk} + 0.2622(0.0287)\text{agedxgtcl}_{ijk} \\ & + 0.0187(0.0004)\text{agedlsq}_{ijk}\end{aligned}$$

$$\beta_{0ijk} = 16.884(0.4344) + v_{0k} + u_{0jk} + e_{0ijk}$$

$$\beta_{1jk} = 1.0825(0.0281) + v_{1k} + u_{1jk} \qquad 1(a)$$

$$\begin{bmatrix} v_{0k} \\ v_{1k} \end{bmatrix} \sim \text{N}(0, \Omega_v) : \Omega_v = \begin{bmatrix} 8.2738(0.7350) & \\ 0.1251(0.0331) & 0.0333(0.0029) \end{bmatrix} \qquad 1(b)$$

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim \text{N}(0, \Omega_u) : \Omega_u = \begin{bmatrix} 61.7917(1.1242) & \\ 1.3,786(0.0498) & 0.1693(0.0045) \end{bmatrix} \qquad 1(c)$$

$$E_{0ijk} \sim \text{N}(0, \Omega_e) : \Omega_e = \begin{bmatrix} 22.4472(0.2693) \end{bmatrix} \qquad 1(d)$$

-2**loglikelihood(IGLS)* = 240210.2000(34390 of 58400 cases in use)

Figure 1. **Model 4 reading.**

While most of the naming of the explanatory variables in Figures 1 and 2 are self-explanatory, additional information is helpful for some. The critical time covarying growth variable, agedev1, refers to age in months at time of testing measured as deviations from the Time Point 1 mean. The variables Cathol and pvtnrc refer to whether a child attends a Catholic or a private non-Catholic school. The missing variable public, identifying children attending a public school, is the contrast group. The variables hsgrd, ltcolgrd, colgrd, and gtcolgd refer to the highest educational level achieved by one or both parents and stands for high school graduate, some college, college graduate, and graduate work beyond a bachelor's degree, respectively. The missing parental group, less than high school graduate, is the contrast or base group for this set of dummy variables. The group of dummy variables reflecting ethnicity, white, hisp, asian, and othmn, refers to White, Hispanic, Asian, and other minority children not including Black, respectively. The missing group, Black children, was the contrast group. The variable aged1sq indicates the age in months at time of testing squared. The cross-product terms refer, of course, to the interactions of age at time of testing with each of the respective main effects. For example, agedxgirl refers to the interaction of the dummy-variable girls with time of testing. If the regression weight associated with this term is positive and significant, one would conclude that girls have a steeper linear slope to their growth curve than do boys.

Equations 1a and 2a in Figures 1 (reading) and 2 (mathematics), respectively, give the average intercept and average slope for Black males in public schools who have parents with less than a high school diploma. In the case of reading, the average intercept is 16.88 and the average slope is 1.08. The comparable figures for mathematics are 14.33 and 1.10. The additional symbols reflect the random components of variance for the intercepts and slopes at both the child and school levels as defined in Equation 1.

Equations 1b and 2b in Figures 1 and 2, respectively, deal with the estimates of the random effects and show the variance-covariance matrix of the intercepts and slopes at the school level. The first main diagonal element is the variance of the intercepts and the second diagonal element is the variance of the slopes. The off diagonal element is the covariance of the intercepts and slopes. Equation 1c in Figure 1 presents the variance-covariance matrix of the intercepts and slopes at the child level. The covariances between the intercepts and slopes for the reading scores are positive and significant at both the school and the child levels. In the case of mathematics, only the child level covariance is significant and positive. When the covariances are standardized, the correlations between the intercepts and slopes for the reading scores are .24 at the school level and .43 at the child level. The comparable figures for mathematics are .02 and .28. The positive correlations between slopes and intercepts at both the school and child levels for reading suggest that the children who enter kindergarten with higher scores tend to gain more during the first 2 years of schooling. Correlations between slopes and intercepts at both the school and child levels are higher for reading than for mathematics, suggesting that it may be more important for later growth in reading to come to kindergarten well-prepared than is the case in mathematics. It also suggests the possibility of a "fan-spread effect" (Campbell & Earlenbacher, 1970), that is, individual differences in the children's scores increasing over time. This phenomenon will be examined in more detail when the subgroup growth curves are plotted.

$$\text{math}_{ijk} \sim \text{N}(XB,\ \Omega)$$

$$\begin{aligned}\text{math}_{ijk} = {} & \beta_{0ijk}\text{cons2}_{jk} + \beta_{1jk}\text{agedevl}_{ijk} + 0.6504(0.1388)\text{girls}_{jk} + 1.6718(0.2960)\text{cathol}_{jk} + 4.3636(0.6099)\text{pvtnrc}_{jk} + \\ & 1.9422(0.3003)\text{hsgrd}_{jk} + 3.7444(0.3094)\text{ltcolgrd}_{jk} + 5.6971(0.3273)\text{colgrd}_{jk} + 7.8019(0.3624)\text{gtcolgd}_{jk} + \\ & 2.5126(0.2313)\text{white}_{jk} + 0.7207(0.3226)\text{hisp}_{jk} + 3.6585(0.3477)\text{asian}_{jk} + 0.3267(0.5532)\text{othrmn}_{jk} +- \\ & 0.0084(0.0068)\text{agedxgirl}_{ijk} + \\ & -0.0605(0.0151)\text{agedxcth}_{ijk} + -0.2098(0.0312)\text{agedxpvt}_{ijk} + 0.0936(0.0115)\text{agedxwht}_{ijk} \\ & + 0.1120(0.0160)\text{agedxhsp}_{ijk} + \\ & 0.0855(0.0173)\text{agedxasn}_{ijk} + 0.0729(0.0274)\text{agedxothr}_{ijk} + 0.0215(0.0147)\text{agedxhsgd}_{ijk} \\ & + 0.0704(0.0152)\text{agedxltcl}_{ijk} + \\ & 0.0692(0.0161)\text{agedxclgd}_{ijk} + 0.0614(0.0178)\text{agedxgtcl}_{ijk} + 0.0022(0.0003)\text{aged1sq}_{ijk}\end{aligned}$$

$$\beta_{0ijk} = 14.3305(0.3335) + v_{0k} + u_{0jk} + e_{0ijk}$$

$$\beta_{1jk} = 1.1099(0.0176) + v_{1k} + u_{1jk} \qquad 2(a)$$

$$\begin{bmatrix} v_{0k} \\ v_{1k} \end{bmatrix} \sim \text{N}(0, \Omega_v) : \Omega_v = \begin{bmatrix} 3.7032(0.3800) & \\ 0.0035(0.0137) & 0.0104(0.0010) \end{bmatrix} \qquad 2(b)$$

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim \text{N}(0, \Omega_u) : \Omega_u = \begin{bmatrix} 38.6141(0.6945) & \\ 0.3481(0.0249) & 0.0406(0.0019) \end{bmatrix} \qquad 2(c)$$

$$E_{0ijk} \sim \text{N}(0, \Omega_e) : \Omega_e = \begin{bmatrix} 13.4250(0.1607) \end{bmatrix} \qquad 2(d)$$

-2**loglikelihood(IGLS)* = 218225.1000(34393 of 58400 cases in use)

Figure 2. **Model 4 math.**

The overall base group for analysis consists of Black males who attend public schools and whose parents have not completed high school. This coding was chosen because it seemed to describe the most disadvantaged with respect to an educational support system and/or economic well-being. As a result, most of the regression weights are positive. Regression weights associated with the main effects (e.g., White, Hispanic, girls) in Figures 1 and 2 give the difference in scale score points between each group's intercept and the contrast group intercept. For example, controlling for all the other demographics, the White children started 1.0662 points ahead of the Black children. That is, their intercepts differed by 1.0662 points. The regression weights associated with an interaction term such as agedxhisp give the difference between the slope of the Hispanic children and the slope of the contrast group, Black children. In reading, this coding led to all but two main effects having statistically significant positive contrasts based on the ratio of their regression coefficients to their standard errors. This indicated that the base group started significantly below all other groups with the exception of the Hispanic group (b = -.1723; t = -.41, p = .42) and the other minority group (b = -.0200; t = .03, p = .49), which were not significantly different from the Black base contrast group at kindergarten entry. The t-statistic is, of course, simply the regression weight shown in Figure 1 divided by its standard error, shown in parentheses also in Figure 1.

The Hispanic children, however, had a significantly greater linear growth rate in reading, as indicated by the regression weight associated with their interaction term (b = .1306; t = 5.0, p = .00), suggesting that, on average, they are growing at a rate of .13 of a reading scale point more per month than are the Black children.

In mathematics, the regression weight associated with the Hispanic children (b = .7207; t = 2.23, p = .00) indicates that they started out significantly higher than the Black children and also showed a significantly greater linear growth rate as reflected in the coefficient for their interaction term (b = .1120; t = 7.0, p = .00).

What is particularly impressive is the advantage that children have who come from homes where the highest parent education is a high school degree or higher. Such children begin kindergarten 2.56 to 9.65 points higher on the reading scale than children from the base parental education group (less than a high school education). At the higher end of the parental education scale, college degree or higher, the children start with a 6.54 to 9.65 advantage as indicated by the regression weights associated with a parental college degree (b = 6.54; t = 15.61, p = .00) and that associated with graduate work beyond college (b = 9.65; t = 20.76, p = .00). Not only do they enter the formal education system with a formidable head start, but they also continue to grow at a faster rate after entering the school system, as evidenced by their significantly higher linear slopes. More specifically, other things being equal, the children whose parents have a college degree are gaining .26 reading scale points more per month than are children whose parents have not finished high school. Similar but less pronounced effects are found in mathematics where the higher education levels of the parents are related to increments in growth rates of .06–07 points per month.

It is interesting to note that while children who attended Catholic and private non-Catholic schools started with significantly higher average scores than those of public school children, the rate of gain in reading for the Catholic school children was not significantly different from that of the public school children. The private non-Catholic school children's rate of gain was significantly less than that of the public school children over the first two years of schooling in both reading and mathematics. It would seem that in these early stages of development the public school children appear to be closing some of the original gap found between their performance in reading at kindergarten entry and that of the private non-Catholic school children.

A summary of the results shown in Figures 1 and 2 suggest that:

- Girls start kindergarten with significantly better reading or prereading skills than boys (b = 2.3139; $t = 13.07$; $p = .00$) and girls are growing their reading skills at a significantly greater rate than are boys ($b = .0957$; $t = 8.78$; $p = .00$). That is, the regression weight associated with girls ($b = 2.314$) in Figure 1 divided by its standard error (.177) gives the t-statistic of 13.07 for intercept differences for girls and boys. Similarly, the significance of the difference in growth rates for girls and boys is given by the regression weight associated with the interaction of the dummy variable girls with age at time of testing ($b = .0957$) divided by its standard error (.0109), also from Figure 1, resulting in the t-statistic of 8.78.

- Girls start kindergarten performing significantly better than boys in mathematics ($t = 4.71$; $p = .00$) but show no significant differences in growth rate ($t = -1.24$; $p = .22$).

- Other things being equal, the public school children enter kindergarten significantly behind in reading compared to their counterparts in private and Catholic schools ($t = 9.37$;$p = .00$: $t = 3.12$; $p = .00$, respectively). However, other things being equal, the public school children are growing significantly faster in reading over the first two years of schooling than are the private school children (*t* = 2.84; *p* = .01). Growth rates in reading show no significant differences between public and Catholic school children.

- Mathematics results are similar to reading: Public school children start kindergarten with deficits in mathematics (*t* = 7.15; *p* = .00: *t* = 5.65; *p* = .00) compared to private and Catholic school children, respectively.

- However, Catholic and private non-Catholic school children grew at a lesser rate than did the public school children in mathematics (*t* = 4.01; *p* = .00: *t* = 6.72; *p* = .00 for the Catholic and private non-Catholic schools, respectively).

- In terms of ethnicity, White and Asian children began kindergarten significantly ahead of Black children in reading (*t* = 3.53; *p* = .00: *t* = 9.33; *p* = .00, respectively). There were no significant differences between Black children and Hispanic children or Black children and other minority children in reading skills at entry to kindergarten. White, Asian, and Hispanic children all grew at a significantly greater rate than did the Black children (*t* = 6.36; *p* = .00: *t* = 8.28, *p* = .00: *t* = 5.00; *p* = .00, respectively). There was no difference in the rate of gain in reading between the other minority and Black children.

- In mathematics, all ethnic groups with the exception of other minority started kindergarten significantly ahead of the Black children (*t*'s ranged from 2.23; *p* = .02 to *t* = 10.90; *p* = .00). With respect to growth rates in mathematics, all subgroups, White, Asian, Hispanic, and other minority, grew at a faster rate than did the Black children (*t*'s ranged from a low of 2.66; *p* = .01 for other minority children to a high of *t* = 8.14; *p* = .00 for the White children). It is interesting to note that Asian children started kindergarten with greater skills in both reading and mathematics than any other ethnic group. They also had the highest growth rate in reading of any ethnic group.

- In terms of parents' education, children from all parental groups possessing a high school degree or more advanced educations started kindergarten significantly ahead in reading compared with children of parents with less than a high school degree. The *t*'s ranged from a low of 6.47; *p* = .00 for children who had at least one parent with a high school degree to 21.67; *p* = .00 for those children who had at least one parent with education beyond a college degree. Growth rates were significantly greater in reading for all other parental education groups when contrasted with children of parents with less than a high school degree. The *t*'s ran from a low of 5.75; $p = .00$ for children of parents with a high school degree to a high of 10.15; $p = .00$ for the children having a college educated parent.

- Mathematics scores for the same parent education contrasts showed similar patterns of advantage at entry to kindergarten. The *t*'s ranged from a low of $t = 6.46$; $p = .00$ for children of high school graduates to a high of $t = 21.52$; $p = .00$ for those children who had one or more parents who did graduate work beyond college. Similar to the case in reading, growth rates in mathematics performance increased with increases in parental education with one exception: the contrast between children of parents with a high school degree and those without a high school degree was not significant ($t = 1.46$; $p = .14$).

Summer Learning Effect

Figures 3 and 4 plot the overall growth curves and the standard deviations at each of the testing occasions for the reading and mathematics scores, respectively. Consistent with the fan-spread hypothesis, the standard deviations in reading are increasing at each succeeding testing occasion. In mathematics, the standard deviations increase at Time Points 2 and 3 and appear to level off at Time Point 4. Gains during the school year are in general quite large and typically exceed the standard deviation of the previous test administration.

Inspection of Figures 3 and 4 suggest that there is a summer learning effect marked by a de-acceleration in growth rates during the summer months (i.e., reflected in the reduced slopes between Time Point 2 and Time Point 3). The more important question here is not whether or not there is a de-acceleration in growth during the summer months, but is there a *differential* de-acceleration that favors the children coming from homes characterized by strong educational support systems? While we cannot directly measure the strength of the home educational support system, we will lean heavily on parents' highest level of education as a reasonably good proxy.

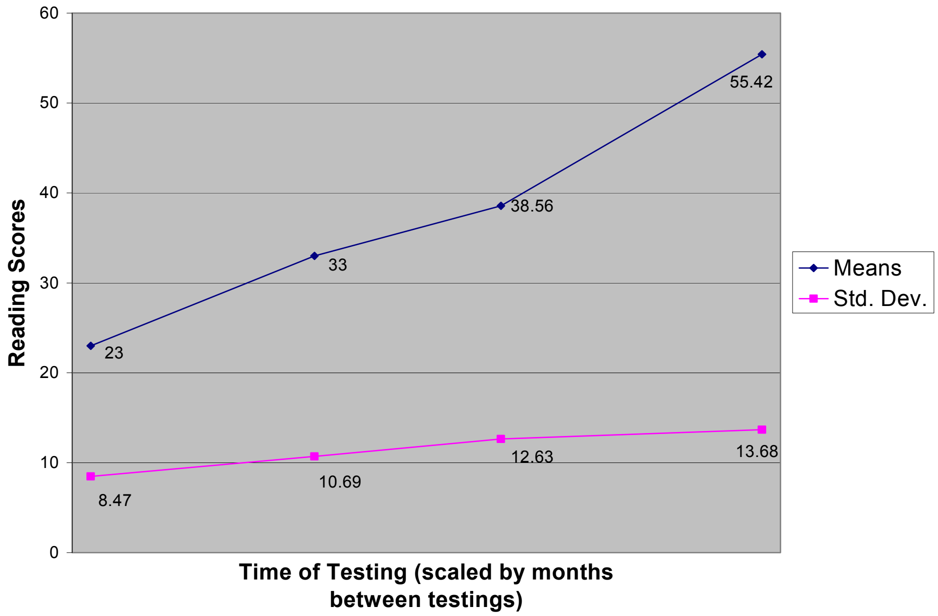

Figure 3. **Bayes estimates of the reading means by time of testing.**

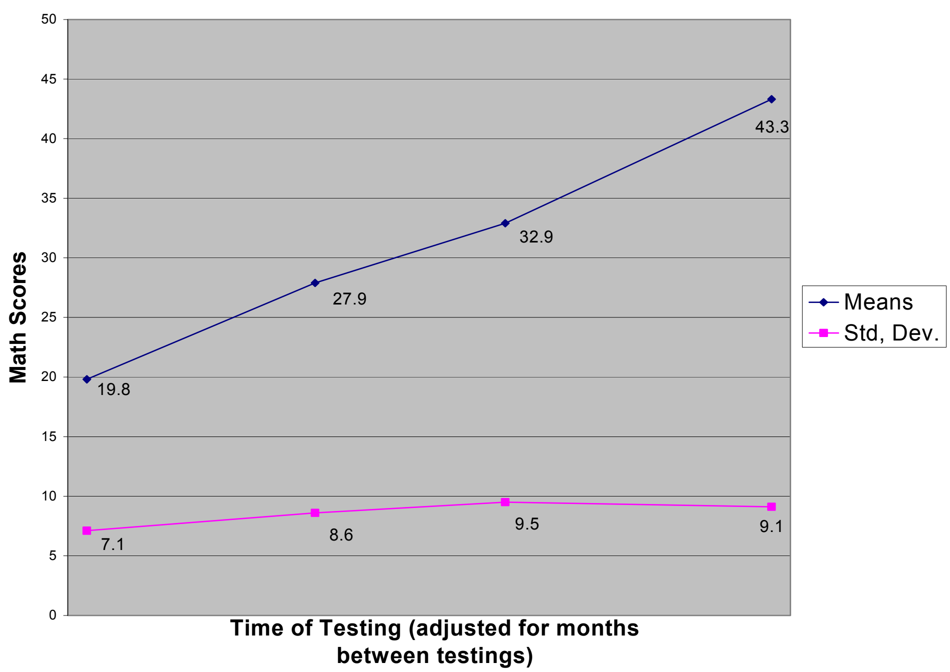

Figure 4. **Math means by time of testing.**

Figure 5 presents a plot of the reading means by time of testing and subgroups based on the highest education level of the parents. The reading score means plotted in Figure 5 clearly shows increased separation over time for the subgroups defined by highest parent education. There also seems to be a differential de-acceleration with the children from parents with less than a high school education showing greater de-acceleration than their counterparts from families with higher parental education levels. The abbreviated legends in Figures 5 and 6 (LTHSDEG, HSGRD, LTCOLDEG, COLDEG, and GTCOLDEG) refer to less than a high school degree, high school degree, some college, college degree, and graduate work beyond a college degree, respectively.

Figure 6 presents the plot of the mathematics means by time of testing and subgroups based on parental education. The pattern of gains in mathematics is very similar to that of reading.

In order to examine the summer effect in detail, separate regressions were run partitioning the time sequence into three parts: the kindergarten year, the summer term, and the first grade year. The summer effect analysis is based on that subsample that had all four test scores (n = 3032). While this approach is less powerful than the earlier analysis that modeled all four time points simultaneously on a larger sample, it does speak more directly to the summer effect. The first regression equation used the kindergarten year gains as the dependent variable, the second the summer gains, and finally the gains during the first grade. Table 4 presents these regressions for the reading gains. Column 1 indicates the regression of the kindergarten year raw gains (RDDIF21) on the full set of explanatory variables. RDDIF21 in column 1 refers to the simple difference between the Time Point 2 and Time Point 1 reading scores. Similarly, column 2 presents the regression of the summer gains (Time Point 3 – Time Point 2 reading scores) on the explanatory variables, and column 3 the corresponding regressions for the gains during the first grade year. The entries in the respective columns are the raw score regression weights with their standard errors in parenthesis. Since there was considerable variability in when a child was tested, both the age of the child at the time of the first of each pair of testings and the gap in time between the two testings are included as control variables for each of the dependent variable gain scores.

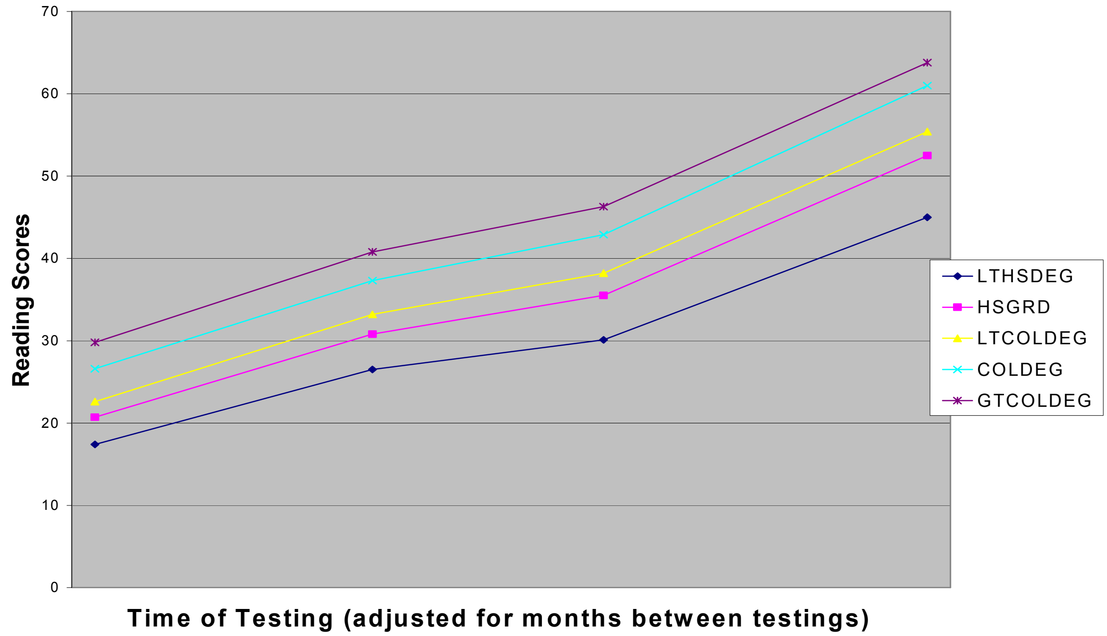

Figure 5. **Reading means by time of testing and parents' education.**

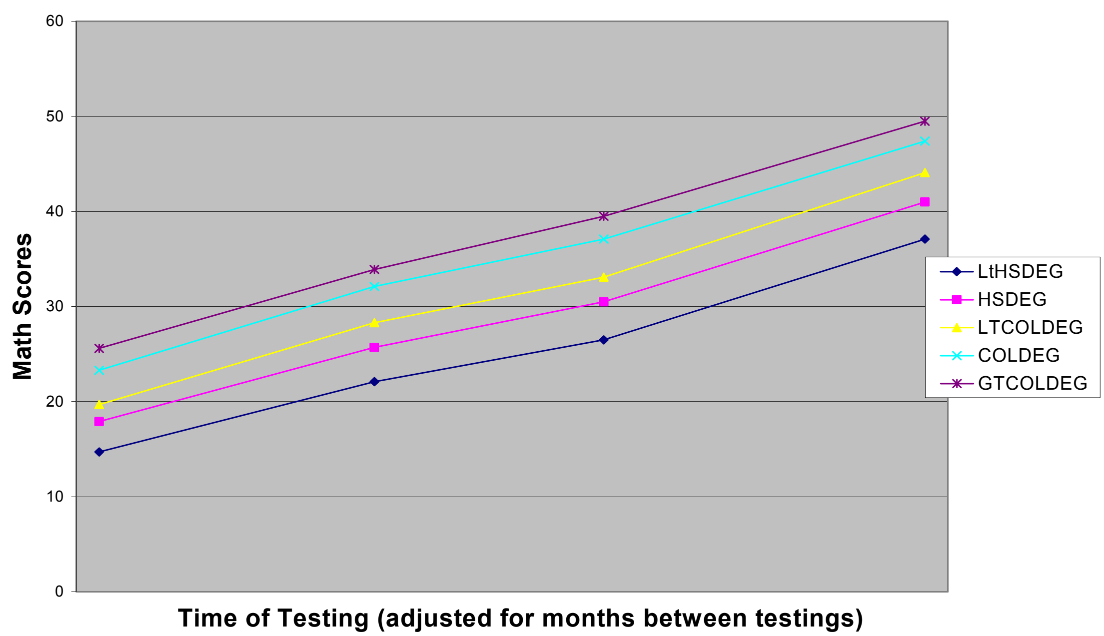

Figure 6. **Math means by time of testing and parents' education.**

Table 4

School Year and Summer Gains in Reading Regressed on Selected Explanatory Variables Based on a Repeated Measures Model

	(1)	(2)	(3)
	RDDIF2 1	RDDIF3 2	RDDIF4 3
AGE FALL KINDERGARTEN	0.003 (0.123)		
TIME BETWEEN TESTS 1 AND 2	1.648 (7.573)[b]		
GIRLS	1.043 (3.573)[b]	0.397 (1.860)	0.354 (0.990)
CATHOLIC SCHOOL	–0.273 (0.378)	0.392 (1.076)	0.938 (1.093)
PRIVATE NON-CATHOLIC	–0.286 (0.260)	–0.289 (0.954)	2.716 (3.865)[b]
WHITE	1.011 (2.028)[a]	0.550 (1.304)	1.554 (3.019)[b]
HISPANIC	0.476 (0.692)	0.789 (1.531)	1.417 (2.050)[a]
ASIAN	1.778 (3.151)[b]	1.062 (2.420)[a]	0.805 (1.183)
OTHER MINORITY	1.733 (2.182)[a]	0.164 (0.104)	1.837 (2.105)[a]

(Table continues)

Table 4 (continued)

	(1) RDDIF21	(2) RDDIF32	(3) RDDIF43
HIGH SCHOOL GRADUATE	0.999	1.044	1.874
	(2.419)[a]	(2.813)[b]	(2.936)[b]
SOME COLLEGE	1.443	1.392	2.004
	(3.497)[b]	(3.387)[b]	(2.958)[b]
COLLEGE GRAD. OR HIGHER	**1.496**	**1.912**	**2.799**
	(3.024)[b]	(4.523)[b]	(3.657)[b]
AGE SPRING KINDERGARTEN		–0.010	
		(0.427)	
TIME BETWEEN TESTS 2 AND 3		0.273	
		(2.718)[b]	
AGE AT TIME OF 3RD TESING			–0.104
			(2.655)[a]
TIME BETWEEN TESTS 3 AND 4			0.412
			(1.138)
CONSTANT	–2.572	2.258	19.077
	(1.055)	(1.306)	(4.554)[b]
OBSERVATIONS	3,032	3,032	3,032
R-SQUARED	0.046	0.020	0.027

Note. Absolute value of t-statistics in parentheses.

[a] significant at 5%. [b] significant at 1%.

This repeated measures scaling of the dependent variable yields a straightforward interpretation of the raw score regression coefficients associated with the dummy variables indicating group membership. For example, the regression weight associated with children who come from families with at least one parent having a college degree or higher indicates a gain, on average, of 1.496 score points more during the kindergarten year than children from homes with neither parent having a high school degree (the contrast group). The regression weight associated with this contrast is shown in bold in each of the succeeding tables. Differences in parent education outweigh other demographic variables as predictors of the summer effect in reading. Moreover, each successive increment in parent education is associated with greater and greater gains during the summer, with a regression weight of 1.912 for children of college graduates corresponding to the differential gain in score points for this group compared with children from homes where neither parent finished high school. While this finding is consistent with the summer effect literature, the comparable regression weight (college grad or higher) for the first grade year is also significant and even higher (2.799), suggesting that even aside from the differential growth during the summer, the gap would be steadily increasing during the kindergarten and first grade years. In fact, all of the parental education subgroups showed this pattern of increasing differentiation from the base group as they go from kindergarten through first grade. Entwisle et al. (1997) found that their measure of socio-economic status was unrelated to performance during the school year and negatively related to performance during the summer months. The results here suggest that the gap between children from different parental education backgrounds increases with each increment in parental education. That is, we have a fan spread effect when the groups are defined by parental education level, with the children from higher parental education levels growing faster both within and out of school in reading and prereading skills. One difference between this study and that of Entwisle et al. (1997) is that they began with first graders and the summer following the first grade. It is possible that as some children proceed beyond first grade they are more likely to be moving from learning to read to reading to learn and as a result they will have developed their comprehension skills to a level where they can make additional gains on their own given a supportive educational environment.

Table 5 presents the analogous results for gains per month in mathematics. Inspection of Table 5 indicates that there is no systematic differential de-acceleration among any of the subpopulations during the summer months. In fact only the kindergarten year shows a significant increase in rate of gain for the children with parents having a college degree or greater when compared with those children having parents with less than a high school degree. There does not seem to be any consistent pattern relating parental education level to rate of gains in or out of school in mathematics.

Table 6 deals with the question of differential summer growth in reading from the perspective of a Lag 1 analysis of covariance model. While Tables 4 and 5 used the repeated measures correction for initial status, the analysis of covariance (ANCOVA) model will estimate the correction for initial status from the data. Inspection of Table 4 suggests the same pattern of an increasing gap in reading scores over time among children from different parental education groups. This gap is widening during both school years as well as during the summer. The estimated differential gain favoring the children of college educated parents during the kindergarten year and the summer term is quite similar to that found in the repeated measures model as reported in Table 4. This replication over different models occurs because the adjustment factor for initial status in the ANCOVA model for kindergarten (.991 for reading score at Time Point 1, in column 1) and summer (1.005 for reading score at Time Point 2, in column 2) both turn out to be very close to 1, which is the adjustment factor for repeated measures.

The adjustment for initial status for the first grade year in Table 6 is less than 1 (.857 for reading score at Time Point 3, in column 3) and thus subgroup differences at the end of first grade are only adjusted for a part of the differences that were present at entry to first grade.

Table 7 presents the analogous ANCOVA results for the mathematics scores. Inspection of Table 7 shows the same trend of a growing achievement gap related to parents' education. As was the case for reading, the ANCOVA results in mathematics suggest that the gap favoring children of parents with more education compared with children of parents with less education is increasing over time, and increases at each increment of the parental education grouping.

Table 5

School Year and Summer Gains in Mathematics Regressed on Selected ExplanatoryVariables Based on a Repeated Measures Model

	(1)	(2)	(3)
	MATHD21	MATHD32	MATHD43
AGE FALL KINDERGARTEN	0.018 (0.714)		
TIME BETWEEN TESTS 1 AND 2	0.788 (3.743)[b]		
GIRLS	0.190 (0.960)	–0.111 (0.525)	–0.370 (1.703)
CATHOLIC SCHOOL	0.207 (0.570)	0.074 (0.221)	–0.691 (1.471)
PRIVATE NON-CATHOLIC	–1.285 (1.610)	–0.694 (1.304)	–2.031 (2.206)[a]
WHITE	0.723 (1.535)	0.702 (1.849)	0.072 (0.218)
HISPANIC	0.491 (0.833)	0.222 (0.504)	0.649 (1.183)
ASIAN	1.540 (2.737)[b]	0.275 (0.558)	–0.786 (1.429)
OTHER MINORITY	0.351 (0.412)	0.444 (0.340)	0.946 (0.926)

(Table continues)

Table 5 (continued)

	(1)	(2)	(3)
	MATHD21	MATHD32	MATHD43
HIGH SCHOOL GRADUATE	0.430	0.220	–0.051
	(1.319)	(0.568)	(0.106)
SOME COLLEGE	1.101	0.247	0.435
	(2.846)[b]	(0.653)	(0.843)
COLLEGE GRAD. OR HIGHER	1.121	0.642	–0.148
	(2.249)[a]	(1.526)	(0.284)
AGE SPRING KINDERGARTEN		0.001	
		(0.065)	
TIME BETWEEN TESTS 2 AND 3		0.248	
		(2.746)[b]	
AGE AT TIME OF 3RD TESTING			–0.100
			(4.252)[b]
TIME BETWEEN TESTS 3 AND 4			0.472
			(1.809)
CONSTANT	0.700	2.728	15.324
	(0.310)	(1.529)	(5.369)[b]
OBSERVATIONS	3,032	3,032	3,032
R-SQUARED	0.023	0.011	0.030

Note. Absolute value of t-statistics in parentheses.

[a] significant at 5%. [b] significant at 1%.

Table 6

School Year and Summer Reading Gains Regressed on Selected Explanatory Variables Based on the ANCOVA Model

	(1) RDSCORE 2	(2) RDSCORE 3	(3) RDSCORE 4
AGE FALL KINDERGARTEN	0.006 (0.218)		
TIME BETWEEN TESTS 1 AND 2	1.645 (7.557)[b]		
READING SCORE AT TIME 1	0.991 (38.740)[b]		
GIRLS	1.058 (3.647)[b]	0.385 (1.713)	0.807 (2.221)[a]
CATHOLIC SCHOOL	-0.261 (0.362)	0.388 (1.057)	1.117 (1.396)
PRIVATE NON-CATHOLIC	-0.223 (0.205)	-0.321 (1.002)	-1.763 (2.139)[a]
WHITE	1.023 (2.039)[a]	0.539 (1.261)	1.981 (3.782)[b]
HISPANIC	0.473 (0.688)	0.788 (1.527)	1.555 (2.192)[a]
ASIAN	1.817 (3.158)[b]	1.034 (2.326)[a]	1.842 (2.809)[b]
OTHER MINORITY	1.716 (2.133)[a]	0.166 (0.106)	1.800 (1.967)

(Table continues)

Table 6 (continued)

	(1) RDSCORE 2	(2) RDSCORE 3	(3) RDSCORE 4
HIGH SCHOOL GRADUATE	1.025	1.026	2.585
	(2.495)[a]	(2.761)[b]	(3.908)[b]
SOME COLLEGE	1.484	1.363	3.079
	(3.633)[b]	(3.306)[b]	(4.412)[b]
COLLEGE GRAD. OR HIGHER	**1.575**	**1.863**	**4.586**
	(2.953)[b]	(4.429)[b]	(5.902)[b]
AGE SPRING KINDERGARTEN		-0.011	
		(0.484)	
TIME BETWEEN TESTS 2 AND 3		0.273	
		(2.717)[b]	
READING SCORE AT TIME 2		1.005	
		(84.380)[b]	
AGE AT TIME OF 3RD TESTING			-0.057
			(1.423)
TIME BETWEEN TESTS 3 AND 4			0.396
			(1.160)
READING SCORE AT TIME 3			0.857
			(45.551)[b]
CONSTANT	-2.613	2.267	19.316
	(1.072)	(1.309)	(4.398)[b]
OBSERVATIONS	3,032	3,032	3,032
R-SQUARED	0.683	0.827	0.675

Note. Absolute value of t-statistics in parentheses.

[a] significant at 5%. [b] significant at 1%.

Table 7

School Year and Summer Gains in Mathematics Regressed Selected Explanatory Variables Based on the ANCOVA Model

	(1) MSCL2	(2) MSCL3	(3) MSCL4
AGE FALL KINDERGARTEN	0.047		
	(1.723)		
TIME BETWEEN TESTS 1 AND 2	0.768		
	(3.604)[b]		
MATH SCORE 1	0.922		
	(34.671)[b]		
GIRLS	0.224	–0.024	–0.245
	(1.121)	(0.112)	(1.254)
CATHOLIC SCHOOLS	0.324	0.307	–0.269
	(0.851)	(1.005)	(0.588)
PRIVATE NON-CATHOLIC	–0.878	–0.148	–1.250
	(1.032)	(0.325)	(1.372)
WHITE	0.945	1.194	1.104
	(1.997)	(3.238)[b]	(3.927)[b]
HISPANIC	0.554	0.402	1.020
	(0.932)	(0.987)	(1.977)
ASIAN	1.768	0.890	0.353
	(2.988)[b]	(1.994)	(0.728)
OTHER MINORITY	0.336	0.461	1.080
	(0.426)	(0.330)	(1.700)

(Table continues)

Table 7 (continued)

	(1)	(2)	(3)
	MSCL2	MSCL3	MSCL4
HIGH SCHOOL GRADUATE	0.644	0.658	0.771
	(2.038)[a]	(1.611)	(1.504)
SOME COLLEGE	1.440	0.999	1.815
	(3.775)[b]	(2.560)[a]	(3.297)[b]
COLLEGE GRAD. OR HIGHER	**1.732**	**1.880**	**2.182**
	(4.249)[b]	(4.008)[b]	(4.149)[b]
AGE SPRING KINDERGARTEN		0.056	
		(2.511)[a]	
TIMEE BETWEEN TESTS 2 AND 3		0.247	
		(2.921)[b]	
MATH SCORE 2		0.862	
		(53.868)[b]	
AGE AT TIME OF 3RD TESTING			–0.009
			(0.362)
TIME BETWEEN TESTS 3 AND 4			0.456
			(2.026)[a]
MATH SCORE 3			0.759
			(47.392)[b]
CONSTANT	–0.138	1.455	13.977
	(0.061)	(0.854)	(4.880)[b]
OBSERVATIONS	3,032	3,032	3,032
R-SQUARED	0.669	0.728	0.674

Note. Absolute value of t-statistics in parentheses.

[a] significant at 5%. [b] significant at 1%.

Qualitative Differences in Reading Gain Scores in the First Grade

Children attending private non-Catholic schools and/or having more educated parents enter kindergarten at a much higher level in reading, on average, than their counterparts in public schools or with less educated parents. Subgroups with different average scale scores are making their gains at different points on the reading scale, meaning that the gains in scale score points are achieved by different groups mastering somewhat different material. Using the first grade year data, children were sorted into two groups: those who were making their maximum gains at Level 5 skills, comprehension of words in context, (coded 1) versus those who were making their maximum gains at any of the four lower level proficiencies (coded 0). A logistic regression of this 0-1 outcome on the demographic variables, including the school sectors, was carried out. Table 8 presents the complete results of the logistic regression with the logistic regression coefficients transformed to odds ratios for ease of interpretation. Inspection of Table 8 indicates that the odds-ratio associated with the private non-Catholic school children is 2.34 ($t = 3.77$; $p = .00$), meaning that these children are 2.34 times as likely as their public school counterparts to be making their maximum gains in the higher level reading skill of beginning reading comprehension during first grade.

In addition to gaining more than the boys on the overall scale, girls were 1.57 ($t = 4.77$, $p = .00$) times more likely to be making their gains in Level 5 reading skills by the end of first grade, as indicated by the logistic regression predicting whether or not the child is gaining in Level 5 skills (beginning reading comprehension).

The extent of the relationship between parents' educational background and their children's achievement gains on the more demanding reading tasks was even more extreme. It was found that children from homes where at least one parent has a college degree or higher are more than 8 times as likely ($t = 8.05$; $p = .00$) as children from a home where neither parent has a high school degree to be making their largest gains on the Level 5 comprehension tasks. The children with strong educational support systems (i.e., high parental educational levels) were not only gaining more in terms of reading scale score points than their counterparts, but were making their maximum gains on the higher level reading tasks.

Asian children were 3.28 ($t = 4.09$, $p = .00$) times as likely as Black children to be making their gains in Level 5 reading comprehension skills, while White children were 1.86

times (t = 3.17, p = .00) times as likely as Black children to be making their gains at this level. There were no significant differences on this criterion for Hispanic and other minority children.

Table 8

Logistic Regression Predicting Whether a Child Was Making His/Her Maximum Gains at the Level 5 Reading Skills Versus Some Other Lower Level Skill

Predictors	Odds ratios	Standard errors	t-statistic	Probability
Age at 4th testing	1.0343	0.0093	3.76	0.00
Time bet. 3rd & 4th testing	0.9660	0.0421	–0.79	0.43
Girls	1.5719	0.1491	4.77	0.00
Catholic school	1.1614	0.1957	0.89	0.38
Private non-Catholic	2.3483	0.5321	3.77	0.00
High school graduate	2.8596	0.7901	3.80	0.00
Some college	4.0629	1.0600	5.37	0.00
College grad. or higher	8.3135	2.1869	8.05	0.00
White	1.8674	0.3684	3.17	0.00
Hispanic	1.4712	0.3111	1.83	0.07
Asian	3.2814	0.9522	4.09	0.00
Other minority	1.5726	0.7685	0.93	0.36

Discussion

The results are encouraging from the viewpoint of the public schools in the sense that they appear to be holding their own or reducing the gap in reading and mathematics with respect to both the Catholic and private non-Catholic school children. It should be kept in mind that although the public school children seem to be gaining more in terms of the total scores, particularly during the first grade year, compared with the private non-Catholic school children, the public school children started out much lower on the scales at entry to kindergarten. As a result, many public school children, by the end of the first grade year, are gaining in skills measured in the middle of the scale that deal primarily with reading mechanics, while the private non-Catholic school children are making their gains at the upper end of the scale, which is more focused on beginning reading comprehension. In other words, there are qualitative differences in gains between the public and private school children. As ECLS-K data becomes available for grades 3 and 5, where the emphasis of the reading assessments is on comprehension of reading passages rather than prereading mechanics and sentence comprehension, it will be interesting to see if the public school children can maintain the same accelerated growth that seemed to characterize their first grade year.

Children who are making their maximum gains during first grade in Level 5 skills (beginning reading comprehension) are likely to be moving from the learning to read mode to the reading to learn mode much earlier than their less advanced counterparts. One might expect these better readers to begin to separate themselves from the others in other subject matter areas where reading can be used as a tool for learning. It is also likely that they will be able to disproportionately increase their gains over the summer months in the succeeding school years.

While the between school sector variation decreased from the time of entry to kindergarten to spring first grade in both reading and mathematics, variation between parental education groups and between ethnic groups increased over the same time period. This phenomenon was more pronounced in the reading domain than in mathematics and for the parental education groups than the ethnic groups.

Black children started kindergarten significantly below White children in both reading and mathematics and had significantly lower growth rates than White children in both areas. This is unfortunate. One would hope that formal schooling might reduce the gap between the traditionally economically disadvantaged groups and the majority group. The higher correlations between slopes and intercepts for reading compared with mathematics, at both the school and child levels, suggest that it may be more important for later growth to come to kindergarten better prepared in reading than is the case in mathematics. This would suggest that, in reading at least, intensive preschool emphasis on prereading and reading mechanics might help reduce the gap in the later growth rates between the disadvantaged and advantaged child.

Girls entered kindergarten with greater prereading and reading skills than did the boys. They also had somewhat better mathematics skills at entry to kindergarten. While girls continued to grow faster than boys in reading during the first two years of schooling, there was no significant difference in their growth rates in mathematics. Girls in the first grade were twice as likely as boys to be making their gains at the highest reading level, beginning reading comprehension. Thus girls are not only growing faster than boys on the overall reading scale, they are also making their gains on the more difficult reading tasks.

The finding that the interaction of the treatment (schooling) and differing parental education levels led to an increased fan spread effect, particularly in reading, is quite important. Children of highly educated parents had *less de-acceleration* in their growth rates during the nontreatment (summer) period, and *greater acceleration* during the school years, when compared with children of less educated parents. This greater acceleration in reading skills during the school year as compared with summer gains for children of more highly educated parents runs counter to much of the summer gains literature, that is, Entwisle and Alexander (1992) and Entwisle et al. (1997). One possible reason for this is that these studies did not look at the summer effects between kindergarten and first grade. Other possibilities might be that their measurement instruments may have had ceiling effects. At any rate, if this nonadditivity continues in the later grades, the reading scores of children from different parental education groups will become even more disparate. This suggests that the presence of a strong educational support system in the home is particularly effective in enhancing growth in the first two years of schooling.

Conclusions

Reading and mathematics gains were relatively large for all subpopulations, but there remained substantial differences in the rates of growth among both individuals and subpopulations. Subpopulations from different demographic backgrounds typically entered kindergarten with significant differences in their level of preparation in both the reading and mathematics domains. In some cases these disparities were reduced, while in other cases the disparities remained the same or even increased.

Mean gains during the school year typically exceeded a full standard deviation in both reading and mathematics. Gains continued over the summer in both reading and mathematics but at a reduced rate. With respect to gender differences, girls began kindergarten performing better than boys in both reading and mathematics. In reading, girls also showed higher growth rates than boys but there was no difference between the gender groups in growth rates in mathematics.

Public school children entered kindergarten performing significantly below children entering Catholic and non-Catholic private schools in both reading and mathematics. This entry deficit was particularly pronounced for the public versus private non-Catholic contrast. However, the gap in reading performance between children in public compared with private non-Catholic schools at entry to kindergarten was significantly reduced by the spring of first grade. Much of this reduction resulted from a more highly accelerated growth rate for public school children in the first grade. A similar pattern was found in mathematics. The gap in reading performance between private non-Catholic school children and Catholic school children was also significantly decreased by spring of first grade. The gap in mathematics performance found at entry to kindergarten between private non-Catholic and Catholic school children was entirely erased by spring of first grade. If the public schools are failing in their teaching role, it does not seem to be happening during the first two years of schooling.

There were relatively large differential growth rates in reading performance for subpopulations based on parental education. This differential growth rate in favor of children from families with highly educated parents was evident over both the summer months and the school year. The gap that remains at the end of first grade between children of highly educated parents versus those from less educated families is the sum of initial differences at entry to kindergarten and differential growth rates during both the summer and the two school years.

In terms of ethnic group membership, Asian and to a lesser extent White and Hispanic children all showed significantly greater linear growth rates in reading than did the Black children. Hispanic, Asian, and White children all had significantly greater linear growth rates in mathematics than did Black children.

In terms of the quality of the gains, while the private non-Catholic school children gained less than the public school children in terms of total scale points, they were more than twice as likely to be gaining in their reading comprehension skills as opposed to the more basic reading mechanics skills. Children from homes having a parent with a college degree or greater were more than eight times as likely as children from homes without a high school graduate parent to be gaining in that part of the scale dealing with beginning reading comprehension.

References

Bryk, A. S., & Raudenbush, S. W. (1992). Hierarchical linear models, applications and data analysis methods. Newbury Park, CA: Sage.

Campbell, D. T., & Earlenbacher, A. E. (1970). How regression artifacts in quasi-experimental evaluations can mistakenly make compensatory education look harmful. In J. Hellmuth (Ed.), *Disadvantaged child: Vol. 3. Compensatory education: A national debate.* New York: Brunner/Mazel.

Cooper, H., Nye, B., Charlton, K., Lindsey, J., & Greathouse, S. (1996). The effect of summer vacation on achievement test scores: A narrative and meta-analytic review. *Review of Educational Research, 66,* 227-268.

Entwisle, D. R., & Alexander, K. L. (1992). Summer setback: Race, poverty, school composition, and mathematics achievement in the first two years school. *American Sociological Review, 57*, 72-84.

Entwisle, D. R., & Alexander, K. L. (1994). Winter setback: The racial composition of schools and learning to read. *American Sociological Review, 59,* 446-460.

Entwisle, D. R., Alexander, K. L., & Olson, L. S. (1997). *Children, schools and inequality.* Boulder, CO; Westview Press.

Goldstein, H. (1995). *Multilevel statistical models* (2nd ed.). London: Arnold.

Goldstein, H., et al. (1998). A user's guide to MlwiN [Computer software manual]. London: University of London, Institute of Education, Multi-level Models Project.

Heyns, B. (1998). *Summer learning and the effects of schooling.* New York: Academic Press.

Lord, F. M. (1980). Applications of item response theory to practical testing problems. Hillsdale, NJ: Erlbaum.

National Center for Education Statistics. (2002, January). *ECLS-K first grade public-use data file.* Washington, DC: Author. (NCES 2002-134)

Rock, D. A., & Pollack, J. M. (2002). *A model-based approach to measuring cognitive growth in pre-reading and reading skills during the kindergarten year* (ETS RR-02-18). Princeton, NJ: ETS.

Snijders, T., & Bosker, R. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling.* London: Sage.