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ABSTRACT

This study investigated whether individual change over time in mathematics and language differs from student to student and whether individual parameters of each of these domains were related within domain. The study also attempted to gain an understanding of individual change in student academic achievement through the application of one of the more powerful analytical tools, covariance structure analysis. The study also investigated whether the pattern of interrelationships among the individual achievement growth parameters were the same for African American and white students. The study used panel data from the Louisiana State Department of Education school data files. Wave 1 had 50,907 students, 24,030 of whom were African American, and wave 2 had 47,003 students, of whom 22,262 were African American. The final wave had 50,157 students, with 23,982 African Americans. For all 3 waves, the subset of students with records for grades 4, 6, and 7 was 26,051. The Iowa Tests of Basic Skills and other norm-referenced tests were administered as part of the state assessment program. Results of this study suggest that initial status differences in achievement levels between African American and white students are rather stable, and in some comparisons, actually increase over time. These differences might be predictive of later differential dropout rates between the two groups. The study also shows that differences between African American and white students become smaller over years of schooling, suggesting that early childhood experiences associated with differing home environments may be somewhat diminished by the effects of schooling over time. Six appendixes provide supplemental information about student achievement. (Contains 7 tables, 8 figures, and 85 references.) (SLD)

A Study of Students' Academic Change in Mathematics and Language Achievement: A Multilevel Structural Equation Model (MSEM) Approach

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Though many theorists have presented models to describe growth and change, these models are infrequently tested with data (Magnusson, 1985). It is apparent that lack of familiarity with many quantitative methods for estimating learning growth curves appears to be a major obstacle to the empirical testing of growth models (Burchinal & Appelbaum, 1991). Bryk and Raudenbush (1992) amplified the same problem by noting that research on change has been plagued by inadequacies in conceptualization, measurement, and design and has long perplexed behavioral scientists. In many situations, instruments used to assess the subjects are developed for fixed points in time, yet individual academic growth is dynamic. These instruments have not adequately captured individual differences in the rate of change. The study of change requires more than two waves of data but frequent studies have utilized only two data points and are thus not able to adequately address the issue of growth (Bryk & Raudenbush, 1987; Rogosa, Brandt, & Zimowski, 1982). When there are only two waves of data on each subject, there is no way to know the exact shape of individual growth over time (Willett, 1988). It has also been stressed that data from two time points and the difference score are less than optimal for the study of change but three or more waves of data are preferable (Olweus & Alsaker, 1991).

The difference score that was initially employed and continues to be used as a measure of change because of the concentration of two-waves measurement has restrictive assumptions and its continued use as a measure of change has been condemned by many researchers (Cronbach, Furby 1970; Lord, 1963; O'Connor, 1972; Thorndike, 1966). These researchers have instead recommended other statistical techniques of evaluating change.

Why study change in education? A focus on the study of change enables an in-depth investigation of how key elements of learning in and other variables exert an influence on student achievement outcomes. A study of change in education lends itself to an indepth evaluation of the extent differences in schooling experiences; in particular, differences in classroom environment and instructional quality, contribute to the development of interindividual differences in achievement. The study of this change in education is important because it is through change that the effectiveness of a curriculum can be assessed and improved.

In recent research on individual change, investigators have used individual growth modeling in order to make use of the enormous volume of multiwave data available in academic and related institutions, while providing better methods for investigating interindividual differences in change (Bryk & Raudenbush, 1987; Rogosa et al., 1982; Rogosa & Willett, 1985; Sayer & Willett, 1998; Willett, 1988; Willett & Sayer,1994, 1996). Further, recently, pioneering researchers have shown how the analysis of change can be conducted conveniently by the methods of covariance structure analysis (Tisak & Meridith,1990; Sayer & Willett, 1998; Willett & Sayer, 1994, 1996).

The application of covariance structure analysis techniques in research subsumes more traditional approaches to the analysis of panel data, such as repeated measures analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA) (Jöreskog & Sörbom, 1989; Meridith & Tisak, 1990; Rao, 1958; Tucker, 1958). For this study, the individual change aspect can be represented through a two-level hierarchical model ("multilevel"). At level 1, each person's development is represented by an individual growth trajectory that depends on the unique set of parameters. In level 2, the level 1 growth parameters become the outcome variables, where they depend on some person-level characteristics. The multiple observations recorded for each individual in the study provide a 'hierarchy' which can be adequately processed by a multilevel data analysis technique.

Multilevel analysis involves estimating growth curves for multiple observations in the first phase and testing the covariation between the estimated indices of growth curve analysis and hypothesized predictors or outcomes of the change process in the second phase (Bryk & Raudenbush, 1992; Muthén, 1997; Sayer & Willett, 1998; Willett & Sayer, 1994, 1996). The multilevel covariance structure analysis model is a flexible procedure and as such an attractive analytical tool for a variety of SEM analyses that can be used to investigate growth and development among variables of interest with multilevel data. This study, with availability of panel data, and particularly for studies of individual growth, will demonstrate how covariance structure models can be set up for hierarchical data (observations nested within person) and how these models can be analyzed by traditional SEM software, such as LISREL.

Cognitive Processes and Learning in Mathematics and Language

To understand growth in mathematics and language, a basic knowledge of learning theory, language acquisition process and cognitive processes in these domains is essential. Several theories have emerged in the realm of psychology and education suggesting that individual learners employ various strategies processing information during classroom experiences (Morgan, 1997). This is because there are five basic components involved in the acquisition of knowledge: perception, sensory organs, short term memory, long term memory and motoric systems. These components work in a complex interactive way through the human central nervous system. Piaget (1929) presented five stages of cognitive development that postulate that as children grow older, their abilities to conceptualize develop. These stages are a) sensori-motor, where the infant learns to differentiate self and objects in the external world (0 and 2 years of age), b) pre-operational thought, which is between 2 and 4 years of age, is characterized by egocentricism and classification of objects in the external world by the child, c) the intuitive stage which ccurs between the ages of 4 and 7. In this stage, the child thinks in classificatory ways but may be unaware of classifications, d) the fourth stage, characterized by concrete operations, takes place between 7 and 11 years. During this stage, the child is able to use logical operations such as reversibility, classification and serialization and, c) the developmental stage is punctuated by growth of formal operations. This takes place during ages 11 through 15. This stage is characterized by trial steps towards abstract conceptualization.

In a similar developmental model Cramer (1978b), describes five stages in the language acquisition process. Stage one is marked by babbling and random experimentation with sounds. The child produces all sounds relevant to his native language as well as sounds significant in languages other than his own. Stage two sets a beginning of recognizable behavior. The child responds to verbal language signals and begins to produce sounds to express needs. Later, utterances such as "*bye-bye, da-da, ma-ma*" become common as the child's vocal mechanism and mental development grow. Stage three is described as "*telegraphic*" because of the preponderance of nouns and verbs over other words (articles, prepositions, conjunctions, and auxiliary verbs). In stage four, acquisition of syntactic structures of language, rules for the generation of the same, and rapid expansion of new vocabulary items are experienced. In stage five, the child has internalized native language grammar. Generation of grammatical sentences becomes evident.

Bandura (1977), accepts that, as a process, learning involves functionalism, interactionism, and significant symbolism. He stresses the depth of how individuals are capable of self-regulation and self-direction. Bandura's theory is based on concepts such as response, conditioning, stimulus, reward, imitation, conformity, deviance among others, in relation to personal development (Jarvis, Holford, & Griffin, 1998).

The notion that a problem or a particular subject matter is difficult to solve is a key organizing concept in the design of any math activity by teachers and that difficulty is a quantitative concept (Ohlsson, Ernst, & Rees, 1992). Case (1985, 1992) investigated how working memory develops in relationship to Piagetian stages of cognitive development and found that working memory is domain specific for mathematics in 12- to 14-year-olds in both traditional and gifted students. Dark and Benbow (1990, 1991) report similar results on working memory and growth in mathematics skills. Most past research has concentrated on the early acquisition of mathematical skills with a focus placed on pace and sequence of skill acquisition. There were few studies that included individual differences and rates of change other than those labeled *disabilities* (Robinson, Abbott, Berninger & Busse, 1996).

Mathematics and language go hand in hand in setting a stage for an understanding of learning aspects in student academic life. This could be because of the intricate nature they both offer in affecting each other and on affecting other domains. Language and mathematics are the cornerstones of student academic growth. A student with a strong foundation in both of these domains is more likely to do well in many other disciplines. Knowledge of how mathematics and language relate and how students grow in them is crucial not only for pedagogical reasons but also for the health of education of any educational system and for the prosperity of student welfare.

Purpose

The purpose of this study was to investigate whether individual change over time in mathematics and language differs from student to student and if the individual growth parameters of each of the two domains were related within domain. In addition, the study sought to gain an understanding of individual change in student academic achievement through the application of one of the more powerful analytical tools - covariance structure analysis. More specifically the study was designed to answer the following questions: (a) are the growth parameters (intercepts and slopes) in mathematics and language related within each domain? (b) is the pattern of interrelationships, among the individual achievement growth parameters, the same for African American and White students? (c) are there discernible patterns in variability in academic growth parameters within each ethnicity?

The conceptual framework guiding this study views learning growth curves and measurement of change as complex strategies for measuring student learning but among the best approaches that provide empirical results. In the past several years, there have been lamentations about the poor performance of U.S. students in mathematics and science as compared to those of US key economic competitors (Kaplan & Elliott, 1997). Reynolds and Walberg (1992) reiterated this fact by citing comparative studies that continue to show the poor performance of U.S. students, especially at the junior and high school levels. Many of these studies have been cross-sectional in nature.

Within the extant literature on the early acquisition of mathematical skills, many studies have focused on the pace and sequence of the skills acquisition, with very few extending to individual differences and the rate of development. Williamson et al. (1991) used individual growth curves to study academic growth in reading and mathematics and found a moderate correlation between rate of change and ability test scores.

The literature is replete in the area of reading and writing especially on causes of developmental changes in knowledge structure and use. Some theorists hold that children have innate ability to acquire knowledge of the structure of a language because of the constraints in all other languages (Wexler & Cullicover, 1980). Chomsky (1972) conducted an extensive study of elementary school children involving their understanding of certain sentence structures and stressed that children's language development is on-going throughout the school-age years.

Willett and Sayer (1996) studied the growth of change in mathematics and language in healthy, asthmatic and seizure groups of children of ages 7, 11 and 16. Their study established that true growth trajectories for healthy and asthmatic children were similar while those with seizures had low averages in both domains. Positive correlation coefficients between the initial status in reading and initial status in mathematics and between the rate of change in reading and the rate of change in mathematics were established. Sanders & Horn (1998), utilized longitudinal data to study student academic growth over time, and found that largest academic gains were in the lowest achievement group. However, limited studies exist that have focused on individual growth trajectories and structural equation modeling in mathematics and language.

In order to capture details of the component of student academic growth, this study was partitioned into four basic parts. First, it investigated the growth curves to compare two groups of learners in language and mathematics. Second, it investigated the patterns of interrelationship among the individual achievement growth parameters for African American and White students. Third, it investigated the variability in learning abilities, gleaned from academic growth parameters for two groups of learners in mathematics and language. Fourth, it utilized a combination of individual academic growth curves and covariance structure analysis, a more flexible and robust technique than the traditional methods in the study of academic growth have been limited in sensitivity in error. For this study, a simple linear model for individual change in the two domain areas, mathematics and language respectively were developed. For simplicity of presentation, the first equation presented in the next section is used for illustration purposes. However the model explanation for model 1 applies equally well to model 2. Second, the study utilized three waves of data with the initial assessment point at grade 4, while the second and third assessment points are grades 6 and 7 respectively. Thus three waves of data or three data-points are modeled. The first data collection point was chosen as the reference. According to this model (1), there is a tendency for the mathematics score of each student to change at a steady rate from grade 4 to grade 6 and then from grade 6 to grade 7.

$$Y_{ip}^{(m)} = \pi_{0p}^{(m)} + \pi_{1p}^{(m)}(\text{GRADE} - 4)_{pt} + \varepsilon_{ip}^{(m)} \qquad (1)$$

$$Y_{ip}^{(l)} = \pi_{0p}^{(l)} + \pi_{1p}^{(l)}(\text{GRADE} - 4)_{pt} + \varepsilon_{ip}^{(l)} \qquad (2)$$

Where

$Y_{ip}^{(m)}$ is the mathematics score for person p at time t, p = 1,. . . . ,n; where n is the total number of persons in the sample;

t=1, 2, 3 (the test-taking occasions: the three data points);

$(\text{GRADE} - 4)_{pt}$ is the grade of the person p at time t minus 4 so that $(\text{GRADE} - 4)_{pt}$ is 0, 2, and 3 at grades 4, 6 and 7 respectively, corresponding to times t = 1, 2, 3;

$\pi_{0p}^{(m)}$ is the intercept of person p, so that, given the coding of (GRADE - 4), $\pi_{0p}^{(m)}$ is the expected mathematics outcome of person p at grade 4;

$\pi_{1p}^{(m)}$ is the expected linear rate of increase per year in the mathematics outcome of person p, which is the key parameter in the measurement of individual change and given the coding of $(\text{GRADE} - 4)_{pt}$, is interpretable as the growth rate of subject p at grade 4.

$\varepsilon_{ip}^{(m)}$ is the random within-subject error of prediction of person p at time t, conditional on that person's change parameters $\pi_{0p}^{(m)}$, and $\pi_{1p}^{(m)}$. These within-subject errors are assumed mutually independent and normally distributed with mean of zero, that is, $\varepsilon_{ip}^{(m)} \sim N(0, \sigma^2)$.

Methodology

Sampling Procedures

This study used panel data drawn from the Louisiana State Department of Education (LDE) school data files. The subset of students involved in this research was obtained as follows. Of all the elementary school students in the LDE data files, only those who attended public schools and were of African American and White ethnic group origins were sampled. The sampled students were tested on the Norm Referenced Tests (NRTs) -- mathematics and language for past academic years up to and including the 1998-1999 achievement records. Wave one had 50,907 students (African Americans=24,030, Whites=26,877), wave two had 47,003 students (African Americans=22,262, Whites=24,741) while the third and last wave had 50,157 students (African Americans=23,982, Whites=26,175). The subsets of students who had complete records for grades 4, 6 and 7 were 26,051 (African Americans=11,627, Whites=14,424).

Instrumentation and Measurement

The Iowa Tests of Basic Skills (ITBS) Norm-Referenced Tests (NRTs) as part of the Louisiana Educational Assessment Program (LEAP), was utilized in this study. The NRT tests provide a measure of how students compare with other students nationally in the specific domain of interest...language, and mathematics. The two domains utilized in this investigation (language and math) were average composites of their respective constituents. Math subscales were math concepts/ estimation and math problem solving/data interpretation while language subscales were spelling, capitalization, punctuation, and usage and expression. The NRT measure is a multiple choice scale for mathematics and language domains. Reliability data for the ITBS meet stringent psychometric standards. The ITBS Complete Battery average test reliabilities (K-R 20) for grades 3 through 8 are 0.86 and 0.87 for the fall and spring, respectively.

Data Analysis Procedures

This study adopted a two-stage strategy of the data analysis procedure as provided in the individual growth curves analysis and covariance structure analysis technique of both Sayer and Willett (1998) and Willett and Sayer (1994, 1996) for single and double populations. First, a series of preliminary data analyses was conducted to check on the normality, skewness, and kurtotic nature of each of the three waves of data to gain familiarity and knowledge of the data at the individual level (See Appendix C). Ordinary least squares (OLS) fitted trajectories summarizing observed growth patterns for both mathematics and language between grade 4 and 7 for the subsample of 27 (See Appendix D) selected students from both ethnic groups was completed (Appendices, E and F).

In the study of change patterns in student academic achievement, over time, the analysis was conducted in two levels. At level 1 (within person), the curve fitting techniques to describe growth events such as the effect of student grade level on mathematics and on language achievement were applied. This level involves fitting, to each individual, a particular curve that is a function of time (grade). In the second level (between-person), comparison of the patterns of the growth parameters was made. The different student background characteristics was presented through the summary descriptions of means of the individual curve coefficients gleaned from the first level analysis. The multilevel data analysis techniques carry out such analysis at two levels simultaneously (Bryk & Raudenbush, 1992; Kaplan & Elliott, 1997; Yang & Goldstein, 1996). The individual growth model

Table 1: Estimated Means and Covariances for Three waves of Mathematics and Language Achievement Scores at grades 4, 6, and 7 for (a) African American (AA) students (n=10,724), (b) White students (n=13,578).

AA	Mathematics			Language		
Grade	4	6	7	4	6	7
Means	186.28	208.06	216.76	189.72	213.53	226.84
Covariances	256.24					
	176.34	358.01				
	225.85	316.87	553.50			
	214.68	185.73	238.85	404.99		
	222.64	319.37	369.70	355.48	726.40	
	226.07	299.66	427.87	349.59	545.47	811.31

N=10,724

WHITE	Mathematics			Language		
Grade	4	6	7	4	6	7
Means	204.50	231.01	246.01	206.66	237.53	251.73
Covariances	411.12					
	329.49	541.72				
	372.02	481.18	687.09			
	322.37	308.73	358.42	574.12		
	355.65	446.36	492.71	517.45	901.85	
	350.66	421.75	541.20	488.67	682.69	959.18

N=13,578

was evaluated in line with the tenets of the classical test theory approach where the observed score is distinguished from the true score. Table 1, presents the sample mean vectors and covariance matrices for language and mathematics and for the two groups of learners--African American and White students respectively. The data in the table was utilized in the computation of individual growth parameters for the two groups of learners.

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Results

First, a series of preliminary data analyses was conducted to check on the normality, skewness, and kurtotic nature of each of the three waves of data to gain familiarity and knowledge of the data at the individual level (See Appendix C). To provide descriptive information and gain familiarity of math and language score distributions for the two groups of learners, boxplots were completed (See Appendices A and B). In the boxplots language scores for the African American and White students are compared. From this plot, the median score for White students is higher at all three grade levels. This is also true with math score. The two groups of learners have discernible spread within, though White students have fewer outlying values both at the lower and at the upper percentile portions of both math and language scores. The within African American math and language score distributions are associated with several outlying values, mostly at the upper percentiles.

The major findings of the study showed that: 1) students vary significantly in knowledge of mathematics at entry into grade 4 and that White students overall initial status in mathematics was higher than that of African American students, 2) language intercepts for the two groups were statistically significant, signifying language knowledge differences at grade 4, 3) mathematics overall slope for the two groups of learners were positive and significantly different from zero, 4) language overall rates of learning within ethnicity were significantly different from zero, 5) the correlation coefficients of the slope and initial status for each domain and within each ethnicity were not statistically significant and 6) variance estimates for language and mathematics slopes were significantly different from zero and that variances increase at lower grade levels as students advance in school from grade 4 through grade seven. Complete results of this study for parts 1 through 6 presented above are presented in Tables 2 and 3. The contents of these tables are discussed in the following section.

The entries in the first two rows of Table 2 for Model 2 estimate the African American population means of true intercept (188.96, $p < 0.05$) and true slope (10.01, $p < 0.05$) for mathematics. The estimated population means of true intercept and true slope for language are 189.02 ($p < 0.05$) and 12.42 ($p < 0.05$), respectively. The true intercept and true slope for the respective domain describe the average trajectory of true change in the dependent variable. On average, African American students' true mathematics scores increase by 10.01 per year while true language scores increase by 12.42 per year.

Table 2: Fitted Models For Interindividual differences in Change in Mathematics and Language in the African American Sample

	Maximum Likelihood Estimates			
Parameter	Mathematics		Language	
	Model 1	Model 2	Model 1	Model 2
μ_{0p} (Intercept [I])	186.59*	188.96*	189.52*	189.02*
μ_{1p} (Slope [S])	10.26*	10.01*	12.31*	12.42*
$\sigma_{\pi 0}^2$ (Intercept Variance)	312.33*	215.86*	619.72*	354.22*
$\sigma_{\pi 1}^2$ (Slope Variance)	51.03*	27.77*	103.58*	62.60*
$\sigma_{\pi 0 \pi 1}$ (I-S Covariance)	-53.31*	0.12	-104.35*	0.48
df	3	1	3	1
χ^2	324.78*	8.56*	742.40*	41.45*
Goodness of Fit Index (GFI)	.985	1.000	.960	1.000
Normed Fit Index (NFI)	.960	.999	.952	.997
Comparative Fit Index (CFI)	.960	.999	.952	.997
Root-Mean-Square Error of Approximation (RMSEA)	.100	.026	.152	.061

Note: N=10,724. Descriptions of the models are given in the text below

* $p < .05$

Table 3 presents parameter estimates and model fitting for mathematics and language scores for the White students. As was the case with the African American model fitting, model 2 was adopted for each domain. An inspection of the parameters in the table show that all the intercept parameters were statistically significant. Entries in the first two rows of Table 3 for Model 2 estimate the White population means of true intercept to be 204.04 ($p < 0.05$) and true slope to be 13.80 ($p < 0.05$) for mathematics.

The estimated population means of true intercept and true slope for language were 207.09 ($p < 0.05$) and 15.00 ($p < 0.05$), respectively. These growth parameters describe the average trajectory of true change in the dependent variable. On average, White students' true mathematics scores increase by 13.80 per year while true language scores increase by 15.00 per year. Students' knowledge in both mathematics and language improved over time, and more rapidly in language than in mathematics.

In both the African American and the White samples, slope parameters were all positive and statistically significant. The domain respective intercepts are initial average achievement scores at grade 4 adjusted for measurement error (Kline, 1998). The intercept is a characteristics of the whole sample while the variance of the same, reflects the range of individual differences in the domain of interest around the intercept. The mean rate of change, on the other hand, reflects a group-level characteristic– its value indicates the average amount of occasion-to-occasion change in mean levels of the domain of interest (also adjusted for measurement error). The statistics provided by the slope (rate of change) presents information about the rate of individual differences in linear occasion-to-occasion changes over time.

Table 3: Fitted Models For Interindividual differences in Change in Mathematics and Language in the White Sample

Parameter	Maximum Likelihood Estimates Mathematics Model 1	Mathematics Model 2	Language Model 1	Language Model 2
μ_{0p} (Intercept [I])	204.25*	204.08*	206.84*	207.09*
μ_{1p} (Slope [S])	13.75*	13.80*	15.08*	15.00*
$\sigma_{\pi 0}^2$ (Intercept Variance)	493.38*	328.74*	840.48*	516.95*
$\sigma_{\pi 1}^2$ (Slope Variance)	60.69*	35.19*	113.76*	63.96*
$\sigma_{\pi 0 \pi 1}$ (I-S Covariance)	-64.40*	0.29	-126.35*	0.20
df	3	1	3	1
χ^2	199.55*	39.24*	584.95*	23.32*
Goodness of Fit Index (GFI)	.992	1.000	.974	1.000
Normed Fit Index (NFI)	.981	.999	.965	.999
Comparative Fit Index (CFI)	.981	.996	.965	.999
Root-Mean-Square Error of Approximation (RMSEA)	.069	.053	.120	.041

Note: N=13,578. Descriptions of the models are given in the text

* $p < .05$

Table 4 shows mathematics and language mean scores for students receiving free/reduced cost lunch and those bearing full costs of lunch. The lunch variable is utilized as a proxy for social economic status (SES). These results show that White students had higher mean values in both mathematics and language than African American students irrespective of whether they were in the

Table 4: Characteristics of the Sample: Sample Sizes and Mean Scores for Students With Lunch and Students Without Free/Reduced Lunch in Mathematics and Language Domains

Mathematics

Race	Gender	Case	Lunch	No Lunch
African-Americans	Female	5375 (1121)	187.9	193.6
	Male	4100 (985)	187.3	193.8
Whites	Female	2654 (4637)	198.5	206.4
	Male	2071 (4185)	200.5	208.2

Language

Race	Gender	Case	Lunch	No Lunch
African-Americans	Female	5375 (1121)	232.8	243.1
	Male	4100 (985)	220.9	231.1
Whites	Female	2654 (4637)	250.1	261.6
	Male	2071 (4185)	237.3	249.1

Note: Values in parentheses are the number of students who did not receive free/reduced cost lunch.

lunch program or not. The initial mean differences in both domains and across the two groups of learners continued to grow as students advanced in school.

Within each ethnicity and whether students were in the lunch program or not, female students outscored their male counterparts in language whereas males and females performed rather similarly in mathematics irrespective of the lunch program assignment. Students who were not in the lunch program tended to show higher mean level differences in language than in mathematics.

Table 5: Estimated Means of Three Waves of Mathematics for Students With and Without Free/Reduced Cost Lunch

Lunch	African American (AAL)	White (WL)	Mean Difference
Grade 4	187.6	199.4	9.8
Grade 6	208.4	225.6	16.6
Grade 7	217.4	238.6	16.8
No Lunch	African American (AANL)	White (WNL)	Mean Difference
Grade 4	193.7	207.3	10.8
Grade 6	213.7	234.0	20.2
Grade 7	225.6	250.0	24.4

Note: The within grade mean difference score was computed by subtracting African American students' mean score from White students' mean score in each of the two lunch categories

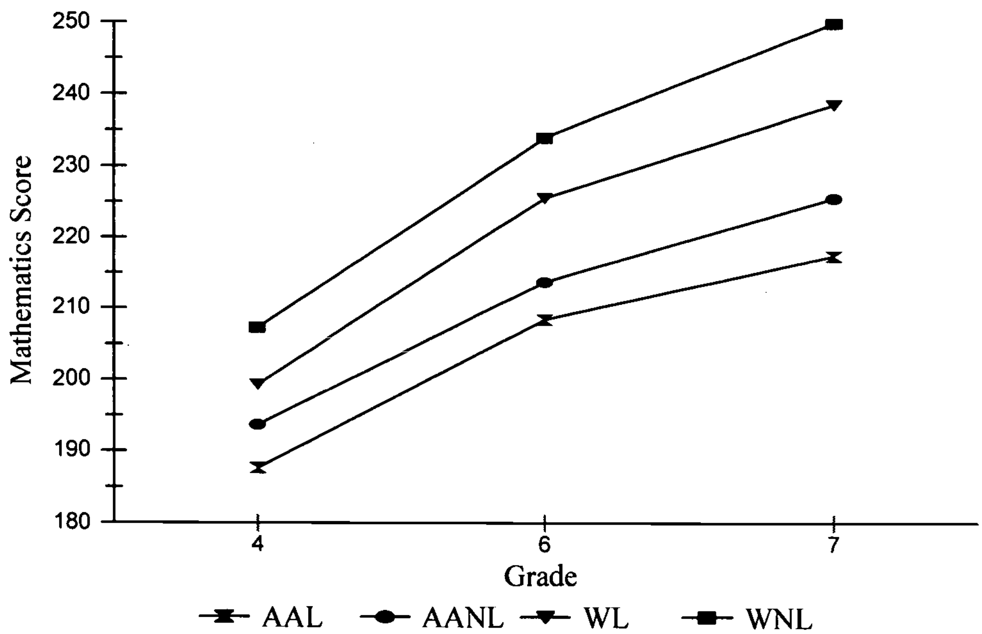

Figure 1: Mathematics Mean Plots for African American and White Students With Lunch (L) and Without Free/Reduced Cost Lunch (NL).

Figure 1 depicts the shapes of mathematics mean curves for each lunch category (African American with lunch=AAL, African American without Lunch=AANL, White with lunch=WL, and White without lunch=NL), using the mean values provided in Table 5. From the mean curves, it is evident that learners continue to diverge in mathematic achievement as they advance in school. Within the two groups of lunch categories, African American students scored lower than their White counterparts in mathematics and the differences continue to widen as students move from grade 4 through grade 7. These results suggest that students initial status in mathematics is important. The results suggest that initial mathematics differences among the groups are maintained, and for students without free/reduced lunch actually widened, from grade 4 through 7.

Table 6: Estimated Means of Three Waves of Language for Students With Lunch and Without Free/Reduced Cost Lunch

With Lunch	African American (AAL)	White (WL)	Mean Difference
Grade 4	191.5	201.3	9.8
Grade 6	213.9	230.5	16.6
Grade 7	227.7	244.5	16.8
No Lunch	African American (AANL)	White (WNL)	Mean Difference
Grade 4	198.8	209.6	10.8
Grade 6	221.2	241.4	20.2
Grade 7	237.5	255.7	18.2

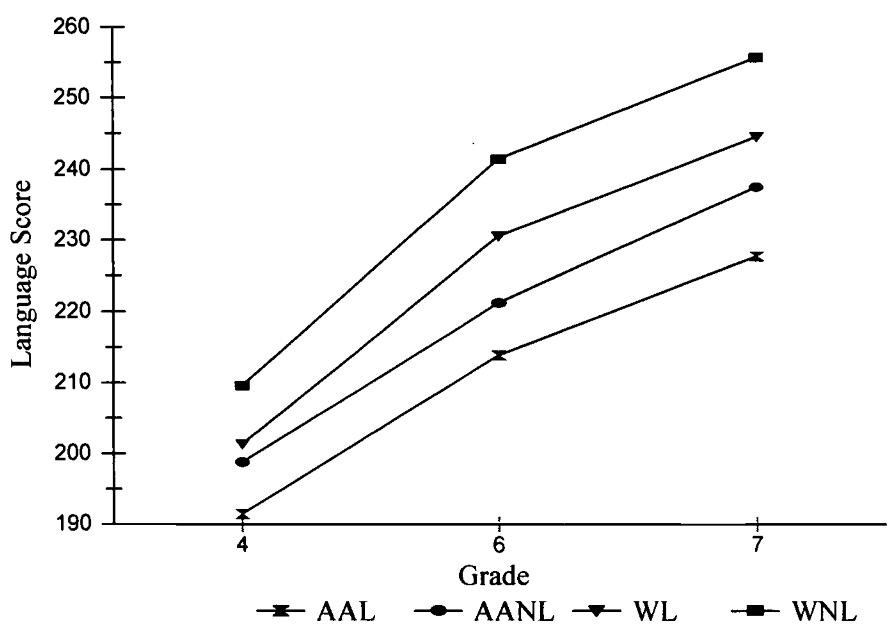

Figure 2: Language Mean Plots for African American and White Students With Lunch (L) and Without Free/Reduced Cost Lunch (NL).

As shown in Figure 1, Figure 2 depicts the shapes of language mean curves for each lunch category (African American with lunch=AAL, African American without Lunch=AANL, White with lunch=WL, and White without lunch=WNL), utilizing the mean values in Table 6. From the mean plots, it is apparent that learners continue to diverge in language achievement as progress from grade 4 through grade seven. Within each ethnicity, the category receiving lunch performs below the non-lunch category. Also, African American group language mean values are lower in both SES categories, than White students' mean values in both mathematics (Figure 1) and in language (Figure 2). For language scores, mean differences first rise between grade 4 and 6 but begin to decline somewhat as students advance to grade seven. As was the case with mathematics, these results show that students' initial status (baseline differences at grade 4) are predictive of differences at grade 6 and grade 7.

Discussion, Significance and Implications

Over the past several years, there have been major concerns about the educational performance of U.S. students. This is well reflected in the publication of *A National at Risk in 1983*. This report highlighted important points that left many education researchers asking themselves questions about achievement growth such as: how much does student achievement change during different stages of a students' schooling?

The language and math SEM fitted models showed that the intercept and the slope parameters were significant. Further, the variances were significant and showed marked interindividual differences in growth curves, both in initial ability status (grade 4) and in individual change slopes (over time). White students' language and mathematics slope parameter estimates were higher than those of African American students. This implies that White students were more variable in their language and mathematics learning rates as compared to the African American students. These differences are very telling in that the differences in the learning rates are larger at lower grade levels than in higher grade levels. The National Center for Educational Statistics (1997) study on reading and mathematics and reading achievement found that racial disparities in 12th grade achievement reflect differences in achievement prior to entering high school. This study also showed that differences between African American and White students become smaller over the years of schooling. This decreasing difference in learning between groups can be explained in part, by the fact that the majority of African American students come from economically deprived environments that are not as academically nurturing as more economically advantaged environments. The proportion of students who come from economically disadvantaged White families is not as large as for African American students. Once in school, early childhood experiences associated with differing home environments that differentially impact students' academic performance may be somewhat diminished by the effects of schooling over time.

The results of this study differ from the findings of other studies and suggest that initial status differences in achievement levels between African American and White students are rather stable, and in some comparisons, actually increase over time (from grade 4 through grade 7). These differences as well, might be predictive of later, differential dropout rates between the two groups. Similar findings were evident when comparisons were made by SES within each of the two groups. The growth curve analyses in these comparisons showed that the growth curve for White students who received free/reduced lunch was higher at all grade levels than the growth curve for African American students who did not receive free/reduced lunch. These findings may well reflect the differential and interacting influences of the nature of differing home environments among groups, as well as differential impacts of schooling over time.

Sanders & Horn (1998) found differences in classroom teacher effectiveness and prior achievement levels of students to be the two most important factors impacting student gains in learning and achievement over time. They further found that students assigned to ineffective teachers continue to show the effects of such teachers even when the students were assigned to very effective teachers in subsequent years. The findings reported in this study are consistent with those of Sanders & Horn.

In the study of individual differences and the learning of mathematics, Fennema, and Behr (1980) suggested that individuals differ on a wide number of cognitive variables such as mathematical aptitudes-- numerical ability, mathematical reasoning, and inductive /deductive ability in problem solving process. The results of the present study suggest that these differences are evident in the early school years (grade 4) and are maintained, and may actually increase, over time (through grade 7).

From measurement theory, research design, practice and future research perspectives, the two domains utilized in this investigation (language and math) were average composites of their respective constituents. Math subscales were math concepts/ estimation and math problem solving/data interpretation while language subscales were spelling, capitalization, punctuation, and usage. It also seems important that factors that directly relate to proper and reliable assessment of student achievement in mathematics and language be observed.

Royer (1990), stated that test using multiple-choice items were measuring offline reasoning processes rather than online comprehension processes and extreme care must be observed when using these tests to make grade placement decisions, diagnosing reading difficulty, or assessing educational gain. Royer (1990) argued that standardized reading comprehension tests that utilize multiple-choice questions do not measure the comprehension of a given passage, but rather measures a reader's world knowledge and his or her ability to reason and think about the content of the passage. For mathematics and language educators need to use multiple data points and multiple forms of assessments of students' knowledge of mathematics and language other than relying only on the scores of standardized tests to evaluate students' learning growth. Both reliability and validity of inferences about student learning and academic progress are enhanced with analyses of longitudinal data. e and expression.

From measurement and research design perspectives, it is worth noting that the LISREL method has a number of extensions that can be utilized in various research environments due to its ability to accommodate any number of data points (waves) of longitudinal data with more data leading to higher precision for the estimation of the individual growth parameters and greater reliability of the measurement of change.

Further, the results of this investigation should be interpreted with some caution because of a number of factors that were beyond the control of the researcher. Important among these was missing data. More often than not, loss of subjects in longitudinal studies of students may result in the pattern of data loss that may not be random. Due to the rather large data set utilized in this study, a test of whether the patterns of missing data were random or systematic was not completed but an assumption was made that the missing cases in the data set were purely random and that missing data would not adversely affect the sample size. However, students who dropped out of school at each wave are perhaps more likely to come from families with particular characteristics (e.g., low SES, job instability of parents). This obviously can create problems with reliability of the data and the generalizability of the results. Further, the growth parameters computed may not be adequately representative of the true change in achievement for the ethnic groups compared over time. It is also important to be cognizant of the fact that when the missing pattern is not random, there is no adequate statistical fix to remedy this problem.

Though this study did not attempt to model the problem of missing data, it employed listwise deletion. The covariance matrix generated by listwise deletion will always be consistent, that is, positive semi-definite (Anderson and Gerbing, 1984). However, if the pattern of missing data is not random, an inconsistent matrix – not positive definite, can result (Rovine , & Delaney, 1990). Despite the fact that listwise deletion can result in a positive semidefinite matrix, it is also known that this technique can present problems for tests of goodness of fit, unless the missing data are missing completely at random (Kaplan, & Elliott, 1997; Muthèn, Kaplan, & Hollis, 1987).

As discussed earlier, intercept changes in both language and mathematics and for the two groups of learners were unrelated to their respective slopes. This suggest that where a student starts in domain achievement is not necessarily related to his or her future growth in the domain of interest. Though this study did not investigate poverty among the two groups of interest, it is worth noting that poverty in the African American sample in Louisiana is much higher than that of White sample. This imbeddedness of poverty within any particular group translates into differential learning environments in terms of per capita learning resources made available at home, which subsequently impacts school learning and achievement. Though a number of individual growth patterns over time were shown in this study with each group, and when comparisons were made within group by SES levels, the total group effects of home and schooling were shown to sustain over time. Recent large scale reviews of the literature to identify both proximal and distal factors impacting student learning and achievement clearly document the importance of proximal factors that include both the school and the educational quality of the home environment (Wang, Haertel, & Walberg, 1993).

African American and White students enter grade 4 with language and mathematics achievement differences. These differences are more than influenced by differing rates of poverty associated with race. However, the results reported here also suggest that proximal factors associated with school (i.e., differing teacher expectations, access to educational resources) may also differentially affect African American and White students. Both the mathematics and language intercept and slope variances were higher for White students than for African American students. These differences suggests that the effects of home and school learning environments witthin groups differ. The White sample in this study remained approximately normally distributed with both low, median and high achievers persisting through the schooling years. This may not be the case with African American students over a greater number of years when differential dropout rates might be expected. These rates might well be predicted by irrecoverable early childhood learning experiences. Thus, shrinkage in differences in achievement between White and African American groups in the later years of schooling might well be expected by differential dropout rates. As well, greater variation in SES within these two groups might account for the greater heterogeneity in White student samples in later school years than in African American student samples (as shown in this study).

It is important also that teachers have a better understanding of their students' literacy development. This helps teachers to recognize patterns of behavior which suggests aspects of students' development behavior out of what is provided in the curriculum. Knowledge of student's literacy development accords teachers an opportunity to develop more flexible curricula to meet the changing needs of specific students or groups of students.

The Louisiana School Effectiveness study (Teddlie, 1994; Teddlie & Stringfield, 1993) discussed areas in which school policies can positively affect teachers behaviors such as appropriate teacher selection and replacement, frequent personal monitoring of classroom behavior, support for teachers through direct assistance and in-service programs, and overall instructional leadership. These strategies lay a fertile ground for effectiveness in classroom instruction and management. Mendro (1998) discussed equity in student access to a quality education as regards the type of help to provide to students who have had an ineffective teacher in the past. Mendro (1998) stated that students who are placed with an ineffective teacher suffer long-term negative effects and there needs to be a policy issue put in place to allow for more equitable distribution of resources to enhance the quality of teaching and learning. In a reent study that aggregated data at the student level, Sanders and Horn (1998) found that ineffective teachers were ineffective with all students regardless of students' prior levels of achievement while teachers of the highest effectiveness were generally effective will all students. Though Sanders & Horn (1998) found teacher effectiveness to be a dominant factor affecting student gains in academic achievement when compared to other classroom context variables (.e.g, class size, classroom heterogeneity), it seems important that schools recognize socioeconomic differences among students in th early years in considering more equitable distribution of educational resources, particularly good teachers.

This study raised a number of important points to consider for future research. First, student language and math achievement change need more research to pinpoint exactly where differences arise within each domain and across ethnicity. Second, lower math achievement scores and rates of change, particularly for African American students needs more intense study. The National Center for Educational Statistics study showed that, on average blacks and Hispanics score lower than Whites on reading and mathematics at the end of grade 8 and that these differences do not increase over the high school years. Sanders and Horn (1998) showed that, regardless of race, students who are assigned disproportionately to ineffective teachers are severely academically handicapped relative to students with other teacher assignment patterns. More research that links students' academic records to those of their teachers seems in order.

Third, the methodology of this study needs to be extended to ethnically diverse samples to further demonstrate its utility for investigating individual change over time. Studies using multi-domain analyses to further investigate the nature of differences that were observed in language and math parameters in this study, and whether these differences are maintained across different groups of learners are needed.

Fourth, a replication of this study with a greater number of occasions, is recommended for agreater number of data points (more waves) might be quite informative. Such studies can yield information that has implications for understanding academic growth differences both within and between differing groups, and information that might be used for educational policy making, resource allocation and school intervention and improvement programs as well. In an era of educational policy making for greater school accountability, longitudinal studies can be used to better understand patterns of school change (or lack of change) over time. This seems particularly the case when such procedures are compared to more traditionally used procedures (i.e., pre and post test analyses from year to year). The data analysis procedures used in this study, and the attained results, also suggest the importance in future research, and in educational policy making as well, of understanding initial status differences and the cumulative effects of schooling among groups of students that differ by race and socioeconomic status.

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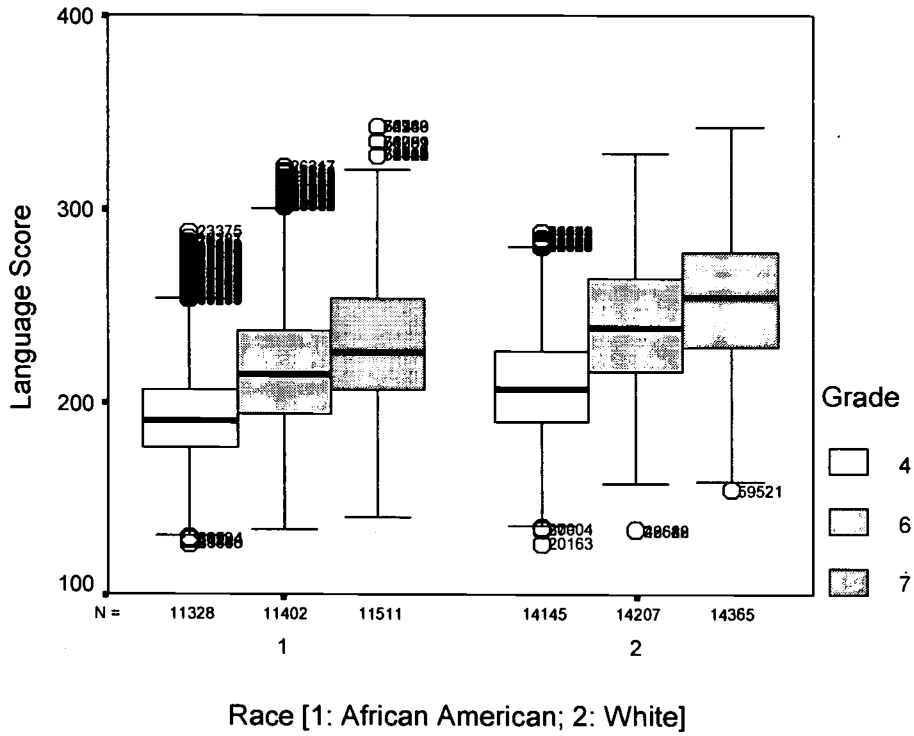
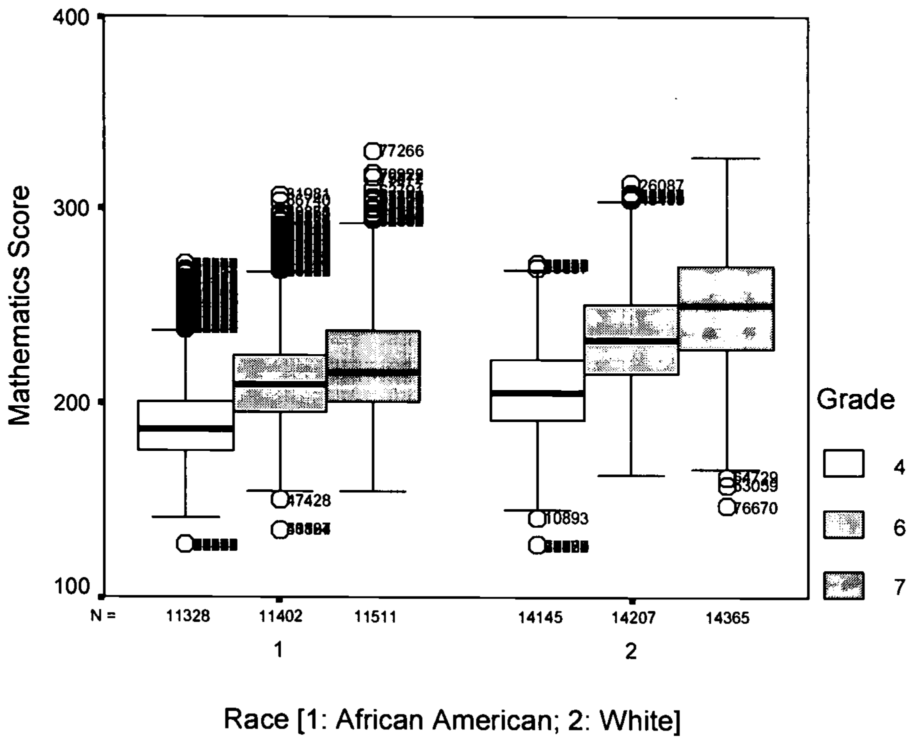
APPENDIX A
BOXPLOTS OF LANGUAGE FOR GRADE 4 THROUGH 7 AND WITHIN RACE



APPENDIX B
BOXPLOTS OF MATHEMATICS SCORE FOR GRADE 4 THROUGH GRADE 7 AND WITHIN RACE



APPENDIX C
DESCRIPTIVE STATISTICS FOR AFRICAN AMERICAN (AA) STUDENTS

Table 1: Descriptive Statistics for African American (AA) Students

AA	Mean	Variance	Skewness	Kurtosis
Domain--- Time				
Mathematics T1	186.28	256.24	0.27	-0.31
Mathematics T2	208.06	358.00	0.20	-2.80
Mathematics T3	216.77	553.50	0.34	-0.38
Language T1	189.72	404.99	0.25	-0.22
Language T2	213.53	726.40	0.38	-0.36
Language T3	226.84	811.31	0.28	-0.42

N=10,724

Table 2: Descriptive Statistics for White Students

WHITE	Mean	Variance	Skewness	Kurtosis
Domain--- Time				
Mathematics T1	204.50	411.12	0.19	-0.41
Mathematics T2	231.01	541.72	0.12	-0.47
Mathematics T3	246.01	687.09	-0.17	-0.69
Language T1	206.66	574.12	0.25	-0.38
Language T2	237.53	901.85	0.02	-0.59
Language T3	251.73	959.18	-0.02	-0.63

N=13,578

APPENDIX D

Table 7: Longitudinal Data on Stratified Random Subsample of 27 Students with: (a) 3 Waves of Language Scores at Grades 4, 6 and 7 (b) 3 Waves of Math Scores at Grades 4, 6 and 7 (c) Values of the Indicator (AA=African American; W=White).

Subject ID	Language			Mathematics			Race/Ethnicity
	Lang_4	Lang_6	Lang_7	Math_4	Math_6	Math_7	
6983	186.25	220	216	202.0	220	196	AA
5979	182.00	200	254	155.0	180	227	AA
6241	185.00	194	235	182.0	200	212	AA
1579	218.25	257	298	224.5	244	260	AA
1033	181.75	196	223	181.5	202	198	AA
7061	187.00	194	207	190.5	220	238	AA
1995	191.50	211	207	178.5	202	196	AA
7848	201.75	258	243	186.0	224	215	AA
3199	146.50	178	194	165.5	186	204	AA
4770	189.50	226	223	195.0	212	236	AA
6537	175.75	210	213	214.5	218	226	AA
7820	188.75	202	223	221.0	235	249	AA
9612	164.50	193	210	182.0	218	224	AA
2597	240.25	292	288	233.5	274	294	W
4186	237.75	229	210	199.5	254	268	W
4696	209.00	248	260	204.0	223	242	W
1535	222.25	235	229	202.0	206	213	W
4431	177.00	202	232	218.0	215	264	W
7540	208.50	198	232	179.5	188	221	W
2179	245.00	274	265	215.5	220	221	W
9674	201.00	246	218	187.0	196	212	W
8021	256.00	266	278	214.5	251	262	W
1351	194.00	224	254	185.0	217	240	W
9364	212.50	228	283	217.5	237	280	W
1809	166.25	188	190	167.5	168	196	W
4158	201.75	199	248	200.0	216	239	W
7038	219.50	273	232	213.5	228	250	W

APPENDIX E

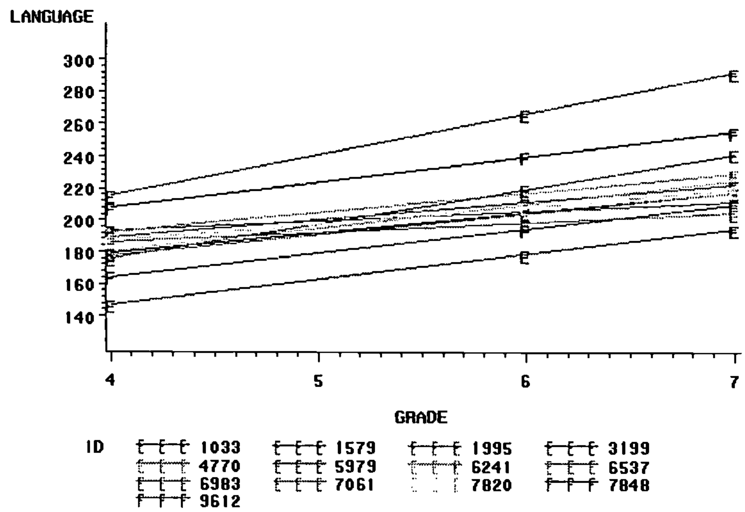


Figure 3: OLS Fitted Trajectories Summarizing Linear Growth in Language between Grades 4 and 7 for a Subsample of 13 Randomly selected African American Students whose associated Empirical Growth Records are provided in Table 4.5.

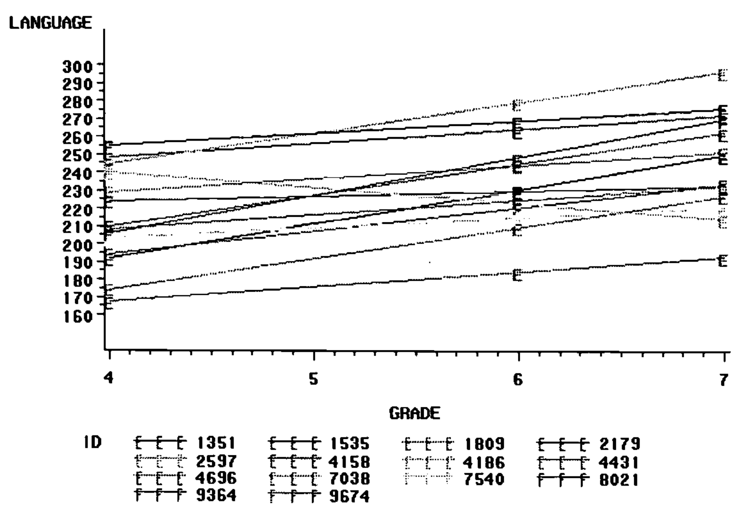


Figure 4: OLS Fitted Trajectories Summarizing Linear Growth in Language between Grades 4 and 7 for a Subsample of 14 Randomly selected White Students whose associated Empirical Growth Records are provided in Table 4.5.

APPENDIX F

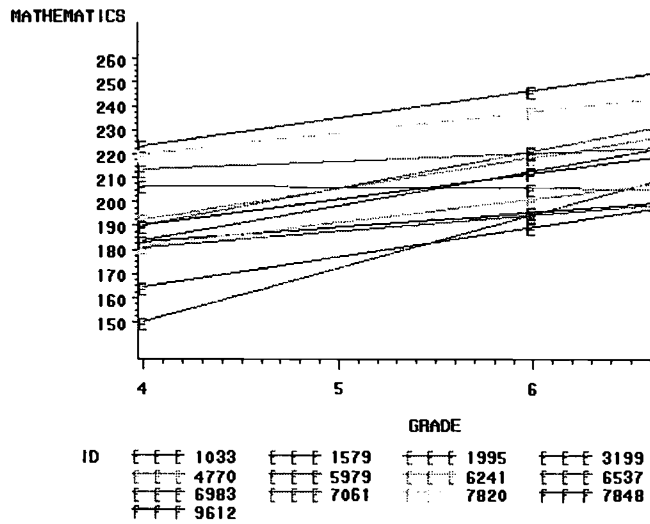


Figure 5: OLS Fitted Trajectories Summarizing Linear Growth in Mathematics between Grades 4 and 7 for a Subsample of 13 Randomly selected African American Students whose associated Empirical Growth Records are provided in Table 4.5.

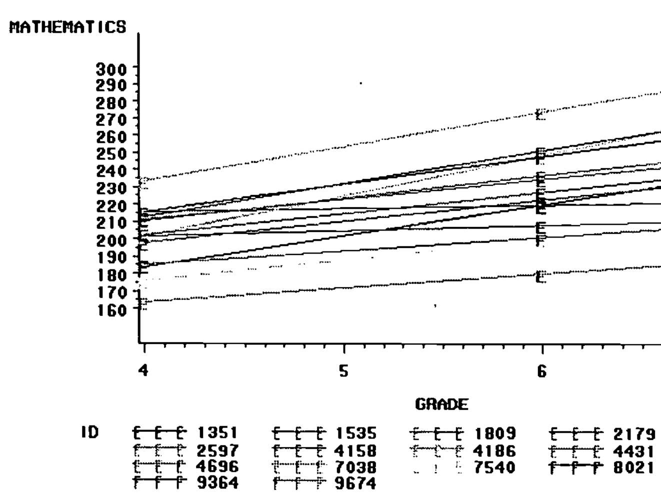


Figure 6: OLS Fitted Trajectories Summarizing Linear Growth in Mathematics between Grades 4 and 7 for a Subsample of 14 Randomly selected White Students whose associated Empirical Growth Records are provided in Table 4.5.

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