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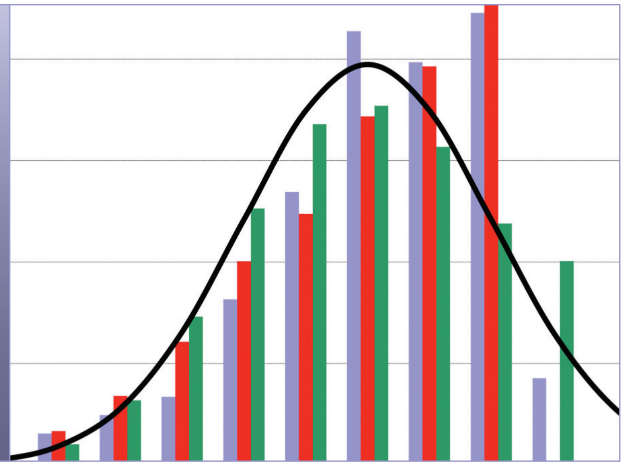

Exploratory Analyses of the Long-Term Effects of Improving Behavior, Attendance, and Educational Achievement in Grades 1–6 and 8–12

Richard Sawyer
Neal Gibson

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Richard Sawyer
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Abstract

We studied relationships among background characteristics, behavioral infractions, punishments, attendance, and educational achievement, using longitudinal data of students in grades 1 - 6 and 8 - 12. We estimated how much hypothesized early improvements in educational achievement or sustained improvements in behavior and attendance might ultimately increase educational achievement in grades 6 and 12. We also calculated similar estimates for increasing the rate of promotion from grade 1 to grade 2.

Reducing infractions and punishments to zero and days absent to the average observed level in grades 1 - 6 would increase the percentage of students attaining proficiency on sixth-grade achievement tests by approximately 3% in literacy and 4% in mathematics. For purposes of comparison, increasing first-grade educational achievement by 0.1 SD would increase proficiency rates in grade 6 by approximately 2% in either area.

For students in grades 8 - 12, the outcome variable was attainment of all four ACT College Readiness Benchmarks, which are indicators of students' readiness to take typical first-year college courses. Reducing infractions and punishments to zero and days absent to average levels would increase attainment of the Benchmarks by about 2%. Increasing eighth-grade achievement by 0.1 SD would increase attainment of the Benchmarks by approximately 3%.

As measured by average changes in scale scores, our results indicate that the benefits of improved prior achievement substantially fade with time. For example, a 0.1 SD increase in grade 1 literacy score corresponds to an expected increase of less than 0.04 SD in grade 6 literacy score. To endure over time, therefore, the benefits of improved prior achievement must be enhanced by sustained interventions (in this study, on behavior and attendance).

Acknowledgments

Chrys Dougherty gave us valuable advice about research on determinants of educational achievement, Julie Noble was crucial in obtaining the data for this study, and Chrys, Julie, and Jeff Allen all gave helpful comments on previous drafts. Karen Zimmerman worked tirelessly to transcribe and proof the data. The authors thank all of them.

Exploratory Analyses of the Long-Term Effects of Improving Behavior, Attendance, and Educational Achievement in Grades 1 - 6 and 8 - 12[1]

The educational achievement of many students in the U.S. is short of what they are capable of, and is insufficient for the well-paying jobs that will likely be available in the future. Furthermore, underachievement continues to be concentrated among traditionally underserved demographic groups defined by race/ethnicity and family income, which in turn undermines social stability and promotes the continued underachievement of future generations. Although the dimensions and consequences of this problem are understood, there is little agreement on its causes or on ways to fix it.

Many different recommendations have been made for improving students' educational achievement. They include restructuring public education bureaucracies, promoting charter schools and voucher systems, imposing accountability systems on schools and teachers, improving teacher training, raising requirements for licensure, instituting special incentives for excellent teaching, improving curricula and methods of instruction, encouraging greater involvement of parents, instituting special programs and services for at-risk students, raising requirements for graduation, adopting stricter policies on student behavior, and raising students' and parents' awareness about the importance of education, among others. Acrimonious debate accompanies many of these suggestions, particularly those that involve punitive sanctions, spending large sums of money, or shifts in political power. Moreover, when particular remedies are implemented, there typically is only modest improvement, as well as inconsistencies in the results among jurisdictions and research studies.

[1] This study is based on data maintained by the Arkansas Department of Education, and is published with its permission.

There are numerous reasons why improving educational achievement on a large scale is difficult. One fundamental problem is that although many proposed drivers of achievement are plausible, we do not know in great detail how they relate either to achievement or to each other. Knowing these relationships would require assembling longitudinal data on all the potentially relevant variables over the entire span of students' schooling, then modeling all of the complex relationships. It is not practically feasible to obtain and organize such data for a large sample that is representative of some population of interest. Furthermore, even if a comprehensive longitudinal data set could be constructed, analyzing the data would be very complicated. Research on educational achievement therefore proceeds with incomplete sets of variables over limited periods of time on samples of students that might not be representative of larger groups.

Prior Achievement, Behavior, and Attendance

We know that among the potential determinants of current educational achievement, prior achievement is very important. Indeed, prior achievement is an essential component of value-added models of school and teacher effectiveness (e.g., Sanders (1998); Nye, Konstantopoulos, and Hedges (2004)). Sawyer (2008) found that students' performance on the eighth-grade test EXPLORE (ACT, 2011a) was more important in predicting their performance on the ACT (grades 11/12) than their background characteristics, the high schools they attended, the courses they took in high school, and the grades they earned in their courses. Moreover, prior achievement interacts with the other variables: Students with higher EXPLORE scores benefitted more from taking more rigorous courses and earning higher grades in those courses than did students with lower EXPLORE scores.

There is also evidence relating behavior and attendance to educational achievement. Using data from the NELS:88 survey, Kauffman and Bradbury (1992) found that eighth-grade students who reported that they had "been sent to the office" more than twice for misbehavior were more likely to have below-basic scores in reading and mathematics. The same result pertained to students who reported missing school five or more days in the preceding month, as compared to those who reported missing no days. The results in this study were adjusted for socioeconomic status (SES), race/ethnicity, and gender, but not for prior achievement.

In another study of middle school students, Lassen, Steele, and Sailor (2006) examined the relationship between suspensions for misbehavior and subsequent scores on reading and mathematics tests. They found standardized regression weights of approximately -0.11 in either subject. Their regression models did not include background characteristics or prior achievement as covariates.

Jennings and DiPrete (2010) studied the relationship between teachers' ratings of student behavior and the students reading and mathematics scores in grades 1 - 3. They reported standardized weights of 0.04 to 0.14. The relationship between behavior and reading achievement increased with grade level, but the relationship between behavior and mathematics achievement decreased with grade level.

Analyzing data of elementary and middle school students in Philadelphia, Gottfried (2010, 2011) found statistically significant relationships between attendance and standardized test scores in reading and mathematics, after controlling for background characteristics, prior test scores, teacher characteristics, and neighborhood characteristics. Effect sizes related to the attendance variables were 0.05 - 0.10. Gottfried (2009) also found that unexcused absences, but not excused absences, have a negative relationship to test scores. Chang and Romero (2008) and Ready (2010) found that good attendance is especially important for socioeconomically disadvantaged children.

There is a larger literature showing that misbehavior and/or poor attendance predict dropping out of high school (see, for example, Rumberger (1995); Rumberger & Larson (1998); Allensworth & Easton (2007); and Balfanz, Herzog, & Mac Iver (2007)). Finn, Fish, and Scott (2008), analyzing the NELS:88 data, found that well-behaved high school students are also more likely than moderately misbehaving students to participate in postsecondary education. Moderately misbehaving students are not more likely than seriously misbehaving students to participate in postsecondary education, however.

The present study is based on data maintained by the Arkansas Department of Education. The data pertain to students who enrolled in Arkansas public schools in academic years 2004-2005 through 2009-2010, and are supplemented by the PLAN and ACT scores[2] of the students who were enrolled in grades 10 - 12 during this time. The data include four important types of variables: background characteristics, behavior (infractions and punishments), attendance, and educational achievement (as measured by test scores).

The research questions addressed by this study are:

- What are the principal predictors of promotion from grade 1 to grade 2?
- How much could consistent improvement in behavior and attendance potentially improve educational achievement in the long term?
- How much could early improvement in educational achievement potentially improve educational achievement in the long term?
- What are the combined benefits of consistent improvement in behavior and attendance and early improvement in educational achievement?

[2] The ACT (ACT, 2007) measures students' knowledge and skills in written English, mathematics, reading, and science. PLAN (ACT, 2011b) measures knowledge and skills in the same areas, but at the tenth-grade level.

The analyses in this study are exploratory: They are intended to discover relationships, rather than to confirm a formal theory. Furthermore, as will be discussed below, variables such as neighborhood characteristics, teacher characteristics, and student grades were not available to be included in the analyses. A few school-level characteristics (e.g., number of students) were available, but we chose to model school characteristics in this exploratory study only as random effects of the model intercepts. Finally, although the data are longitudinal, they come from a single state. Nevertheless, we hope that the results will provide useful preliminary answers to the research questions posed and will assist in the further development of theory.

The outcome variables in our study primarily involve students' educational achievement, as measured by test scores. The data available could also permit modeling students' progression in grades over time, dropping out, and timely graduation. In this study, we modeled promotion to grade 2, test scores, and proficiency status as outcomes. Modeling other outcomes would be worthy goals of future studies.

Data

The target population for this study consists of students who enrolled in Arkansas public schools in the academic year ending in June 2005 (denoted as AY2005). We studied two separate subsets of these students: those who enrolled in grade 1 in AY2005, and those who enrolled in grade 8 in AY2005.[3] Data for the AY2005-g1 students continued through AY2010 (when they would typically have been enrolled in grade 6). Data for the AY2005-g8 students continued through AY2009 (when they typically would have been enrolled in grade 12).

[3] The time span for which data were available did not permit including the data of students in grade 7 in the analyses.

Variables

Table A-1 in the appendix describes the variables for these two cohorts. The background variables include gender, race/ethnicity (categorized as membership in a minority group), English language spoken at home, and income-related variables (e.g., eligibility for free or reduced lunch). The attendance variables for each student are the numbers of days absent, by grade level.

The Arkansas Department of Education has a detailed coding scheme of behavioral infractions and punishments. For modeling promotion to grade 2, we used the type and the frequencies of infractions, and the type and the frequencies of punishments, as predictors. To simplify the modeling of the other outcome variables, we used the total number of infractions (summed over all types) and the total number of punishments (summed over all types) as predictors.

Arkansas requires that public school students take various state-sponsored tests, which are developed by private companies under contract to the state. Students in grades 1 and 2 took norm-referenced tests in literacy and writing. Students in grades 3 - 6 and 8 took criterion-referenced tests in literacy and mathematics.[4] Scores and proficiency levels on the grade 6 literacy and mathematics test served as the final outcome variables for the AY2005-g1 cohort.

Students in grade 9 took norm-referenced tests in literacy, mathematics, and writing. Students in grades 10 - 12 took various end-of-course exams; among these, we used only the score in grade 11 English/Language Arts in our models. We used the PLAN Composite score and the ACT Composite scores as measures of students' educational achievement in grades 10 and 11/12, respectively, instead of scores on state-sponsored tests.

[4] Students in grade 5 also took a criterion-referenced test in science, but we did not use it in the models.

Our models do not contain other variables that have been hypothesized or shown to predict student achievement. There are many such variables. Examples include:

- psychosocial characteristics, such as engagement, academic discipline, and socialization skills (Akey, 2006; Jones & Byrnes, 2006; Collaborative for Academic, Social, and Emotional Learning, 2007; Casillas, Allen, Kuo, Pappas, Hanson, & Robbins, 2011; Demaray & Jenkins, 2011);
- parental involvement (Ogbu, 2003; Charles, Roscigno, & Torres, 2007; Jeynes, 2007);
- teacher effects (Nye, Konstantopoulos, & Hedges, 2004);
- curriculum (Edvantia, 2005; The Core Knowledge Foundation, 2012);
- school socioeconomic characteristics (Griffith, 1997; Konstantopoulos, 2006); and
- students' and parents' beliefs and values about the importance of education (Dillon, 2010).

Note that psychosocial characteristics (first bullet) might predict the behavior variables (infractions and punishments) used in this study. Psychosocial characteristics might also, however, directly predict educational achievement as measured by test scores separately from the behavior variables. In other words, psychosocial characteristics might have both direct and indirect effects on educational achievement.

As we noted previously, it is not feasible to collect data on all the variables that could contribute to a large group of students' educational achievement. With observational data, omitting variables in a model can, in principle, bias the estimates of coefficients of variables included in the model. On the other hand, we have included in our models what we believe is the primary predictor of current achievement; namely, prior achievement. Acknowledging the limitation of potential omitted variable bias, we hope that this study nevertheless will contribute to the development of strategies for improving students' educational achievement.

Description of Student Populations and Samples

The students who enrolled in grade 1 or grade 8 in AY2005 are summarized in the "All students" columns of Table A-2 in the appendix. Approximately a third of the students in either population are minority. Both populations contain substantial proportions of economically disadvantaged students; for example, 51% of the AY2005-g1 students and 42% of the AY2005-g8 students were eligible for free or reduced price lunch.

All analyses in this study are based on subsets of these two populations, as determined by the schools in which they enrolled. About one-third of schools reported discipline data (behavior infractions and punishments) for the entire time span of the study. Because all of the models are based in part on the discipline variables, we estimated them only from data of students who attended schools that reported these variables. For example, of the 41,432 students who enrolled in grade 1 in AY2005, 18,769 enrolled in schools that reported discipline data. In Table A-2, this subset is designated the "AY2005-g1 cohort analysis file".

There are three groups of models in this study (see Table 1 on page 11), as defined by final outcome variable:

- Promotion to grade 2,
- Educational achievement in grade 6 (as measured by scores on state achievement tests), and
- Educational achievement in grades 11/12 (as measured by ACT scores).

Each group of models is based on a different sample.

The models for predicting promotion to grade 2 are based on all students in the AY2005-g1 cohort analysis file. The models for predicting educational achievement in grade 6 are based on the 14,420 students who were enrolled in grade 6 in AY2010. This subset is designated the "AY2005-g1 at-grade-level analysis file". Of the remaining 4,349 students, approximately 900 were retained in grade 1 (and were focus of the models for predicting promotion to grade 2). Approximately 600 students were retained in grades 2 - 6. The remainder either transferred to a non-public school or moved out of state before grade 6.

The analysis file for the AY2005-g8 cohort was defined by three conditions on students:

- attended schools that reported discipline data,
- enrolled in grade 12 in AY2009, and
- took PLAN in grade 10 and the ACT in grades 11/12[5].

Among the 37,891 students who enrolled in grade 8 in AY2005, 10,196 met all three conditions. This subset is designated the "AY2005-g8 ACT-tested at-grade-level analysis file". Note that because it pertains to students who remain enrolled in school through grade 12, this file is not representative of all students, some of whom dropped out of school. The outcome variables in the analyses of this file involve observed ACT scores, however: We do not attempt to make inferences about the ACT scores that students might have obtained if they had not dropped out.

Students represented in either the AY2005-g1 cohort analysis file or the AY2005-g1 at-grade-level analysis file are slightly less likely to be minority, from non-English speaking homes, and eligible for free or reduced price lunch than are all students (Table A-2). The differences among the three groups are five percentage points or less. Students in the AY2005-g1 at-grade-level analysis file also had slightly lower average numbers of infractions and punishments and

[5]In the data available for this study, over 90% of students took the ACT in grade 12. The data did not include scores on EXPLORE (an ACT test administered in grade 8).

slightly higher average test scores in grade 1 than did students in the entire AY2005-g1 analysis file.

The differences noted in the preceding paragraph for the AY2005-g1 students also pertain to the AY2005-g8 cohort, but to a larger extent. For example, 29% of all AY2005-g8 students were minority, but only 20% of the AY2005-g8 ACT-tested at-grade-level students were minority. There were very pronounced differences in the average numbers of infractions, punishments, and days absent in grade 8 (0.92, 0.85. and 8.5, respectively, for all AY2005-g8 students, versus 0.43, 0.36, and 5.8, respectively, for the AY2005-g8 ACT-tested at-grade-level analysis file). These differences likely reflect the strong relationship of dropping out with behavior and attendance (Rumberger (1995), Rumberger & Larson (1998), and Balfanz, Herzog, & Mac Iver (2007)).

Missing Data

Some of the background variables had missing data. The variables Male, Minority, and HomEngl (see Table A-1) had negligible percentages of missing cases (less than one-tenth of one percent). The percentage of cases with missing values in the variable FreeMeal differed by year. For the AY2005-g1 cohort, AY2010 had the largest percentage of missing values (13 percent). For the AY2005-g8 cohort, AY2008 had the largest percentage (22 percent).

Using SAS PROC MI, we created five data sets with missing values imputed from nonmissing values. We then estimated models for several outcome variables (InfrTot, PunTot, and test scores), and obtained very similar results from all five imputation data sets. We therefore based all subsequent analyses on only one of the imputation data sets.

General Methodological Features

We did seven separate analyses in three groups, as defined by the outcome variables being predicted:

Table 1

Summary of analyses

Type of outcome	Analysis file	Final outcome variable
Promotion to grade 2	AY2005-g1 cohort analysis file	1. Promotion to grade 2 (InGr2)
Educational achievement in grade 6	AY2005-g1at-grade-level analysis file	2. Grade 6 literacy scale score (LtcyScalScr_g6)
		3. Attainment of proficiency in grade 6 literacy (LtcyPrf_g6)
		4. Grade 6 mathematics scale score (MathScalScr_g6)
		5. Attainment of proficiency in grade 6 mathematics (MathPrf_g6)
Educational achievement in grades 11/12	AY2005-g8 ACT-tested at-grade-level analysis file	6. ACT Composite score (ACT_g11/12)
		7. Attainment of all four ACT College Readiness Benchmarks (ACT_CRB)

The parenthesized outcome variable names in Table 1 refer to the variables listed in Table A-1 in the Appendix. In this section, we describe the common methodological characteristics of the predictive modeling in all seven analyses. We describe the particular features and results of each analysis in separate sections that follow this one.

Predictive models can tell us not only which variables are related to educational achievement; they can also tell us how variables from previous years relate to the *predictors* of educational achievement. By assembling relevant predictive models in a network ordered by time, we can begin to develop an understanding of how early characteristics of students' educational careers affect later characteristics, including their educational achievement at the conclusion of their schooling. With a network of models, we can also estimate how much hypothesized improvements that occur early (or consistently) in students' schooling would increase their educational achievement later on.

In all the analyses, the data are structured hierarchically, with students nested within schools.[6] The schools in which students were enrolled are likely related to the outcome variables, for example, through curriculum (Edvantia, 2005) and other school characteristics (Konstantopoulos, 2006). We therefore estimated hierarchical models to predict the outcome variables. For interval-scale outcome variables, we estimated linear models with random intercepts:

$$E(Y_{ij} \mid X_1 = x_1, ..., X_K = x_K) \quad = \quad b_o + \sum_k b_{ik} x_{ik} + \tau_j \,,$$

where Y_{ij} is the outcome for student *i* enrolled in school *j*; $x_1, ..., x_K$ are values of the predictors $X_1, ..., X_K$; $b_0, b_1, ..., b_K$ are associated fixed effects; and τ_j is the value associated with school *j* of a normal random variable with mean 0. We used the MIXED procedure in SAS (SAS, 2012) to estimate the hierarchical linear models.

For dichotomous outcome variables, we estimated hierarchical logistic models:

$$\ln[\frac{p_{ij}}{1 - p_{ij}}] \quad = \quad b_o + \sum b_{ik} x_{ik} + \tau_j \,,$$

[6] Schools are also nested within school districts, but we did not attempt to estimate school district effects in the models.

where P_{ij} is the probability that the outcome variable for student *i* in school *j* is equal to 1, and the other terms are as defined previously. We used the GLIMMIX procedure in SAS (Bauer & Curran, 2006) to estimate the hierarchical logistic models.

For most of the dependent variables, there are a huge number of potential predictor variables, only some of which have relationships strong enough to be detectable with the data. Consistent with the exploratory intent of this study, we constructed parsimonious models, using a statistical significance cutoff of $p<.01$, that include only the predictors that we can be reasonably confident do not have a zero or trivial relationship with the outcomes. Of course, not including a predictor variable in a model does not guarantee that it has no relationship, however small, with the outcome variable. Variables not in a model, however, have relationships with the outcome variable that we could not reliably distinguish from 0 (in the sense that a 99% confidence interval excludes 0).

Our models include only main effects of the predictor variables; they do not include interaction terms. Models with interaction terms would permit more nuanced inferences. With interaction terms, for example, we would be able to determine whether behavior is more important in predicting the final educational achievement for students with low prior achievement than for students with high prior achievement.

Models with random slopes would also permit more nuanced analyses. For example, we might be able to determine whether behavior is more important in predicting achievement at some schools than at others. Random effects associated with the behavior variables would also adjust for differences among schools in how they collect and code the behavior variables. To keep the complexity of these exploratory analyses within reasonable bounds, however, we estimated only main-effects random-intercept models.

Also missing from our models are teacher effects. Nye, Konstantopoulos, and Hedges (2004) estimated variances in reading and mathematics achievement in grades 1 - 3 that could be attributed to teachers and schools. For grade 3, they estimated teacher variances of 0.07 and 0.12, and school variances of 0.02 and 0.05 in the respective two subjects. This result would suggest that larger gains in achievement might result from improvements in teachers than from improvements in schools. Nevertheless, the teacher variances were small compared to the variances jointly associated with background characteristics and prior achievement. The teacher variances were also small compared to the student-level residual variances.

Increasing Promotion to Grade 2

Children's experiences in first grade are critical to their later success or failure in school. Patterns of behavior and attendance, which we hypothesize influence educational achievement, are established then. Furthermore, students' failure to be promoted to the second grade on time, essentially guarantees that they will lag their age cohort throughout their schooling. In our data, for example, AY2005-g1 students with no disadvantaging background characteristics and with average grade 5 literacy and mathematics scores had only a 1% chance of enrolling in grade 6 during AY2010 if they had not been enrolled in grade 2 on-time in AY2006.

Modeling Promotion to Grade 2

From the AY2005-g1 cohort analysis file (N=18,769), we modeled the probability of enrollment in grade 2. The predictor variables were students' background characteristics, type and number of infractions and punishments, number of days absent in grade 1, and first-grade literacy and writing scores.

There were 19 types of infractions (most of which were present in few cases) and 9 types of punishments (in addition to a tenth category, "no action taken"). To simplify building the model, we considered only the types of infractions associated with 1% or more of students: insubordination (4%) and disorderly conduct (11%). Some types of infractions (e.g., assaults on students or staff, or carrying explosives or hand guns) are much more serious than insubordination and disorderly conduct, and they likely have larger effects on the future achievement of the students who commit them. These other types of infractions are rare, however, and are unlikely to affect achievement for the broad population of students.

For the same reason, we included in the model only the types of punishments associated with 1% or more of students: in-school suspension (2%), out-of-school suspension (3%), and corporal punishment (8%). We used as predictors in the models the frequency of each type of infraction or punishment. Note that approximately 11% of the school districts in Arkansas, including the largest school district (Little Rock), prohibit corporal punishment in their schools. Therefore, the corporal punishment variable in our analyses might be confounded with unmeasured district effects.

The total number of infractions (over all 19 types) and the total number of punishments[7] are each associated with approximately 10% of first-grade students in AY2005. Therefore, we also considered the infraction total frequency and the punishment total frequency as alternative predictors.

Because individual teachers and administrators decide whether to report and punish an infraction, the infraction and punishment variables are not standardized measures of misbehavior: Misbehavior that one individual reports and punishes might not be reported or punished by another individual or at another school. Although we did not do so in this study,

[7] We did not use the frequency of the tenth category "no action taken" in calculating the total number of punishments.

estimating random effects for the infraction and punishment slopes would address this issue at the school level.

There are also different potential interpretations of the types and frequency of punishments. In one interpretation, the imposition of a particular type of punishment is an indication of the perceived severity of an infraction. In another interpretation, a punishment is simply an intervention which can have an effect, either positive or negative, on days absent and test scores. These interpretations are not mutually exclusive; both might be true.

After standardizing all predictor variables to mean 0 and variance 1, we estimated a parsimonious hierarchical logistic model using SAS PROC GLIMMIX and a statistical significance level $p<.01$ (see Table 2). The strongest predictors, as indicated by their standardized weights, are the literacy and writing test scores in grade 1. The number of days absent is a moderately strong negative predictor, and the number of occurrences of corporal punishment is a weak negative predictor. Neither of the infraction counts and none of the background variables are in the model. The standard deviation of the random intercept suggests moderately strong variation among schools in promotion rate.

Table 2

Predictors of Promotion to Grade 2

Variable	Coefficient
Fixed effects (standardized)	
Corporal_g1	-0.08
DaysAbs_g1	-0.29
LtcyNPR_g1	1.55
WrtgNPR_g1	0.85
Random effect SD	
Intercept	0.78

As was noted previously, the absence of infraction variables in the model can be interpreted in different ways. One interpretation is that for predicting promotion to grade 2, infractions are important only if they are severe enough to result in corporal punishment, but their type (insubordination or disorderly conduct) and frequency are statistically irrelevant. Another interpretation is that corporal punishment might or might not be related to the perceived severity of infractions, but that when it is used, decreases the likelihood of promotion to grade two.

Although the infraction counts and the background variables are not direct predictors of the outcome variable, they are indirect predictors, through their associations with the direct predictors. Unfortunately, the available data do not indicate the dates of infractions, punishments, and absences within a given academic year; therefore, it was not possible to relate these variables temporally within year. Instead, we constructed models according to the following assumptions:

- All of the non-test score variables are potential predictors of first-grade test scores.
- Punishments, infractions, and background variables are potential predictors of days absent.
- Infractions and background variables are potential predictors of punishments.
- Background variables are potential predictors of infractions.

The logic behind this structure is that at least one of the punishments (out-of-school suspension) obviously increases days absent from school, and punishments result from infractions. The background variables are proxies for other, unmeasured, variables that are causes of infractions, punishments, and test scores. This chain of relationships is undoubtedly incomplete and incorrect in certain respects. For example, corporal punishment might provoke additional infractions or aggression (Gershoff, 2002; Durrant & Ensom, 2012). Nevertheless, this simple structure provides a way to begin to understand in this data set how students ultimately pass or fail first grade.

Figure 1 on the next page shows the resulting indirect relationships. The solid arrows show the direct predictors listed in Table 2. The large dotted arrows show relationships in which days absent and the discipline variables are predictors. The small dotted arrows show relationships in which the background variables are predictors. Red arrows denote positive relationships, and blue arrows denote negative relationships. To reduce the complexity of the diagram, there is no indication of the strength of individual predictor variables; instead, we present model R^2 (or pseudo-R^2) for all predictors jointly.

There are several interesting results:

- Promotion to grade 2 is predicted moderately well (pseudo-R^2=.26). Among its direct predictors, test scores are predicted weakly (R^2=.15), and days absent is predicted very weakly (R^2=.05). Frequency of corporal punishment is predicted moderately strongly by frequency of insubordination, frequency of disorderly conduct, gender, and minority status (R^2=.45).
- Days absent predicts literacy score, but not writing score.
- Frequency of corporal punishment predicts the final outcome variable (promotion to grade 2), but not days absent or either test score. As one would expect, frequency of out-of-school suspension predicts days absent and both test scores. In-school suspension did not enter into any model.
- The infraction frequency variables are predicted only very weakly by the background variables.

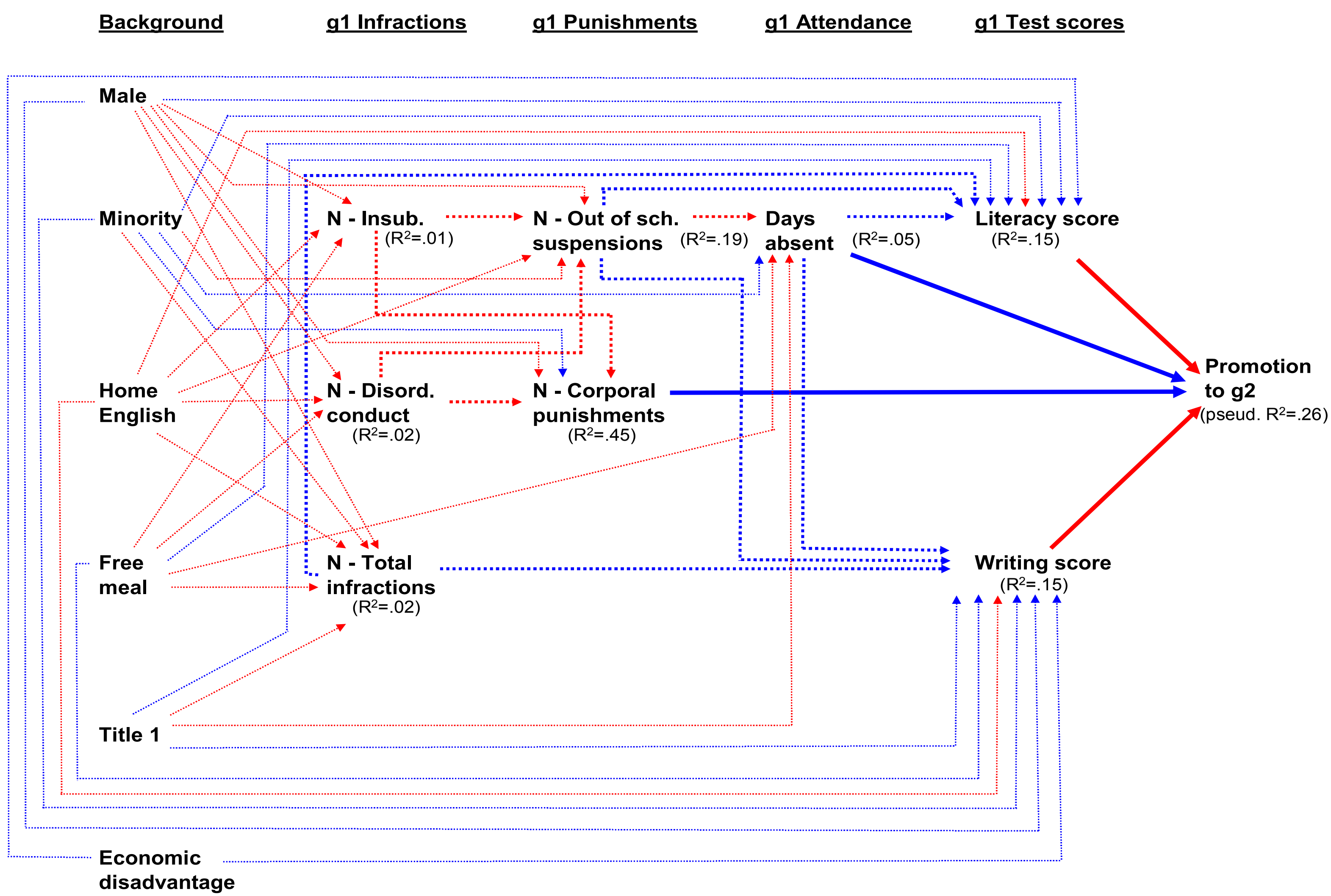

Figure 1. Statistically significant (p<.01) predictive relatonships related to promotion to grade 2. (Blue arrows denote negative relationships; red arrows denote postive relationships.)

- The background variables have both direct and indirect relationships with the discipline, attendance, and test score variables, but they have no direct relationship with promotion to grade 2. In other words, variables such as gender, ethnicity, and socio-economic status appear to affect promotion to grade 2 only through their relationships with behavior, punishments, attendance, and test scores.

Simulations

To estimate the benefits of improved behavior and attendance on promotion to grade 2, we did simulations using the prediction models illustrated in Figure 1. The first two scenarios involve behavior and attendance:

1. No infractions or punishments in grade 1.
2. No infractions or punishments, and average or better attendance in grade 1.

Note that we are not saying how these improvements would come about; attaining them would undoubtedly be difficult. For this reason, the estimated promotion rates associated with the scenarios should be thought of as upper bounds to what could plausibly be attained through improved behavior and attendance.

To estimate the effects of improved behavior, for example, we calculated for each student the predicted number of days absent, assuming zero infractions and punishments in grade 1. We then used the predicted number of days absent, along with the observed values of the background variables and the assumed zero values of infractions and punishments, to calculate predicted test scores. We then used the observed values of the background variables, the assumed zero values of infractions and punishments, the predicted number of days absent, and the predicted test scores, to calculate a probability of promotion to grade 2. We followed a similar strategy assuming zero infractions and punishments and average or better attendance.

We also estimated benefits for two other scenarios, involving improved prior achievement:

3. Increase grade 1 literacy and writing scale scores by 0.1 SD.
4. No infractions or punishments, and average or better attendance in grade 1; and increase grade 1 literacy and writing scale scores by 0.1 SD.

In contrast to Scenarios 1 and 2, Scenario 3 is more easily accomplished, at least at small scale. Numerous studies show that interventions in early childhood to improve educational achievement, behavior, health, and parenting skills result in cognitive skill gains in first grade exceeding the hypothesized 0.1 SD (Schweinhart, Barnes, & Weikart (1993); Campbell & Ramey (1995); Campbell, Ramey, Pungello, Sparling, & Miller-Johnson, (2002); U.S. Department of Health and Human Services (2005)). Interventions that continue into grade school and involve significant participation by parents are even more effective (Reynolds, Temple, Robertson, & Mann, 2002). Fuller (2007), however, questioned whether the intensive interventions behind the benefits of some early childhood programs are practical or affordable at large scale, and whether they benefit non-minority and middle-class students.

Interventions in grade 1 are another way to improve educational achievement. Magnuson, Ruhm, and Waldfogel (2007) found that high levels of instruction in the first year of school also improve reading skills.

Table 3 shows the average estimated probabilities of promotion to grade 2, as calculated from our models:

Table 3

Estimated Rate of Promotion to Grade 2, Given Scenarios of Improved Behavior and Attendance in Grade 1

Scenario in grade 1		Estimated rate of promotion
	(Base rate)	0.95
1.	No infractions or punishments; modeled attendance	0.96
2.	No infractions of punishments and average or better attendance in grade 1	0.96
3.	Increase grade 1 literacy and writing scale scores by 0.1 SD	0.96
4.	No infractions or punishments, average or better attendance in grades 1 - 6 , and increase grade 1 literacy and writing scale scores by 0.1 SD.	0.97

Improved behavior (Scenario 1), increased behavior and attendance (Scenario 2), and improved first-grade achievement (Scenario 3) each increased promotion rate by approximately 0.01. Making all three improvements (Scenario 4) increased promotion rate by approximately 0.02. Although these increases are small in absolute terms, they are large in relation to the maximum possible increase (0.05).

Improving Educational Achievement in Grade 6

Students in the AY2005-g1 cohort who were promoted on schedule were in grade 6 during AY2010. Arkansas administers to its sixth-grade students two criterion-referenced achievement tests, in literacy and mathematics, and reports both scale scores and proficiency levels, based on state standards. We developed models to predict the scale scores and attainment of proficiency.

Models for Grades 1 - 6

From the AY2005-g1 at-grade-level analysis file (N=14,420), we modeled behavior, attendance, and educational achievement at each grade level (1 - 6). To simplify the modeling, we used the total number of infractions (summed over all types of infractions) and the total number of punishments (summed over all types of punishments) as predictors. We structured the chain of predictive models according to the scheme in Table 4 (see next page): In a given academic year, test scores are preceded by days absent, which are preceded by punishments, which are preceded by infractions, which are preceded by background variables and by all types of variables from prior academic years. We transformed all predictor variables to have mean 0 and variance 1.

Table 4

Model Structure for Chained Predictions in Grades 1 - 6

	Dependent variables						
	Grade 1			Grades 2-6			
Predictor variables	Total pun.	Days abs.	Test scores	Total infr.	Total pun.	Days abs.	Test scores
Background variables	X	X	X	X	X	X	X
Current year predictor variables							
Total infr.	X	X	X	. . .	X	X	X
Total pun.	. . .	X	X	. . .	. . .	X	X
Days abs.	. . .	. . .	X	. . .	. . .	. . .	X
Prior years' predictor variables							
Total infr.	. . .	. . .	. . .	X	X	X	X
Total pun.	. . .	. . .	. . .	X	X	X	X
Days abs.	. . .	. . .	. . .	X	X	X	X
Test scores	. . .	. . .	. . .	X	X	X	X

Note: An X indicates that a predictor variable (row) is eligible to appear in the model for the indicated dependent variable (column).

Table A-3 in the appendix summarizes the resulting models.

The models for infraction frequencies have moderate strength (R^2= .14 - .25). In grades 2 - 3, the principal predictors are infraction frequencies from the preceding year. In grades 4 - 6, the principal predictors are prior year punishment frequencies; prior year literacy scores are weak negative predictors. There is moderate variation in the intercept among schools (SD=0.23 - 0.35). This variation might reflect actual differences in misbehavior, or it might reflect differences in reporting. One way to investigate causes of this variation would be to interview officials at schools with large or small estimated residuals.

The models for punishment frequencies are very strong (R^2=.90 - .94), reflecting the obvious dependence of punishment frequencies on current year infraction frequencies. Prior year punishment frequencies are also in the models, but are much less important. Prior year Writing or Literacy scores are weak negative predictors. Males and minority students have slightly larger punishment frequencies, given the other variables in the models, than female or non-minority students. This result is consistent in direction with that reported by Pfleger and Wiley (2012).[8] Variation among schools in the intercept is small (SD=0.08 - 0.12).

The models for days absent in grades 2 - 6 are moderately strong (R^2=.34 - .39); the principal predictor is days absent in the preceding year. Current year punishment frequency is a weak predictor. Current year infraction frequency is not in the model, given its strong correlation with punishment frequency. The intercept standard deviations are moderately large (0.15 - 0.30). The grade 1 model for days absent is weak (R^2=.04), given that it has no variable measuring days absent in the preceding year.

The models for educational achievement test scale scores in grades 2 - 6 are strong (R^2=.53 - .71). Not surprisingly, the principal predictors are prior year test scores. Prior year punishment frequencies and days absent are weak, but consistent, predictors at all grades. The coefficients for days absent (-0.01 to -0.06) are slightly smaller in magnitude than those reported

[8] Because of limitations in their data, Pfleger and Wiley were not able to control for infraction frequency in predicting punishment frequency.

by Gottfried (2010, 2011). The intercept standard deviations are small to moderate (0.14 - 0.25), suggesting unmeasured school effects.

In the models for educational achievement in grades 2 and 3, the intercept standard deviations range from 0.15 to 0.25, which correspond to intercept variances of approximately 0.02 to 0.06. Nye, Konstantopoulos, and Hedges (2004) estimated three-level models (students within classrooms within schools) of reading and mathematics test score data from grades 2 and 3 in Tennessee. Like our models, their models included background characteristics and prior achievement as student-level predictors. They reported between-school intercept variances of approximately 0.02 to 0.05. Thus, both studies show that schools are associated with considerably less than 10% of the total variance in test scores in grades 2 and 3.

We also predicted attainment of state achievement standards at the proficient or higher level in grade 6 literacy and mathematics, with hierarchical logistic regression models.[9] As in the linear models for grade 6 scale scores, the principal predictors in the proficiency models are grade 5 scale scores. Grade 5 punishment frequencies and days absent are also in the proficiency models.

Summary. For predicting educational achievement in grades 2 - 6, prior achievement is by far more important (as measured by its standardized regression weight) than any other class of variables considered in this study. This result holds at all grade levels. Nevertheless, behavior and attendance consistently contribute in small amounts to educational achievement;

[9] We used the same subset of data to estimate the proficiency models that we used to estimate the scale score models. Alternatively, one could include in the proficiency models data for students who were retained in grades 1 - 5, assuming that they would not have met the mathematics proficiency standards for grade 6. Doing so would have likely improved the fit of the models. To avoid making additional assumptions and to simplify interpreting the results, however, we used the same subset of data to estimate both types of models.

furthermore, educational achievement contributes in small amounts to predicting future behavior and attendance.

Simulations

A principal goal of this study is to estimate the potential benefits of improved behavior, attendance, and prior achievement on achievement in grade 6. To do this, we did simulations using the prediction models in Table A-3. There were four scenarios:

1. No infractions or punishments in grades 1 - 6.
2. No infractions or punishments and average or better attendance in grades 1 - 6.
3. Increase grade 1 literacy and writing scale scores by 0.1 SD.
4. No infractions or punishments and average or better attendance in grades 1 - 6 ; and increase grade 1 literacy and writing scale scores by 0.1 SD.

The first two scenarios involve improvements in behavior and attendance only. Scenarios 3 and 4, involving increased test scores in grade 1, are intended to provide a comparison to the first two scenarios. Scenarios 3 and 4 could represent the effects of interventions in grade 1 alone, the effects of interventions before grade 1, or the effects of interventions before and during grade 1. By structuring the simulations around the chained predictive models summarized in Table 4, one can estimate how a change in a particular kind of variable (e.g., infractions) at one time affects all other variables (infractions, punishments, attendance, test scores) at later times.

Attaining zero infractions and punishments for every student throughout grades 1 - 6 is a laudable, but unrealistic goal. Reducing absence to the current average would also likely be very difficult to attain. Therefore, the estimated benefits associated with Scenarios 1 and 2 should be thought of as upper bounds to what can feasibly be attained. Lassen, Steele, and Sailor (2006), Skaggs and Bodenhorn (2006), and What Works Clearinghouse (2012) describe programs that improve behavior and attendance, though not to this ideal level.

In Scenario 1, we calculated for each student predicted days absent and test scores, assuming zero infractions and punishments in each grade and observed values of the background variables. We also used the predicted days absent and test scores in a given grade to predict days absent and test scores in higher grades.

We followed a similar strategy in Scenario 2, assuming zero infractions and punishments and average or better attendance. The number of days absent for a particular student at a given grade level was taken to be the minimum of the student's predicted value and the average observed number of days absent over all students.

We next repeated Scenarios 1 and 2, assuming different starting grades (2 - 6) for the improvements. For example, we calculated the benefit of zero infractions and punishments, and average or better attendance, beginning in grade 2, but assuming observed infraction and punishment frequencies and days absent in grade 1. These simulations provide information on how soon improvements need to begin to realize benefits.

In Scenario 3, we assumed that each student's literacy and writing scores in grade 1 were 0.1 SD higher than the observed scores. As we have already noted, this improvement is more feasibly attained than the improvements hypothesized in Scenarios 1 and 2. Scenario 4 involves all the improvements: behavior, attendance, and prior achievement.

Although school ID was available in this study, we did not estimate benefits associated with scenarios involving improvements in schools. Some rough idea of potential benefits, however, can be had by examining the variances associated with student-level characteristics and intercepts. In grade 6, the variances associated with student-level characteristics are 0.71 and

0.69 for literacy and mathematics, respectively; the residual student-level variances are 0.27 for both areas, and the intercept variances are 0.02 and 0.04, respectively. This would suggest that larger improvements in test scores would result from interventions on characteristics other than schools. Of course, school characteristics are also related to achievement in grades 1 - 5; it is plausible that consistent improvement in schools throughout these earlier grades would result in greater improvement in grade 6 achievement than would be suggested by the intercept variance in the model for grade 6 achievement.

Figures 2 and 3, on pages 30-31, show the increase in average predicted standardized grade 6 scores in literacy and mathematics, respectively, by scenario. Figures 4 and 5, on pages 34-35, show comparable results for the estimated increase in proficiency rates. In each graph, the increase in grade 6 achievement (vertical axis) is plotted against the starting grade of the hypothesized prior improvement in behavior or attendance (horizontal axis). Each graph also has an indication of the increase in grade 6 achievement associated with improved test scores in grade 1 (Scenarios 3 and 4).

The benefit of all types of improvement is modest. In Figure 2, for example, improving behavior starting in grade 1 (Scenario 1) increases grade 6 literacy scores by 0.03 SD. Improving both behavior and attendance starting in grade 1 (Scenario 2) results in an increase of 0.05 SD. Starting improved behavior and attendance as late as grade 3 would preserve about three-quarters of the benefits associated with starting in grade 1. Starting improved behavior and attendance in grade 4 or grade 5 would preserve about half of the benefits.

Increasing grade 1 literacy and writing scores by 0.1 SD (Scenario 3) increases average predicted grade 6 literacy score by somewhat less than 0.04 SD; this result indicates a decay over time in the effects of early interventions on educational achievement. Dougherty (2010) reported similar results when predicting test scores of middle school students from the school-level residuals associated with the elementary schools that they had previously attended.

Making all improvements (Scenario 4), however, increases average predicted grade 6 literacy score by approximately 0.09 SD, a level nearly comparable to the hypothesized initial improvement (0.1 SD) in educational achievement. This result suggests that to sustain the initial benefits of early childhood programs, we must follow them with continued interventions in grade school. In this study, the hypothesized continued interventions pertained only to behavior and attendance; continued improvement in educational achievement directly would, of course, yield greater gains by grade 6.

Similar patterns pertain to improvements in grade 6 mathematics score (Figure 3), although the amount of improvement is smaller than for literacy. Starting improved behavior and attendance (Scenario 2) as late as grade 3 preserves nearly all of the benefits for mathematics achievement that are associated with starting in grade 1. Increasing grade 1 literacy and writing scores by 0.1 SD (Scenario 3) increases average predicted grade 6 mathematics score by less than 0.04 SD, indicating a decay over time in the effects of early interventions. Making all improvements (Scenario 4), however, increases average predicted grade 6 mathematics score by approximately 0.08 SD, a level more nearly comparable to the hypothesized initial improvement (0.1 SD) in educational achievement.

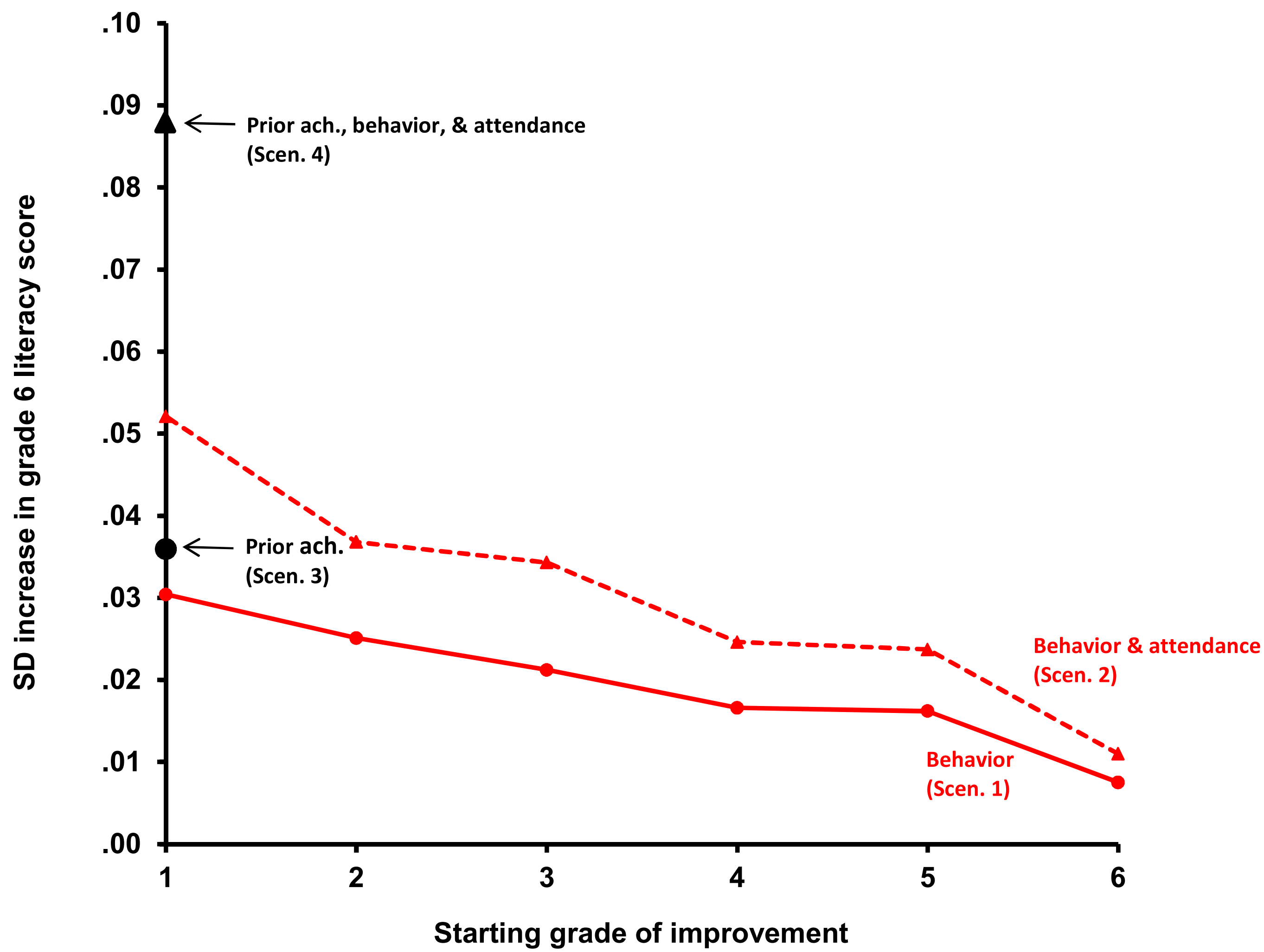

Figure 2. Average standard deviation increase in grade 6 literacy score, by type and starting grade of improvement.

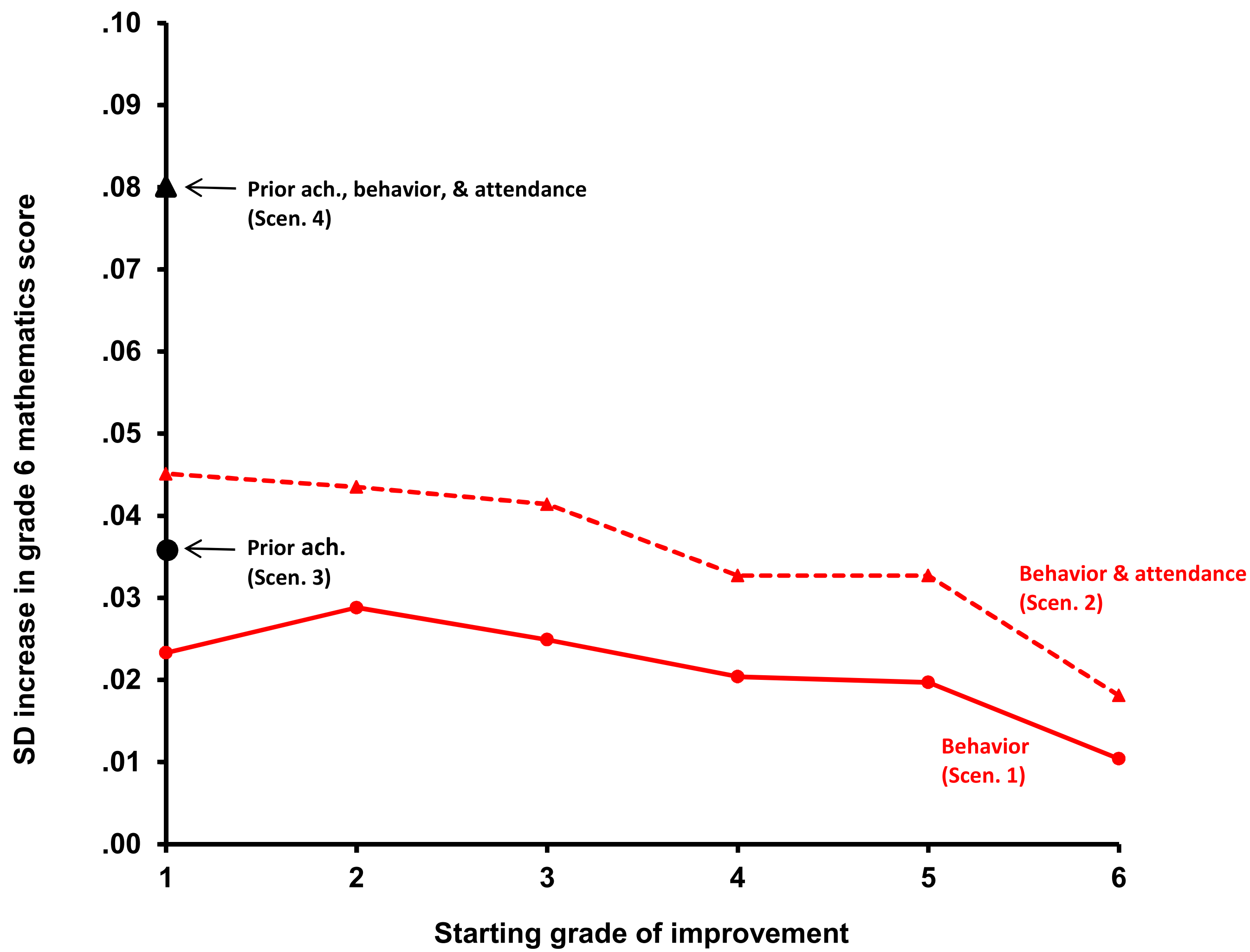

Figure 3. Average standard deviation increase in grade 6 mathematics score, by type and starting grade of improvement.

Figures 4 and 5 show estimated increases in proficiency rates for literacy and mathematics, respectively. Improving behavior and attendance beginning in grade 1 and sustaining it thereafter (Scenario 2) increases the literacy proficiency rate by 0.03 beyond the base rate of 0.73. The corresponding improvement in mathematics proficiency rate is 0.04 beyond its base rate of 0.77. By way of comparison, increasing first-grade test scores by 0.1 SD (Scenario 3) improves proficiency rates by about only 0.02 in either subject. Making a one-time improvement in first-grade achievement and sustained improvements in behavior and attendance (Scenario 4) improves proficiency rates by approximately 0.05.

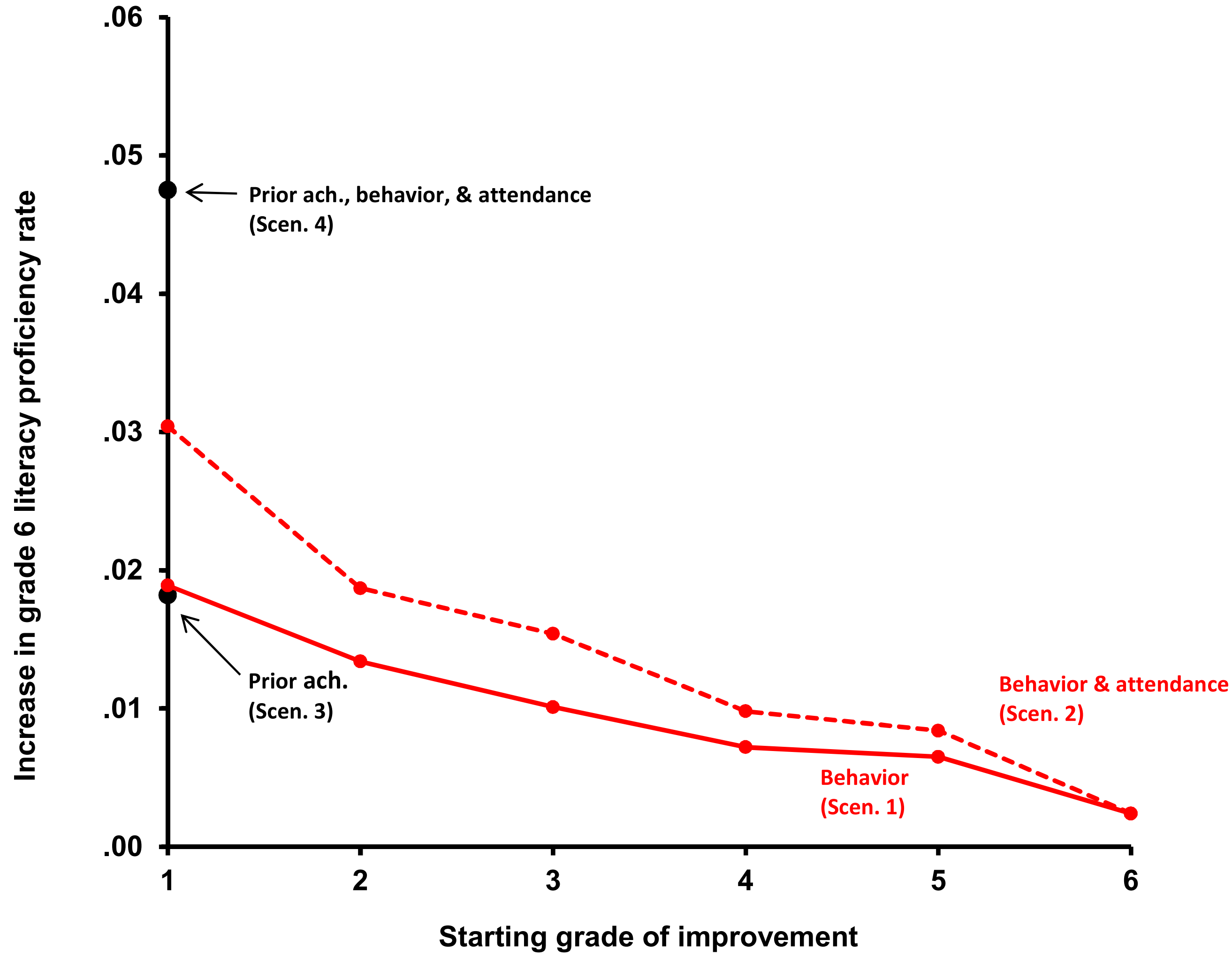

Figure 4. Average increase in grade 6 literacy proficiency rate, by type and starting grade of improvement.

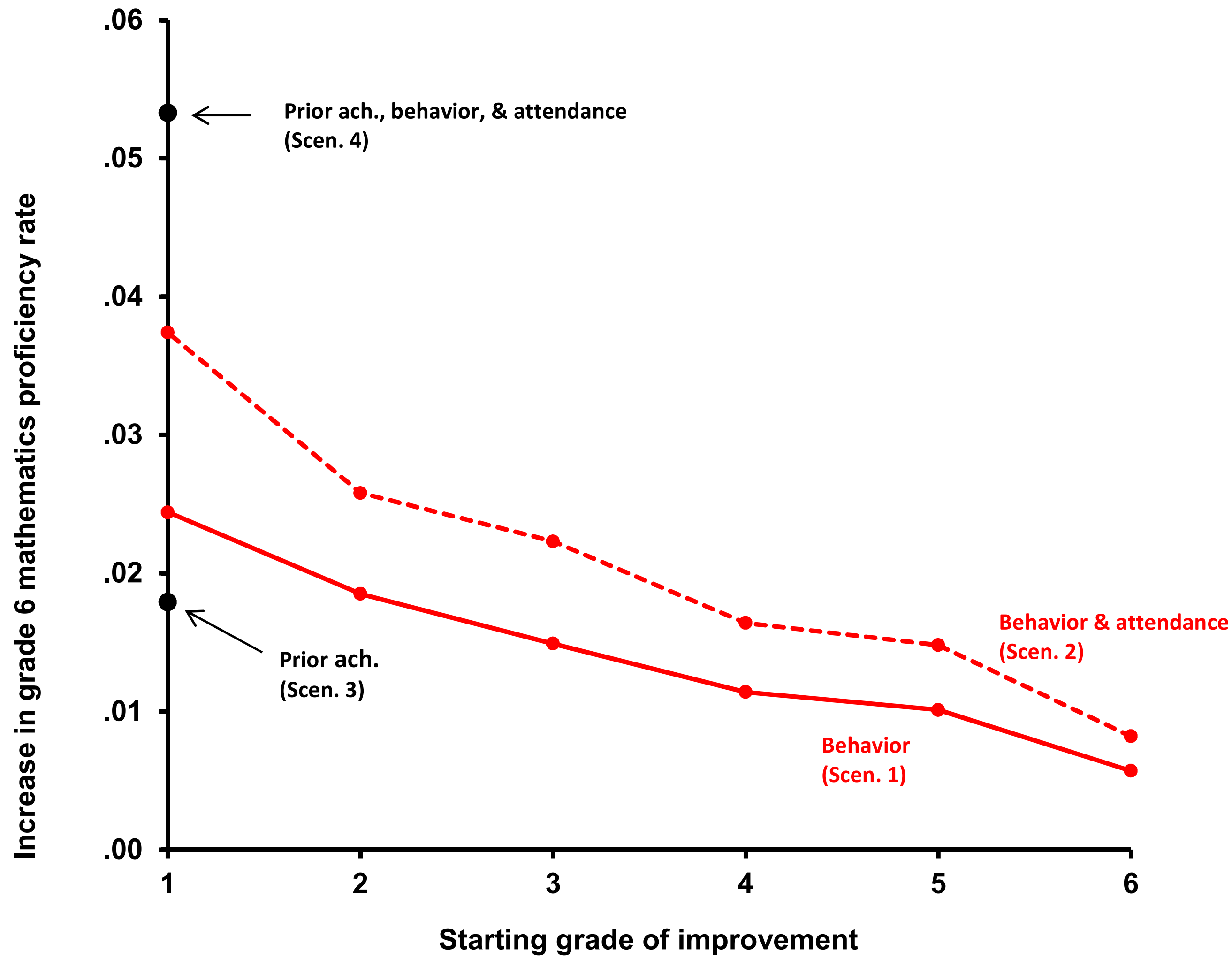

Figure 5. Average in grade 6 mathematics proficiency rate, by type and starting grade of improvement.

Improving College Readiness

Our analyses of the AY2005-g1 cohort focused on students' literacy and mathematics skills in grade 6 and on their proficiency relative to state standards. Our analyses of the AY2005-g8 cohort, in contrast, focused on students' readiness to take college-level courses when they graduate from high school. The outcome variables for these analyses were ACT_g11/12, the rounded average of the four ACT scores in English, mathematics, reading, and science (ACT, 2007), and ACT_CRB (a variable indicating whether a student's four ACT scores met all of the associated ACT College-Readiness Benchmarks). We used the most recent scores of students who took the ACT more than once.

The ACT College Readiness Benchmark in a subject area is the score at which a student enrolled in a typical postsecondary institution has approximately a 50% chance of earning a B or higher grade in a related first-year college course (Allen & Sconing, 2005; ACT, 2010). The ACT subject areas, their associate Benchmark scores and related college courses are: English-18 (English Composition), Mathematics-22 (College Algebra), Reading-21 (social sciences courses), and Science-24 (Biology). In the 2009 high school graduating class (which corresponds to the last year of the AY2005-g8 cohort data), approximately 23% of ACT-tested students nationally and 18% of ACT-tested students in Arkansas attained all four Benchmarks.

Arkansas' state-administered tests for middle-school and high-school students are more varied than those for students in grades 1 - 6. Eighth-grade students take criterion-referenced tests in literacy and mathematics, analogous to those geared to grades 3 - 7. Ninth-grade students take norm-referenced tests in literacy, mathematics, and writing. Students in grade 11 take an end-of-course test in English/Language Arts (denoted here as ELA_g11). Students in grades 9 - 12 can also take end-of-course tests in other subjects, such as algebra, geometry, and biology.

Where possible, we aligned the measures of educational achievement in grades 8 - 11 with the principal outcome variables, ACT_g11/12 and ACT_CRB: For grade 8, we used LitMath_g8, an equal SD-weighted average score of the two criterion-referenced test scores. For grade 9, we used LitMathWrtg_g9, an equal SD-weighted average of the three norm-referenced test scores. For grade 11, we used the score on ELA_g11, the only state-sponsored test taken by most students at that grade level.

No individual state-sponsored tests are taken by most students in grade 10. To measure educational achievement in grade 10, we used the PLAN Composite score (denoted here as PLAN_g10), the rounded average of the four PLAN scores in English, mathematics, reading, and science. The content of PLAN (ACT, 2011b) is aligned with that of the ACT, and most students in Arkansas who take the ACT also take PLAN.

Models for Grades 8 - 12

We developed models for behavior, attendance, and educational achievement for the 2005-g8 ACT-tested at-grade-level analysis file (N=10,196). The chaining structure of the models is analogous to that for grades 1 - 6 (see Table 4)[10]. Table A-4 in the appendix summarizes the resulting models.

The models for infraction frequencies are moderately strong (R^2= .18 - .32). The principal predictors vary by grade. In grades 9 and 11, the principal predictors are infraction frequencies from the preceding year; in grades 10 and 12, the principal predictors are punishment frequencies from the preceding year. There is moderate variation in the intercept among schools (SD=0.16 - 0.30). As with grades 1 - 6, we do not know whether this variation reflects actual differences in misbehavior, or whether it reflects differences in reporting.

[10] For students who took the ACT in grade 11, the grade 12 infraction frequencies, punishment frequencies, and number of days absent are actually “postdictors” of the ACT outcome variables.

The models for punishment frequencies are very strong (R^2=.87 - .96), reflecting the obvious dependence of punishment frequencies on infraction frequencies in the current year. Punishment frequencies in the prior year are also in the models, but are much less important. Variation among schools in the intercept is small (SD=0.06 - 0.11).

The models for days absent in grades 9 - 12 are moderately strong (R^2=.32 - .38); the principal predictors are days absent in preceding years. The intercept standard deviations are fairly large (0.30 - 0.45). The grade 8 model is weak (R^2=.04), because it has no variable measuring days absent in the preceding year.

The models for educational achievement scale scores in grades 9 - 11 are strong (R^2=.60 - .72). The model for grade 8 test score is weaker (R^2=.14), because it does not include test scores from the preceding year. The principal predictors are test scores from previous years (weights 0.69 - 0.84). Current year days absent is a weak predictor at grades 8, 9, and 11.

The model for predicting ACT_g11/12 is also strong (R^2=.79). Not surprisingly, the principal predictors of ACT_g11/12 measure prior achievement: PLAN_g10 (weight 0.60) and ELA_g11 score (weight 0.31). PLAN_g10 is a stronger predictor than ELA_g11 because of the similarity of the PLAN and ACT Composite scores in their subject area coverage (English, Mathematics, Reading, and Science) and their targeted content standards.

The regression weights associated with days absent in the ACT_g11/12 model are -0.03 (for grade 12) and -0.02 (for grade 11); when combined, they are in line with the 0.05 result reported by Gottfried (2010, 2011), Our ACT_g11/12 model does not include infraction frequency as a predictor, but the regression weight for punishment frequency is -0.02. This result is considerably smaller than the magnitude 0.11 weight reported by Lassen, Steele, and Sailor (2006), and might be due to the latter study not including prior achievement in the model.

The ACT_g11/12 model has an intercept standard deviation of 0.09, which corresponds to an intercept variance of approximately 0.01. Sawyer (2008) estimated two-level models (students within schools) for the ACT English, Mathematics, Reading, and Science scores, using background characteristics, EXPLORE (grade 8) scores, and high school course work and grades as predictors. He obtained intercept variances, which when standardized, range from 0.01 to 0.03. The slightly larger variances in the Sawyer (2008) study might be due in part to their being based on a broader sample (more than one state) and on different covariates. In both studies, however, the variance associated with high schools is considerably smaller than 0.05.

We also predicted attainment of the ACT College Readiness Benchmarks, using a hierarchical logistic model. As in the ACT_g11/12 model, the principal predictors are PLAN_g10 and ELA_11 scores, but days absent in grades 10 and 11 are also in the model.

Summary. The results for predicting educational achievement in grades 8 and higher are similar to those for predicting achievement in grades 2 - 6: Prior achievement is the most important variable, but behavior and attendance consistently contribute in small amounts to educational achievement. Moreover, educational achievement contributes in small amounts to predicting future behavior and attendance.

Simulations

In a manner similar to what we did for grades 1 - 6, we estimated the potential benefits of various scenarios of improved behavior, attendance, and prior achievement on students' readiness for college as measured by the variables ACT_g11/12 and ACT_CRB. There were four scenarios:

1. No infractions or punishments in grades 8 - 12.
2. No infractions or punishments, and average or better attendance in grades 8 - 12.
3. Increase grade 8 literacy/writing average score by 0.1 SD.
4. No infractions or punishments and average or better attendance in grades 8 - 12; and increase grade 8 literacy/writing average score by 0.1 SD.

As we noted about the simulations for grades 1 - 6, Scenarios 1 and 2 are idealistic; they provide upper bounds to the benefits that could be obtained from improving behavior and attendance. Given the results from grades 1 - 6, however, Scenario 3 is more easily attainable. In estimating the benefits for these scenarios, we followed the same chaining structure described in Table 4.

It is unlikely that waiting until grade 8 to begin interventions in behavior, attendance, and prior achievement would achieve the improvements hypothesized in the scenarios; interventions would need to begin well before grade 8. Moreover, assessment and interventions throughout middle school and high school, such as those enabled by ENGAGE[11] (ACT, 2012), EXPLORE, and PLAN, would likely be needed to sustain the improvements.

Figure 6 on page 42 shows the simulation results for the average ACT Composite score. Figure 7 on page 43 shows comparable results for the estimated proportion of students attaining all four ACT College Readiness Benchmarks. Each graph shows the increase, beyond the

[11] ENGAGE Grades 6-9 measures psychosocial characteristics that predict academic performance and persistence in high school. It has ten scales organized in the domains of motivation, social engagement, and self-regulation.

observed average of students in AY2009, plotted against the starting grade of the improvement. On each graph there is also an indication of the increased achievement associated with Scenarios 3 and 4.

The benefit of all types of improvement is modest. In Figure 6, for example, improving behavior in grades 8 - 12 increases ACT Composite scores by 0.03 SD. Improving both behavior and attendance in grades 8 - 12 results in an increase of slightly less than 0.04 SD. By way of comparison, increasing grade 8 literacy/mathematics average score by 0.1 SD (Scenario 3) increases average ACT Composite score by 0.05 SD. Making all improvements (Scenario 4) increases average predicted ACT Composite score by slightly less than 0.09 SD.

Figure 7 shows the estimated increase in the proportion of students attaining all four ACT College Readiness Benchmarks. Improving behavior and attendance beginning in grade 8 and sustaining the improvement thereafter (Scenario 2), increases the attainment rate by somewhat less than 0.02 beyond the base rate of 0.19. A one-time improvement in grade 8 achievement (Scenario 3) results in an increase of 0.03. Improving behavior, attendance, and prior achievement (Scenario 4) results in an increase of 0.04.

As in the grade 6 analyses, we did not estimate benefits associated with scenarios involving improved schools. Sawyer (2008) found in a simulation study that improving below-average high schools (as measured by their Empirical Bayes estimates) to the average would improve ACT College Readiness Benchmark attainment rates by 0.02 or less, depending on subject area.

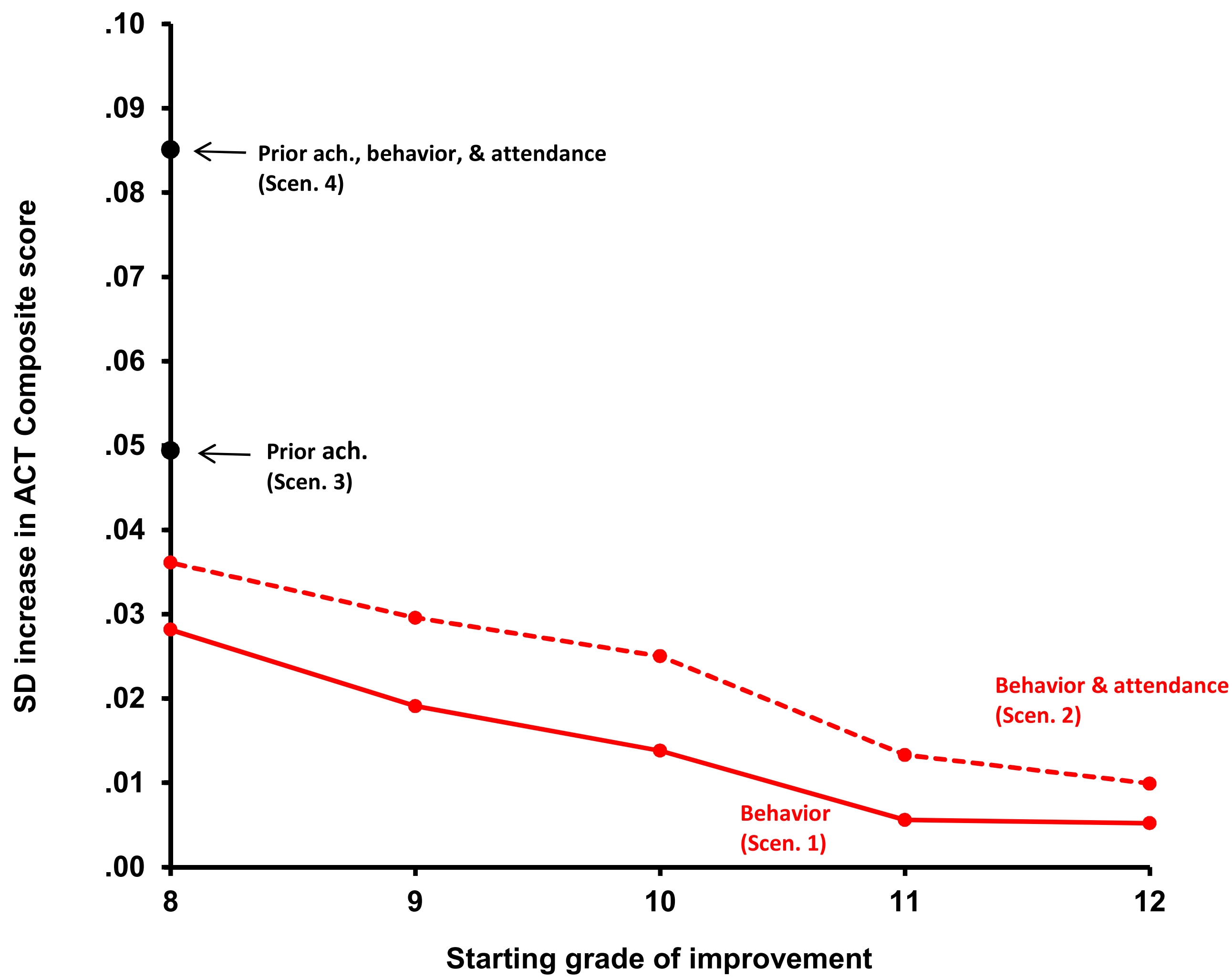

Figure 6. Average standard deviation increase in ACT Composite score, by type and starting grade of improvement.

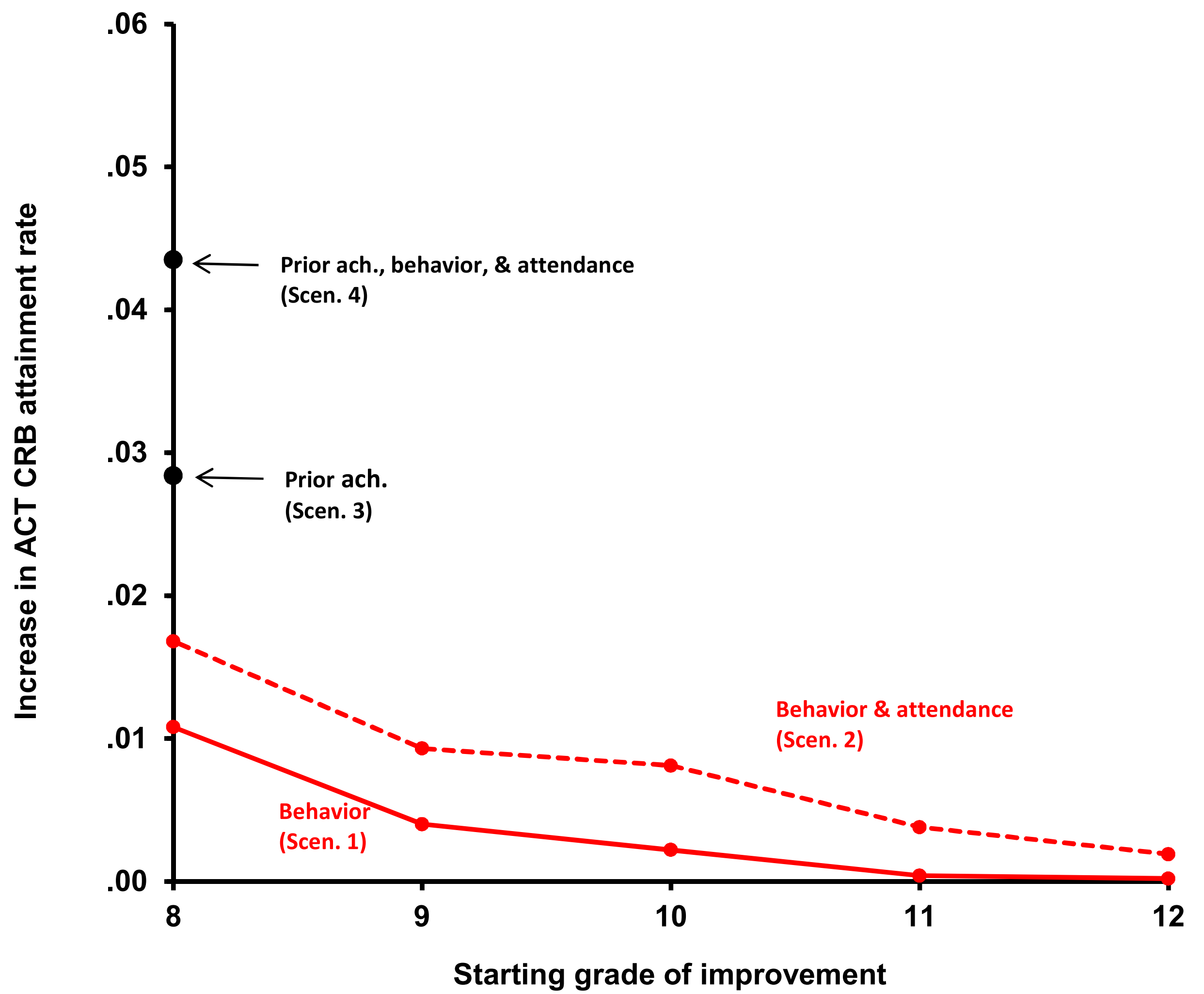

Figure 7. Average increase in ACT College Readiness Benchmark attainment rate. by type and starting grade of improvement.

Discussion

There are many variables that plausibly contribute to educational achievement, but it is not feasible to collect data on all of them, especially over an extended period of time. The predictor variables available in this study involve student background characteristics, school ID, behavior, attendance, and prior achievement. Among the potentially important predictor variables not included are student psychosocial characteristics, parental involvement, variables related to teacher effectiveness, school characteristics (other than school ID), and neighborhood characteristics.

We studied three groups of students at schools that reported data on infractions, punishments, and attendance:

- all first-grade students (to learn characteristics that predict promotion to grade 2),
- all sixth-grade students who were at expected grade level (to learn characteristics that predict achievement on state proficiency tests), and
- all twelfth-grade students who were at expected grade level (to learn characteristics that predict academic readiness for college, as measured by the ACT Composite score and the ACT College Readiness Benchmarks).

In the last two analyses, we did not attempt to make inferences about the educational achievement of students who had been held back a grade, moved out of the Arkansas public school system, or dropped out of high school entirely. These students would be an important focus of future research.

We learned that educational achievement in grade 1 (as measured by scores on state tests) is strongly and positively related to promotion. Corporal punishment and absenteeism in grade 1 are negatively related to promotion. Infraction frequencies and background characteristics predict promotion to grade 2 only indirectly, through their effects on corporal punishment, absenteeism, and test scores.

We also learned that prior achievement dominates background characteristics, behavior, and attendance in predicting long-term achievement. Moreover, the benefit of plausible improvements in prior achievement decays over time: Continued interventions (in this study, pertaining to behavior and attendance) are needed to sustain the initial improvement. Given the research results of others, improved curriculum, teaching, and parental support are also beneficial (and might be required) for sustained gains in achievement. Interventions to improve psychosocial characteristics, such as those measured by ENGAGE, could also provide important additional benefits. No single intervention or reform, however, seems likely to achieve sustained and large-scale improvement. Such an outcome will require persistent efforts on multiple fronts, each of which will contribute incrementally to the goal.

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Appendix

Table A-1
Variables in the Study

Variable name	Description
Background characteristics	
Male	Gender (Female=0, Male=1)
Minority	Underserved minority (Caucasian Am., Asian Am. = 0; all others =1)
HomEngl	Primary language spoken at home (English = 1)
FreeMeal	Free / reduced lunch (Eligible=1)
Title1	Title I (Eligible=1)
EconDis	State-designated as economically disadvantaged (1)
Enrollment variables	
SchoolID	State ID of school in which student was enrolled
GrdLvl	Grade level in which student was enrolled (1 - 6 , 8-12)
Discipline variables	
DisordCond_g1	Number of instances of disorderly conduct in grade 1
Insub_g1	Number of instances of insubordination in grade 1
Corporal_g1	Number of instances of corporal punishment in grade 1
OutSchlSusp_g1	Number of instances of out-of-school suspension in grade 1
InfrTot_g1	Total number of infractions reported in grade 1
InfrTot_g2	Total number of infractions reported in grade 2
InfrTot_g3	Total number of infractions reported in grade 3
InfrTot_g4	Total number of infractions reported in grade 4
InfrTot_g5	Total number of infractions reported in grade 5
InfrTot_g6	Total number of infractions reported in grade 6
InfrTot_g8	Total number of infractions reported in grade 8
InfrTot_g9	Total number of infractions reported in grade 9
InfrTot_g10	Total number of infractions reported in grade 10
InfrTot_g11	Total number of infractions reported in grade 11
InfrTot_g12	Total number of infractions reported in grade 12
PunTot_g1	Total number of punishments reported in grade 1
PunTot_g2	Total number of punishments reported in grade 2
PunTot_g3	Total number of punishments reported in grade 3
PunTot_g4	Total number of punishments reported in grade 4
PunTot_g5	Total number of punishments reported in grade 5
PunTot_g6	Total number of punishments reported in grade 6
PunTot_g8	Total number of punishments reported in grade 8
PunTot_g9	Total number of punishments reported in grade 9
PunTot_g10	Total number of punishments reported in grade 10
PunTot_g11	Total number of punishments reported in grade 11
PunTot_g12	Total number of punishments reported in grade 12

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Table A-1
(continued)

Variable name	Description
Attendance	
DaysAbs_g1	Days absent in grade 1
DaysAbs_g2	Days absent in grade 2
DaysAbs_g3	Days absent in grade 3
DaysAbs_g4	Days absent in grade 4
DaysAbs_g5	Days absent in grade 5
DaysAbs_g6	Days absent in grade 6
DaysAbs_g8	Days absent in grade 8
DaysAbs_g9	Days absent in grade 9
DaysAbs_g10	Days absent in grade 10
DaysAbs_g11	Days absent in grade 11
DaysAbs_g12	Days absent in grade 12
Scores on state-sponsored tests	
Scale for NRT scores in g1 – g2: $\approx$ 1 – 99	
Scale for CRT scores in g3 – g8: $\approx$ 20 – 990	
Scale for NRT average score in g9: $\approx$ 1 – 99	
Scale for ELA_g11 score: 30 – 315	
LtcyNPR_g1	Literacy NRT national percentile rank in grade 1
WrtgNPR_g1	Writing NRT national percentile rank in grade 1
LtcyNPR_g2	Literacy NRT national percentile rank in grade 2
WrtgNPR_g2	Writing NRT national percentile rank in grade 2
LtcyScalScr _g3	Literacy CRT score in grade 3
MathScalScr_g3	Mathematics CRT score in grade 3
LtcyScalScr _g4	Literacy CRT score in grade 4
MathScalScr_g4	Mathematics CRT score in grade 4
LtcyScalScr _g5	Literacy CRT score in grade 5
MathScalScr_g5	Mathematics CRT score in grade 5
LtcyScalScr_g6	Literacy CRT score in grade 6
MathScalScr_g6	Mathematics CRT score in grade 6
LitMath_g8	SD-weighted average Literacy and Mathematics CRT score in grade 8
LitMathWrtg_g9	SD-weighted average Literacy, Mathematics, and Writing NRT score in grade 9
ELA_g11	English/Language Arts end-of-course test score in grade 11

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Table A-1
(continued)

Variable name	Description
Scores on ACT-sponsored tests	
PLAN_g10	PLAN Composite score in grade 10 (scale: 1 – 30)
ACT_g11/12	ACT Composite score in grades 11/12 (scale: 1 – 36)
Success indicators	
InGr2	Enrolled in grade 2 in AY2006 (Yes=1)
LtcyPrf_g6	At or above proficient level on grade 6 Literacy test (Yes=1)
MathPrf_g6	At or above proficient level on grade 6 Mathematics test (Yes=1)
ACT_CRB	Meets all four ACT College Readiness Benchmarks (Yes=1)

Table A-2
Summary of Variables, by Analysis File

	AY2005-g1 students			AY2005-g8 students	
	All students	Cohort analysis file	At-grade-level analysis file	All students	ACT-tested / at-grade-level analysis file
Sample size					
Number of schools	536	343	343	363	266
Number of students	41,432	18,769	14,420	37,891	10,196
Background characteristics: Percent					
Male	51	51	50	52	46
Minority	33	30	28	29	20
HomEngl	93	95	95	96	97
FreeMeal	51	51	48	42	25
Title1	66	66	65	...	...
EconDis	58	59	56	...	...
Promotion to grade 2: Percent					
InGr2	95	95	...	...	...
Behavior variables: Mean (SD)					
Disord_g1	0.08 (0.45)	0.11 (0.53)	0.09 (0.49)	...	...
Insub_g1	0.04 (0.28)	0.04 (0.32)	0.04 (0.29)	...	...
InfrTot_g1	...	0.26 (1.30)	0.21 (1.18)	...	...
InfrTot_g2	...	...	0.22 (1.21)	...	...
InfrTot_g3	...	...	0.24 (1.27)	...	...
InfrTot_g4	...	...	0.25 (1.24)	...	...
InfrTot_g5	...	...	0.22 (0.89)	...	...
InfrTot_g6	...	...	0.26 (0.90)	...	...

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Table A-2
(continued)

	AY2005-g1 students			AY2005-g8 students	
	All students	Cohort analysis file	At-grade-level analysis file	All students	ACT-tested / at-grade-level analysis file
Behavior variables [continued]: Mean (SD)					
InfrTot_g8	. . .	. . .	. . .	0.92 (3.08)	0.43 (1.99)
InfrTot_g9	. . .	. . .	. . .	. . .	0.46 (2.08)
InfrTot_g10	. . .	. . .	. . .	. . .	0.46 (2.01)
InfrTot_g11	. . .	. . .	. . .	. . .	0.39 (1.75)
InfrTot_g12	. . .	. . .	. . .	. . .	0.18 (0.73)
Corporal_g1	. . .	0.08 (0.46)	0.08 (0.44)	. . .	. . .
InSchlSusp_g1	. . .	0.02 (0.19)	0.02 (0.22)	. . .	. . .
OutSchlSusp_g1	. . .	0.03 (0.23)	0.02 (0.19)	. . .	. . .
PunTot_g1	. . .	0.23 (1.03)	0.19 (0.94)	. . .	. . .
PunTot_g2	. . .	. . .	0.20 (0.97)	. . .	. . .
PunTot_g3	. . .	. . .	0.21 (1.02)	. . .	. . .
PunTot_g4	. . .	. . .	0.23 (1.04)	. . .	. . .
PunTot_g5	. . .	. . .	0.23 (0.81)	. . .	. . .
PunTot_g6	. . .	. . .	0.28 (0.90)	. . .	. . .
PunTot_g8	. . .	. . .	. . .	0.85 (2.49)	0.36 (1.49)
PunTot_g9	. . .	. . .	. . .	. . .	0.39 (1.56)
PunTot_g10	. . .	. . .	. . .	. . .	0.39 (1.51)
PunTot_g11	. . .	. . .	. . .	. . .	0.33 (1.35)
PunTot_g12	. . .	. . .	. . .	. . .	0.19 (0.69)

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Table A-2
(continued)

	AY2005-g1 students			AY2005-g8 students	
	All students	Cohort analysis file	At-grade-level analysis file	All students	ACT-tested / at-grade-level analysis file
Attendance variables: Mean (SD)					
DaysAbs_g1	8.3 (7.1)	8.1 (6.9)	7.9 (6.6)	. . .	. . .
DaysAbs_g2	. . .	. . .	7.5 (6.3)	. . .	. . .
DaysAbs_g3	. . .	. . .	8.4 (6.7)	. . .	. . .
DaysAbs_g4	. . .	. . .	5.8 (5.3)	. . .	. . .
DaysAbs_g5	. . .	. . .	8.0 (7.0)	. . .	. . .
DaysAbs_g6	. . .	. . .	8.2 (7.7)	. . .	. . .
DaysAbs_g8	. . .	. . .	. . .	8.5 (9.4)	5.8 (5.5)
DaysAbs_g9	. . .	. . .	. . .	. . .	5.5 (5.4)
DaysAbs_g10	. . .	. . .	. . .	. . .	6.3 (6.2)
DaysAbs_g11	. . .	. . .	. . .	. . .	5.2 (5.6)
DaysAbs_g12	. . .	. . .	. . .	. . .	9.3 (9.4)

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Table A-2
(continued)

	AY2005-g1 students			AY2005-g8 students	
	All students	Cohort analysis file	At-grade-level analysis file	All students	ACT-tested / at-grade-level analysis file
g1 – g6 test scores: Mean (SD)					
LtcyNPR_g1	52 (33)	52 (32)	56 (31)	. . .	. . .
WrtgNPR_g1	55 (29)	54 (29)	58 (28)	. . .	. . .
LtcyNPR_g2	. . .	. . .	62 (28)	. . .	. . .
WrtgNPR_g2	. . .	. . .	60 (28)	. . .	. . .
LtcyScalScr_g3	. . .	. . .	538 (178)	. . .	. . .
MathScalScr_g3	. . .	. . .	562 (94)	. . .	. . .
LtcyScalScr_g4	. . .	. . .	645 (182)	. . .	. . .
MathScalScr_g4	. . .	. . .	621 (98)	. . .	. . .
LtcyScalScr _g5	. . .	. . .	678 (173)	. . .	. . .
MathScalScr_g5	. . .	. . .	653 (95)	. . .	. . .
LtcyScalScr_g6	. . .	. . .	731 (163)	. . .	. . .
MathScalScr_g6	. . .	. . .	712 (98)	. . .	. . .
g6 proficiency rates: Percent					
LtcyPrf_g6	. . .	. . .	73	. . .	. . .
MathPrf_g6	. . .	. . .	77	. . .	. . .
g8 – g12 test scores: Mean (SD)					
LitMath_g8	. . .	. . .	. . .	684 (185)	750 (93)
LitMathWrtg_g9	. . .	. . .	. . .	. . .	63 (22)
PLAN_g10	. . .	. . .	. . .	. . .	18.3 (3.4)
ELA_g11	. . .	. . .	. . .	. . .	209 (18)
ACT_g11/12	. . .	. . .	. . .	. . .	20.8 (4.7)

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Table A-2
(continued)

	AY2005-g1 students			AY2005-g8 students	
	All students	Cohort analysis file	At-grade-level analysis file	All students	ACT-tested / at-grade-level analysis file
ACT College Readiness Benchmark attainment: Percent					
ACT_CRB	. . .	. . .	. . .	. . .	0.19

Table A-3
Prediction of Infractions, Punishments, Attendance, and Achievement in g1-g6 (Parsimonious models; p<.01)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Infractions				
InfrTot_g2	.29	.20	Male	.07
			Minority	.05
			HomEngl	.05
			FreeMeal	.02
			InfrTot_g1	.31
			PunTot_g1	.08
InfrTot_g3	.30	.17	Male	.07
			Minority	.05
			HomEngl	.04
			FreeMeal	.04
			InfrTot_g2	.27
			PunTot_g2	.11
InfrTot_g4	.35	.14	Male	.07
			Minority	.03
			HomEngl	.05
			FreeMeal	.03
			PunTot_g3	.32
			LtcyScalScr_g3	- .05
InfrTot_g5	.33	.17	Male	.07
			Minority	.06
			HomEngl	.04
			FreeMeal	.04
			PunTot_g4	.34
			LtcyScalScr_g4	- .04
InfrTot_g6	.23	.25	Male	.08
			Minority	.06
			HomEngl	.05
			FreeMeal	.03
			InfrTot_g5	.13
			PunTot_g5	.29
			LtcyScalScr_g5	- .06

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Table A-3
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Punishments				
PunTot_g1	.08	.93	Male	.02
			Minority	.01
			HomEngl	.01
			FreeMeal	.01
			InfrTot_g1	.96
PunTot_g2	.09	.94	Male	.01
			FreeMeal	.01
			PunTot_g1	.03
			WrtgNPR_g1	- .01
			InfrTot_g2	.95
PunTot_g3	.08	.94	Male	.02
			FreeMeal	.01
			PunTot_g2	.03
			WrtgNPR_g2	- .01
			InfrTot_g3	.96
PunTot_g4	.08	.94	Male	.01
			Minority	.01
			PunTot_g3	.04
			LtcyScalScr_g3	- .01
			InfrTot_g4	.96
PunTot_g5	.12	.90	Male	.02
			Minority	.01
			HomEngl	.01
			FreeMeal	.01
			PunTot_g4	.04
			LtcyScalScr_g4	- .02
			InfrTot_g5	.93
PunTot_g6	.12	.90	Male	.02
			PunTot_g5	.05
			DaysAbs_g5	.01
			LtcyScalScr_g5	- .02
			InfrTot_g6	.93

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Table A-3
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Attendance				
DaysAbs_g1	.27	.04	Minority	- .14
			HomEngl	.03
			FreeMeal	.19
DaysAbs_g2	.15	.39	Male	- .03
			Minority	- .05
			DaysAbs_g1	.61
			LtcyNPR_g1	- .04
			PunTot_g2	.03
DaysAbs_g3	.18	.36	Minority	- .08
			HomEngl	.02
			FreeMeal	.06
			DaysAbs_g2	.58
			WrtgNPR_g2	- .03
			PunTot_g3	.04
DaysAbs_g4	.20	.39	Minority	- .08
			FreeMeal	.06
			PunTot_g3	- .02
			DaysAbs_g3	.58
			LtcyScalScr_g3	- .02
			PunTot_g4	.06
DaysAbs_g5	.24	.34	Minority	- .09
			HomEngl	.02
			FreeMeal	.08
			DaysAbs_g4	.54
			LtcyScalScr_g4	- .04
			PunTot_g5	.06
DaysAbs_g6	.30	.37	Minority	- .08
			FreeMeal	.07
			PunTot_g5	- .02
			DaysAbs_g5	.55
			MathScalScr_g5	- .04
			PunTot_g6	.12

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Table A-3
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Educational achievement				
LtcyNPR_g1	.29	.14	Male	- .09
			Minority	- .17
			HomEngl	.06
			FreeMeal	- .16
			PunTot_g1	- .06
			DaysAbs_g1	- .07
WrtgNPR_g1	.31	.15	Male	- .14
			Minority	- .17
			HomEngl	.03
			FreeMeal	- .16
			PunTot_g1	- .07
			DaysAbs_g1	- .08
LtcyNPR_g2	.15	.65	Minority	- .07
			HomEngl	.03
			FreeMeal	- .05
			LtcyNPR_g1	.59
			WrtgNPR_g1	.20
WrtgNPR_g2	.21	.58	Male	- .06
			Minority	- .07
			HomEngl	- .02
			FreeMeal	- .05
			LtcyNPR_g1	.34
			WrtgNPR_g1	.39
			PunTot_g1	- .02
			DaysAbs_g1	- .04
LtcyScalScr_g3	.21	.60	Male	- .09
			Minority	.02
			HomEngl	- .03
			FreeMeal	- .04
			PunTot_g2	- .02
			LtcyNPR_g2	.50
			WrtgNPR_g2	.30
			PunTot_g3	- .04
			DaysAbs_g3	- .05

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Table A-3
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Educational achievement (continued)				
MathScalScr_g3	.25	.53	Male	.04
			Minority	- .07
			HomEngl	- .05
			FreeMeal	- .02
			PunTot_g2	- .02
			LtcyNPR_g2	.37
			WrtgNPR_g2	.37
			PunTot_g3	- .03
			DaysAbs_g3	- .06
LtcyScalScr_g4	.17	.68	Male	- .08
			Minority	- .03
			FreeMeal	- .03
			LtcyScalScr_g3	.55
			MathScalScr_g3	.29
			DaysAbs_g4	- .01
MathScalScr_g4	.19	.66	Male	.03
			Minority	- .06
			HomEngl	- .02
			FreeMeal	- .03
			LtcyScalScr_g3	.23
			MathScalScr_g3	.61
			DaysAbs_g4	- .02
LtcyScalScr_g5	.15	.71	Male	- .03
			Minority	- .03
			FreeMeal	- .04
			LtcyScalScr_g4	.61
			MathScalScr_g4	.23
			PunTot_g5	- .03
			DaysAbs_g5	- .02
MathScalScr_g5	.23	.67	Male	.03
			Minority	- .04
			HomEngl	- .03
			FreeMeal	- .02
			LtcyScalScr_g4	.27
			MathScalScr_g5	.56
			PunTot_g6	- .04
			DaysAbs_g6	- .05

(continued on next page)

Table A-3
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Educational achievement (continued)				
LtcyScalScr_g6	.14	.71	Male	- .10
			FreeMeal	- .03
			LtcyScalScr_g5	.64
			MathScalScr_g5	.20
			PunTot_g6	- .02
			DaysAbs_g6	- .02
LtcyPrf_g6 (logistic model)	. . .	. . .	Male	- .32
			FreeMeal	- .15
			LtcyScalScr_g5	2.25
			MathScalScr_g5	.70
			PunTot_g6	- .06
MathScalScr_g6	.20	.69	Male	- .02
			Minority	- .03
			HomEngl	- .02
			FreeMeal	- .03
			LtcyScalScr_g5	.21
			MathScalScr_g5	.64
			PunTot_g6	- .03
			DaysAbs_g6	- .04
MathPrf_g6 (logistic model)	. . .	. . .	LtcyScalScr_g5	.71
			MathScalScr_g5	2.28
			PunTot_g6	- .15
			DaysAbs_g6	- .13

Table A-4
Prediction of Infractions, Punishments, Attendance, and Achievement in g8-g12
(Parsimonious models; p<.01)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
<u>*Infractions*</u>				
InfrTot_g9	.24	.31	Male	.03
			Minority	.08
			InfrTot_g8	.50
			LitMath_g8	- .03
InfrTot_g10	.22	.24	Minority	.06
			PunTot_g9	.42
			DaysAbs_g9	.04
			LitMathWrtg_g9	- .04
InfrTot_g11	.16	.32	Male	.02
			Minority	.05
			InfrTot_g10	.52
			PLAN_g10	- .04
InfrTot_g12	.30	.18	Male	.05
			Minority	.05
			PunTot_g11	.36

(continued on next page)

Table A-4
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
<u>*Punishments*</u>				
PunTot_g8	.06	.96	Male	.01
			Minority	.01
			FreeMeal	.01
			InfrTot_g8	.98
PunTot_g9	.08	.95	Male	.01
			Minority	.01
			PunTot_g8	.03
			LitMath_g8	- .02
			InfrTot_g9	.96
PunTot_g10	.09	.94	PunTot_g9	.03
			LitMathWrtg_g9	- .02
			InfrTot_g10	.97
PunTot_g11	.07	.94	Male	.01
			PunTot_g10	.03
			PLAN_g10	- .02
			InfrTot_g11	.97
PunTot_g12	.11	.87	Male	.02
			PLAN_g10	- .02
			PunTot_g11	.04
			InfrTot_g12	.93

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Table A-4
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Attendance				
DaysAbs_g8	.37	.03	Minority	- .13
			HomEngl	.05
			FreeMeal	.14
			PunTot_g8	.08
DaysAbs_g9	.31	.36	Male	- .04
			FreeMeal	.04
			DaysAbs_g8	.58
			PunTot_g9	.05
DaysAbs_g10	.33	.38	Male	- .04
			Minority	- .04
			FreeMeal	.05
			DaysAbs_g9	.58
			PunTot_g10	.06
DaysAbs_g11	.30	.32	Male	- .07
			Minority	- .05
			FreeMeal	.06
			DaysAbs_g10	.56
			PLAN_g10	- .02
			PunTot_g11	.07
DaysAbs_g12	.45	.34	Male	- .04
			Minority	- .03
			DaysAbs_g10	.48
			ELA_g11	- .04
			PunTot_g12	.10

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Table A-4
(continued)

Outcome variable	Intercept SD	Level-1 R^2	Level-1 predictor variable	Fixed effect
Educational achievement				
LitMath_g8	.27	.14	Male	- .04
			Minority	- .27
			FreeMeal	- .12
			PunTot_g8	- .07
			DaysAbs_g8	- .07
LitMathWrtg_g9	.14	.72	Minority	- .08
			LitMath_g8	.81
PLAN_g10	.09	.71	LitMthWrgt_g9	.84
			DaysAbs_g10	- .03
ELA_g11	.17	.60	Male	- .11
			Minority	- .10
			FreeMeal	- .06
			PunTot_g10	- .02
			PLAN_g10	. 69
			DaysAbs_g11	- .04
ACT_g11/12	.09	.79	Male	.09
			Minority	- .04
			PLAN_g10	.60
			DaysAbs_g11	-.02
			ELA_g11	. 31
			PunTot_g12	- .02
			DaysAbs_g12	- .03
ACT_CRB (logistic model)	. . .	. . .	Male	.48
			DaysAbs_g10	- .14
			PLAN_g10	2.00
			ELA_g11	.64
			DaysAbs_g11	- .18