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Performance, Perseverance, and the Full Picture of College Readiness

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Although college readiness is a centerpiece of major educational initiatives such as the Common Core State Standards, few systems have been implemented to track children's progress toward this goal. Instead, college-readiness information is typically conveyed late in a student's high-school career, and tends to focus solely on academic accomplishments—grades and admissions test scores. Late-stage feedback can be problematic for students who need to correct course, so the purpose of this research is to develop a system for communicating more comprehensive college-readiness diagnoses earlier in a child's K-12 career. This article introduces college-readiness indicators for middle-school students, drawing on the National Education Longitudinal Study of 1988 (NELS), a nationally representative longitudinal survey of educational inputs, contexts, and outcomes. A diversity of middle-school variables was synthesized into six factors: achievement, behavior, motivation, social engagement, family circumstances, and school characteristics. Middle-school factors explain 69% of the variance in college readiness, and results suggest a variety of factors beyond academic achievement—most notably motivation and behavior—contribute substantially to preparedness for postsecondary study. The article concludes with limitations and future directions, including the development of college-readiness categories to support straightforward communication of middle-school indicators to parents, teachers, and students.

Keywords: college readiness, nonacademic skills, principal components analysis

Between 1870 and 1980, the United States made tremendous strides in educational attainment as schooling was made public, universal, and compulsory. High-school graduation rates rose from 2% to 77%, literacy rates followed suit, and college completion rates increased sevenfold (Snyder, 1993). Unfortunately, progress has stalled since then. Graduation rates have remained relatively stable in the intervening years, and at present only 78% of high-school students finish on time (Stillwell & Sable, 2013). Even those who graduate often do so underprepared. Between 1975 and 1980, the number of remedial mathematics courses in public 4-year colleges increased 72% (U.S. Department of Education, 1983). High remediation rates have persisted, and they are not limited to 4-year schools; approximately 60% of students entering community colleges need developmental education before they are ready for entry-level credit-bearing courses (Bailey, 2009). A recent report from ACT echoes these rather dismal statistics: Only 26% of ACT takers meet all four exams' college-readiness benchmarks. Thirty-one percent meet none of them (ACT, 2013).

Flatlining rates of educational attainment have caught the attention of educators, researchers, and policymakers, and in consequence a variety of reforms have taken aim at college readiness. Twenty-one states and the District of Columbia now require students to complete a college- and career-ready curriculum—including 4 years of grade-level English and mathematics through Algebra II—to earn a high-school diploma (Achieve, 2011). Moreover, 45 states have adopted the Common Core State Standards, which specifically target postsecondary readiness (Camara, 2013). Even states that have opted out of the Common Core, such as Texas and Virginia, have independently developed college- and career-readiness content standards and assessments to ensure that a high-school diploma signals preparedness for further study.

These efforts understandably focus attention and funding on educational outputs at the end of students' K-12 careers, but college readiness begins long before high school exit. To that end, it is unfortunate that the first diagnoses of college readiness most students will receive—cumulative GPAs and SAT or ACT scores—arrive toward the end of eleventh grade. At this point, there is little time for students to correct course, catch up, and graduate ready for life after high school. Moreover, grades and test scores are measures of academic achievement; they are generally not designed to capture other characteristics such as motivation, behavior, and social engagement that may be integral to later-life success.

To address these gaps in the college-readiness research literature, we developed a college-readiness index for middle-school students. The index includes a diverse set of indicators collected in eighth grade, which explains a large proportion of the variance in conventional college-readiness measures reported at the end of high school. Given their predictive power and their focus on affective and behavioral data

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in addition to academic accomplishments, these indicators may help parents and teachers assess students' strengths and weaknesses across multiple dimensions and intervene early. In this article, we outline the conceptual foundation of the middle-school college-readiness index and detail the statistical methods used to construct it. Furthermore, we decompose the variance explained in college readiness to demonstrate how a variety of nonacademic factors contribute substantially to preparedness for college-level work. Finally, we compare the predictive validity of middle-school college-readiness indicators with SAT and ACT to show that useful projections of college success can be obtained as early as eighth grade.

The design, analyses, and discussion presented in this article are undergirded by a fairly simple educational premise: not everyone goes to college, and not everyone wants to go (Hossler & Gallagher, 1987), but the economic and social rewards tied to earning a postsecondary degree are substantial and lasting (Carnevale, Jayasundera, & Cheah, 2012). Therefore, all students should be encouraged to at least consider pursuing higher education, and we should leverage all available diagnostic and predictive data to inform this pivotal choice.

Background and Conceptual Framework

The middle-school index was conceived to support early diagnosis and intervention. These concepts are not new to educational research. Indeed, states and districts have made substantial progress in the identification of K-12 students at risk of dropping out prior to graduation. These research efforts are broadly termed "early warning indicator systems," and they focus on the host of measurable characteristics associated with an early exit from high school. Early warning systems commonly employ measures of attendance, behavior, and course performance—the "ABCs"—and research supports this focus. For example, in middle school, students with a 95% attendance rate, no record of misbehavior, and a B average have a high likelihood of graduation (Balfanz, 2009). The inverse is also true; low marks on ABC indicators signal an increased risk of early exit. Researchers in Montgomery County Public Schools determined students absent from school nine or more days in first grade were twice as likely to drop out by high school (West, 2013). The ABC evidence-based early-intervention strategy has intuitive appeal, and seems to confirm that attitudes and behaviors, not just academic achievement, play a vital role in boosting students' odds of future success. However, such systems focus on reducing the risk of dropout, or put another way, increasing the chances of graduation. This is a worthy goal, but simply graduating from high school is not yet a reliable indicator of college readiness. For example, the majority (60%) of students who graduate high school and enter community college need remediation before they are ready for college-level work (Bailey, 2009). Similar patterns emerge at public 4-year universities, where one in five students begin their postsecondary careers in developmental education (Sparks & Malkus, 2013). The disconnect between high-school graduation and college readiness suggests that, despite their value, early warning indicator systems could be usefully extended. Specifically, switching the target outcome from a binary dropout indicator to a measure of college readiness could support inferences about students' likelihood of succeeding *after* high school, not just staying *in* high school.

The available literature suggests making accurate projections of future performance requires looking beyond the narrow dimension of academic achievement. For example, Balfanz's (2009) ABCs, Tinto's (1975) model of retention, Veenstra's nine pillars for student success (Veenstra, Dey, & Herrin, 2009), and the framework for student success in college (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006) all acknowledge the importance of academic achievement, but they also emphasize nonacademic factors such as commitment and social engagement. Our middle-school indicators draw on these frameworks, and we identified six dimensions shown to influence college readiness and success: academic achievement, behavior, motivation, social engagement, family circumstances, and school characteristics.

Achievement. Intuitively, current academic achievement is a useful predictor of future academic success. Grades and test scores are of course associated with future performance (Kurlaender, Reardon, & Jackson, 2008; Long, Iatarola, & Conger, 2009), but beyond grades and test scores, course rigor (Adelman, 1999; Wyatt, Wiley, Camara, & Proestler, 2012), grade skipping (Kulik & Kulik, 1984), and grade retention (Kurlaender et al., 2008; Roderick & Nagaoka, 2005) have all been shown to predict later-life academic achievement.

Behavior. Multiple studies have demonstrated the incremental validity of behavior indicators in predictions of academic outcomes. Above and beyond academic achievement, behavioral measures such as self-management (Robbins, Allen, Casillas, Peterson, & Le, 2006) and temperament (Camara, 2005) positively influence performance, not only in K-12 and college settings, but also in the workplace (ACT, 2007). Attendance and disciplinary actions may be the most popular ways to operationalize concepts like self-management and temperament in middle school (Allensworth & Easton, 2005; Balfanz, Herzog, & Mac Iver, 2007), but additional variables such as tardiness (Gottfried, 2014), suspensions (Arcia, 2006), and study habits (Cooper, Robinson, & Patall, 2006) are also associated with future academic success.

Motivation. Better grades, higher test scores, and positive academic behaviors have all been linked to student motivation (Dalton, 2010). Students who have confidence in their academic abilities (Rosen, 2010), believe in their power to control their own outcomes (i.e., internal locus of control; Findley & Cooper, 1983), and persist toward their goals (e.g., grit; Duckworth & Quinn, 2009) tend to achieve at higher levels. A recent National Research Council report (2012) focused on 21st-century skills reinforces these findings: intrapersonal competencies such as self-efficacy, striving, and locus of control all positively contribute to college and career readiness. Moreover, middle-school students with college aspirations are more likely to meet minimum academic standards for college admission (Cabrera & La Nasa, 2001).

Social engagement. Retention and success in higher education have been repeatedly linked to social engagement. Taking part in extracurricular activities can raise educational aspirations and reduce delinquent behaviors (Marsh & Kleitman, 2002), and building strong relationships with both teachers and peers can improve motivation and achievement (Kenny & Stryker, 1996; Montalvo, Mansfield, & Miller, 2007).

Family circumstances. It is well established in educational research literature that students' academic outcomes are linked to their socioeconomic circumstances. First-generation college students and those of lower socioeconomic status (SES) are less likely to have college-level aspirations, take advanced coursework in high school, and ultimately enroll in college (Choy, 1999; Terenzini, Springer, Yaeger, Pascarella, & Nora, 1996). They also have fewer sources of college information than more affluent students or those whose parents attended college (Olson & Rosenfeld, 1984; Tierney, 1980). Parental encouragement, on the other hand, has a significant positive effect on student aspirations and achievement (Flint, 1992). Additional risk indicators include mobility (Rumberger & Larson, 1998), family size and composition (Marks, 2006), and student employment (Singh, 1998).

School characteristics. This dimension includes both school composition and school environment. With respect to composition, a school's racial and socioeconomic makeup tends to be associated with student achievement (Borman & Dowling, 2010; Caldas & Bankston, 1997; Tate, 1997). Likewise, achievement can be influenced by teacher factors such as salary schedule, certification, and student-to-teacher ratio (Goldhaber & Brewer, 2000; Grissom & Strunk, 2012; Slavin, 1990). With respect to school environment, student outcomes are linked to learning opportunities (Gamoran, 1987), safety (Cornell & Mayer, 2010), and building a college-going culture, which means creating an environment that promotes students' college aspirations and facilitates preparation for, application to, and enrollment in college (Corwin & Tierney, 2007).

In sum, college-readiness research suggests enabling postsecondary success requires monitoring students' progress along a variety of dimensions and at an early age. The most widely used indicators of college readiness (SAT and ACT scores and high-school GPAs) offer little advance warning that students are off track. They also offer a somewhat narrow portrait readiness—focused only on academic achievement to the exclusion of affective, behavioral, and contextual factors. Although the shortcomings of cumulative GPAs and admissions test scores are widely acknowledged, we have seen little in the way of quantitative alternatives. Moreover, despite extensive research on the nonacademic factors that contribute to college readiness, little is known about the relative importance of those factors. This study is intended to address those gaps. Our analyses were driven by three research questions:

1. What are the key middle-school predictors of college readiness (and their relative importance)?
2. How can college-readiness information in middle school be synthesized and communicated effectively to stakeholders?
3. How do middle-school college-readiness indicators compare to college admissions tests in terms of predicting college outcomes?

Methods

The Data

This research relies on the National Education Longitudinal Study of 1988 (NELS). NELS tracks a nationally representative cohort of students beginning in middle school, through high school, and beyond. Specifically, Grade 8 students were sampled in 1988, and NELS followed up in 1990 (Grade 10), 1992 (Grade 12), 1994 (two years out of high school), and 2000 (eight years out of high school). NELS data derive from student, parent, and teacher surveys, as well as students' college and high-school transcript records and school-level characteristics. Student-level data include not only an array of K-12 and postsecondary academic achievement measures, but also psychological and contextual variables (e.g., academic self-concept, locus of control, parents' education), making NELS the most complete national data source available for estimating the relationships between students' middle-school surroundings, behaviors, attitudes, and accomplishments and their later-life outcomes.

The Variables

Outcomes. In detailing the construction of the middle-school index it is perhaps simplest to start with the outcome—college readiness. The college-readiness composite used in this research is based on three measures: combined SAT (mathematics and verbal sections), ACT composite, and cumulative high-school GPA (HSGPA). These outcomes were selected for three reasons. First, SAT, ACT, and HSGPA are the most heavily researched and relied upon college-readiness indicators in the United States. In many university admissions departments, these are the only measures used to forecast an applicant's first-year college grades (and thereby gauge his readiness for postsecondary study). Second, SAT, ACT, and HSGPA are available beginning in Grade 11. It was important that the middle-school index maintain its focus within the K-12 space and not solely predict college outcomes such as retention and graduation. Linking middle-school measures to high-school outcomes leaves ample time for improvement (three years between Grades 8 and 11), while avoiding a focus on college outcomes so distal that an intervention in middle school would seem premature. Third, SAT and ACT exams both have publicly available college-readiness benchmarks. The SAT's were set at the score points[1] where an examinee has a 65% chance of earning at least a 2.67 GPA in his first-year college courses (Wyatt, Kobrin, Wiley, Camara, & Proestler, 2011). The ACTs were set at the score points[2] where an examinee would have a 50% chance of earning at least a B or a 75% chance of earning at least a C in a corresponding college course (ACT, 2013). These readiness benchmarks are useful for the middle-school index because they inform an overall college-readiness cut, which can be used to differentiate the middle-school students who are on track from those who are not.

Constructing the college-readiness composite involved three straightforward steps. First, SAT and ACT scores were standardized and averaged to create an "admissions test z-score." Next, HSGPA was standardized (thus creating a "HSGPA z-score"). Finally, these two z-scores were averaged to produce the college-readiness composite. Standardization was required at each step to ensure the variables being averaged had equal variances and therefore equal effective weights in the resulting composite. Research is mixed as to which component of a student's high-school record better predicts college success, though a recent study places the incremental validity coefficient for both HSGPA and SAT scores at .08 (Patterson & Mattern, 2012). Given this evidence, and because no compelling alternative weighting schemes have been proposed, we weighted grades and test scores equally.

[1]Mathematics = 500 and verbal = 500, summing to 1,000 for the SAT combined cut.

[2]English = 18, mathematics = 22, reading = 22, and science = 23, averaging to 21.25 for the ACT composite cut.

To establish a college-readiness benchmark on the outcome measure we first calculated z-score equivalents for the SAT and ACT cuts at 1,000 and 21.25, respectively, and then averaged those z-scores. We found the HSGPA college-readiness cut by identifying the HSGPA with the same percentile as the admissions test z-score cut. Specifically, 73% of NELS students scored at or below the admissions test z-score cut, and 73% of NELS students had a HSGPA at or below 3.23. Therefore, the HSGPA equivalent of SAT and ACT college-readiness benchmarks is 3.23. That HSGPA was converted to a z-score and averaged with the admissions test z-score representing SAT and ACT benchmarks. The resulting college-readiness threshold is .71 standard deviations above the NELS mean. By this measure, 25% of NELS students were college-ready at the end of high school.

Predictors. To predict the college-readiness composite summarizing high-school grades and admissions test scores, we used 140 middle-school variables available in NELS. To reduce this expansive list of variables and provide a more condensed and interpretable predictor set, we grouped observed variables in NELS into the six factors previously discussed: (1) academic achievement, (2) motivation, (3) behavior, (4) social engagement, (5) family circumstances, and (6) school characteristics. For ease of presentation and the sake of parsimony, in this section we briefly describe the types of NELS variables grouped within each factor. The full list of NELS predictors is included in the appendix.

The achievement factor focuses on academic accomplishments. It includes not only course grades in English, mathematics, science, and social studies and eighth-grade standardized test scores in the same subjects, but also enrollment in honors courses, advanced enrollment in Algebra I, and grade-skipping and retention (i.e., being held back). Motivation is focused on affective qualities and students' self-efficacy, including locus of control, academic self-concept, effort, and postsecondary goals. For the behavior factor, NELS includes not only absences and suspensions, but also tardies, discipline referrals, and incomplete assignments. The social engagement factor includes involvement indicators such as participation in clubs and after-school activities,[3] along with relationship measures such as the number of times a student speaks with a teacher or guidance counselor about academic issues.

Achievement, motivation, behavior, and social engagement represent student-level characteristics that students (given appropriate support and guidance) can change. The last two factors—family circumstances and school characteristics—are a bit different. They represent environmental variables over which students have little influence. Nonetheless, school and family characteristics can affect later-life outcomes, and were therefore included in the middle-school index. The family circumstances factor includes financial indicators such as household income along with environmental measures such as the family's attitude toward school, family structure (e.g., single-parent home), and parents' education level. School characteristics include opportunities such as school-sponsored clubs, along with teacher qualifications, school-wide safety measures, and demographics (e.g., percentage of students eligible for free lunch).

[3]Because the availability of school clubs may be a function of school size, we regressed club participation variables on school size and used the residuals to construct the social engagement factor.

Missing Data

When data are missing on outcome or predictor variables, biased estimates may result if observations with nonmissing data are not representative of the population (Cox, McIntosh, Reason, & Terenzini, 2014). When relevant NELS data were missing, we used multiple imputation (Rubin, 1987). As the name suggests, multiple imputation involves creating multiple data sets, each one with an imputed value corresponding to a given missing value in the original data. Missing data are imputed based on observed data, and in each data set a random error term is added to each imputed value. The inclusion of random error terms allows multiply imputed data to reflect some of the uncertainty inherent in generating values where none existed originally (Gelman, Carlin, Stern, & Rubin, 1995).

All of the variables included in the middle-school index—both outcomes and predictors—were used in the imputation procedure (Little & Rubin, 2002). Following the advice of Allison (2002) and Gelman et al. (1995), we also included auxiliary variables not used in the middle-school index to improve the precision of the imputation model and reduce bias in the imputed data set. The auxiliary variables included NELS Grade 10 and Grade 12 standardized assessment scores in mathematics, reading, history, and science. These measures were particularly attractive as auxiliary variables not only because they are correlated with middle-school indicators, but also because they are rarely missing in NELS (only 1.5% of the NELS students were missing all Grade 10 and all Grade 12 test scores).

Starting values for the multiple imputation were generated via the expectation-maximization (EM) algorithm, and the Markov chain Monte Carlo (MCMC) method proposed by Schafer (1997) was used to impute missing data. Ten imputed data sets were created. Although the default in many statistical software packages is five, statisticians have called for additional imputed data sets when at least some data are missing on most variables (Graham, Olchowski, and Gilreath, 2007). Missingness rates are presented alongside each middle-school variable in the appendix; every variable had at least some missing data, and missingness rates ranged from 5% to 49%. We used 200 burn-in iterations and 100 iterations between each imputation, although doubling the number of burn-in and between-imputation iterations had no effect on our substantive findings. Data were not imputed when either all high-school outcomes or all middle-school predictors were missing, reducing the available sample size from 12,144 to 11,612.

Ultimately, we view imputation as an imperfect remedy for missing data and we agree with Allison's (2002) observation that the "only really good solution to the missing data problem is not to have any" (p. 2). Unfortunately, NELS does not offer such a solution, so we argue imputation is critical to this analysis. Ignoring missingness in NELS—in either outcomes or predictors—could bias our conclusions by discarding a lower performing group of students. The case for imputing outcomes is intuitive: college-readiness measures such as SAT and ACT scores tend to be systematically missing in national data sets. Lower performing students are less likely to take these tests. Indeed, on the NELS Grade 12 standardized assessments, students who took neither the SAT nor the ACT (50% of the sample) scored a full standard deviation below students who took at least one of these admissions exams.

There are good reasons to impute predictors as well. For example, listwise deletion (removing any NELS students with any missing middle-school data) would eliminate 10,099 students—87% of the available sample. The 1,513 remaining students would constitute a small and disproportionately high-performing group; their NELS Grade 12 assessment scores were between .25 and .5 standard deviations above the NELS mean, and 36% were college-ready upon high-school exit—a 44% increase over the 25% estimated for all NELS students. Imputation was therefore essential to avoid restricting our analyses to a dramatically smaller and higher performing group than the NELS sample at large. Nevertheless, in the Results section we report the sensitivity of our findings to the imputation of predictor and outcome measures.

Statistical Methods

Once the predictor variables were assigned to categories, principal components analysis (PCA) was used to summarize observed variables within each category. PCA served two important purposes: reducing data and reducing multicollinearity. First, 140 middle-school predictors would produce an unwieldy model of college readiness; parameter estimates given so many related predictors would be difficult to interpret. Six theory-driven predictors, on the other hand, simplify things. Furthermore, including 140 middle-school variables would virtually assure multicollinearity in predictors. Reducing the predictor set via PCA is a common approach to addressing that problem (Greene, 2003). Of course, examining six predictors rather than 140 does not rule out the possibility of multicollinearity; we turn to this point next.

The first principal component was extracted from each of the six categories of predictors, creating six component scores for each NELS student—one score for achievement, one for motivation, and so on. To estimate the variance explained in college readiness by each of these six middle-school factors, one option at this stage would be to regress the college-readiness composite on the six factors and examine squared standardized regression coefficients. It would not be a very good option, unfortunately; the six component scores represent vastly reduced but still correlated predictors of college readiness. In the presence of correlated predictors, squared standardized regression coefficients do not represent unique variance explained. So, to mitigate multicollinearity and examine the relative contribution of each factor to college readiness, we performed an eigendecomposition of the six components' covariance matrix. Eigendecomposition creates n orthogonal components from n original variables, and the orthogonal components explain 100% of the variance in the original variables.

The next step was regressing the outcome composite (based on SAT, ACT, and HSGPA) on the six orthogonal component scores. To address our research questions we examine a variety of statistics generated by this principal components regression approach. Overall variance explained (R^2) in college readiness helps us gauge the predictive utility of middle-school indicators. Additionally, squared loadings from the eigendecomposition and squared standardized coefficients from the subsequent regression allow us to calculate the variance explained in college readiness by each middle-school factor and therefore present college readiness information to stakeholders in a more simplified and interpretable way (Nathans, Oswald, & Nimon, 2012). Finally, regressing college outcomes (e.g., first-year GPA) on both the middle-school indicators and admissions test scores allows us to compare the accuracy with which these measures predict postsecondary success.

Results

Predictive Power

Summarizing the NELS middle-school predictors via PCA produced an eigenvector for each of the six factors (achievement, motivation, and so on). These eigenvectors are presented in the appendix. Values in eigenvectors are component loadings. They simply represent the correlation between an observed variable (e.g., eighth grade math test score) and a factor (e.g., achievement). Across the six PCA solutions, the first principal component explains between 6% and 21% of the variance in observed middle-school variables. These proportions are not particularly high, but the objective of PCA in this case was not to explain variance in observed middle-school variables, but rather to reduce the number of middle-school predictors without sacrificing much prediction accuracy. From that perspective, the PCA was quite useful. Including all 140 middle-school variables in an OLS regression predicting the college-readiness composite yields an R^2 of .78—unsurprisingly high, given the number of predictors. However, once the model is reduced from 140 variables to six principal components, those six predictors still explain 69% of the variance in college readiness.

Another approach to evaluating predictive power is through *area under the curve* (AUC), a statistic commonly examined in receiver operating characteristic analysis (ROC; Swets, 1973). For this statistic the outcome is converted into a binary variable—college-ready versus not, as determined by the SAT, ACT, and HSGPA benchmarks discussed previously. The AUC represents the probability that the middle-school index will rank a randomly chosen college-ready student above a randomly chosen noncollege-ready student. AUC values can range from .5 to 1; the AUC for the middle-school index is .94. That is, there is a 94% chance that in eighth grade, the middle-school index will rank a student who later achieves college readiness higher than a student who does not.

It is important to emphasize the middle-school index does not simply use eighth grade test scores to predict eleventh grade test scores. First, HSGPA counts as much toward the college readiness composite as SAT and ACT. Second, even if all eighth grade test scores are removed from the set of middle-school indicators, predictive power remains strong—reducing R^2 from .69 to .49. Even with all eighth grade test scores *and* course grades removed, the R^2 is .39.

Partitioning Variance Explained

By inspecting both squared loadings from the eigendecomposition and squared standardized coefficients from the subsequent regression, we were able to estimate the proportion of college readiness explained by each category of middle-school predictors. Table 1 shows how the variance was partitioned.

In Table 1, partitioned coefficients are obtained by multiplying squared standardized regression coefficients by squared loadings. So, for example, to determine achievement's contribution to college readiness through Component 1, we multiply $.4962 \times .2392 = .1187$. Each factor's variance explained in college readiness is obtained by summing partitioned coefficients across each row. To continue with the achievement example, $.1187 + .0000 + .0000 + .0153 + .0346 + .0023 = .171$; achievement explains 17.1% of the variation in college readiness. The same process is repeated for behavior, motivation, social engagement, family circumstances, and school characteristics.

Table 1. Variance Explained in College Readiness by Middle-School Factors

Squared Standardized Regression Coefficient[a]	Orthogonal Components												
	Component 1 .4962		Component 2 .0137		Component 3 .0006		Component 4 .0714		Component 5 .0704		Component 6 .0414		College Readiness Variance Explained
Middle-School Factors	Squared Loading	Partitioned Coefficient	Squared Loading	Partitioned Coefficient	Squared Loading	Partitioned Coefficient	Squared Loading	Partitioned Coefficient	Squared Loading	Partitioned Coefficient	Squared Loading	Partitioned Coefficient	
Achievement	.2392	.1187	.0004	.0000	.0001	.0000	.2137	.0153	.4911	.0346	.0554	.0023	17.1%
Behavior	.2242	.1113	.0307	.0004	.1920	.0001	.1048	.0075	.0981	.0069	.3501	.0145	14.1%
Motivation	.2556	.1268	.1184	.0016	.0520	.0000	.0091	.0006	.0019	.0001	.5631	.0233	15.3%
Social	.0533	.0264	.1645	.0023	.6822	.0004	.0817	.0058	.0016	.0001	.0167	.0007	3.6%
Family	.1587	.0788	.1942	.0027	.0641	.0000	.2427	.0173	.3387	.0238	.0016	.0001	12.3%
School	.0690	.0342	.4919	.0068	.0095	.0000	.3480	.0248	.0685	.0048	.0131	.0005	7.1%
Sum	1	.4962	1	.0137	1	.0006	1	.0714	1	.0704	1	.0414	69.4%

[a]Standardized regression coefficients were obtained by regressing the college-readiness composite on the six orthogonal components.

Ultimately, and as we might expect, achievement explains more variance in college readiness than any other factor at 17.1%. That said, motivation and behavior—independent of achievement—explain substantial variation in college readiness at 15.3% and 14.1%, respectively. Together, these two factors explain more variation in college readiness (29.4%) than achievement, and both motivation and behavior are better predictors of college readiness than family circumstances (12.3%). School characteristics and social engagement explain comparatively little variation in college readiness, at 7.1% and 3.6%, respectively.

Two notes are important to keep in mind. First, with or without the eigendecomposition, the regression model R^2 is .69. Eigendecomposition does not affect prediction accuracy and it does not change middle-school students' six factor scores; it simply allows us to partition variance explained and more easily illustrate middle-school variables' influence on college readiness. Second, imputation does not dramatically affect the results, although some differences are evident. When only high-school outcomes (SAT, ACT, and HSGPA) are imputed, the sample size shrinks from 11,612 to 1,513, and R^2 is .63 rather than .69. Partitioned variance explained is similar for most factors, although imputation increases the estimated influence of school characteristics (from 3% to 7%) and decreases the estimated influence of social engagement (from 9% to 4%). When neither the outcome nor any predictors are imputed, variance explained across factors remains stable, but the sample size shrinks to 894 and R^2 is reduced to .52.

Finally, PCA represents just one approach to measurement, so as a robustness check we also estimated a structural equation model (SEM) predicting the college-readiness composite. The SEM was not the focus of this study but rather a tool that allowed us to examine the sensitivity of our findings to alternate analytic methods, so we provide a high-level description of the model here. Manifest variables in the SEM are the same set specified in the appendix. Six latent constructs in the SEM representing the six middle-school factors predicted the exogenous college-readiness composite. Like the PCA approach, the SEM produced middle-school index scores. The PCA and SEM index scores were highly correlated ($r = .96$), suggesting an alternate approach to predicting college readiness yields nearly identical results. In addition, SEM-based measures of variance explained were similar to PCA results.[4]

Predicting College Outcomes

Our final research question concerns the forecasting of college outcomes. The principal use of the SAT and the ACT—whether the user is an examinee reviewing a score report or a university reviewing an application for admission—is gauging college readiness, or more specifically, the likelihood of academic success at a 4-year university. If that likelihood could be estimated with a similar degree of certainty multiple years in advance, students, parents, and teachers would have additional time to correct course and address specific areas of weakness. Middle-school indicators may offer such advance warning, but only if their predictions of college outcomes are reasonably accurate relative to the admissions tests' predictions. Predictive accuracy may be evaluated via R^2, which we

[4]Achievement = 18%; behavior = 13%; motivation = 12%; social engagement = 3%; family circumstances = 14%; school characteristics = 10%.

Table 2. Variance Explained in Postsecondary Outcomes by Middle-School and High-School Measures

		R^2			
Postsecondary Outcome	N[a]	**Grade 8 Test Scores**	**Middle-School Indicators**	**SAT**	**SAT and HSGPA**
First-Year GPA	3,173	.119	.173	.158	.242
Years 1 and 2 GPA	3,234	.131	.193	.180	.271
Cumulative GPA	3,305	.135	.196	.187	.271
Graduation[b]	3,488	.148	.273	.244	.293
	N[c]	**Grade 8 Test Scores**	**Middle-School Indicators**	**ACT**	**ACT and HSGPA**
First-Year GPA	2,712	.122	.161	.163	.248
Years 1 and 2 GPA	2,759	.122	.162	.170	.260
Cumulative GPA	2,838	.122	.173	.172	.270
Graduation[b]	3,043	.155	.282	.232	.290

[a]Sample restricted to SAT takers.
[b]Nagelkerke R^2.
[c]Sample restricted to ACT takers.

present in Table 2 for NELS Grade 8 standardized test scores, middle-school indicators, admissions test scores, and HSGPA across a variety of postsecondary outcomes in NELS.[5]

Table 2 illustrates three important points about middle-school and high-school predictors of postsecondary outcomes. The first two are not major foci of this section but they do bear some emphasis: (1) as noted previously, the middle-school index offers substantially more accurate forecasts of future performance than middle-school test scores alone (compare the first two columns), thanks to the inclusion of additional nonacademic student- and school-level predictors; (2) considering HSGPA alongside admissions test scores substantially improves predictions of college outcomes (compare the last two columns). This finding will not surprise college admissions researchers (Zwick, 2004), but it underscores one of the middle-school index's guiding principles—all else equal, more information is better.

The third point answers our final research question, and it is the focus of this section: using data 3 years prior, middle-school indicators predict college outcomes just as well as the SAT and ACT (compare the middle two columns). In fact, the middle-school index offers more accurate predictions than SAT for every outcome and more accurate predictions than ACT for two later-life outcomes—cumulative GPA and graduation. For earlier outcomes (e.g., first-year GPA) the ACT's predictions are slightly superior. Given the results in Table 2, it seems another benefit to collecting and summarizing college-readiness information in middle school is obtaining credible forecasts of college success. Put simply, when students are off track according to one or more college-readiness dimensions, an early warning may be useful.

Discussion

Middle-school indicators can offer powerful predictions of future success that may help educators more confidently assess students' odds of graduating high school ready for college. Consider the following: there were 1,881 NELS students (15% of the full sample) who did not attend any postsecondary institution in the year after high-school graduation, but who believed in high school their chances of going to college were "very high" or had teachers who believed they would go to college. Ninety percent of these students would have been flagged by the middle-school index in eighth grade (i.e., they would have been projected to land below the SAT, ACT, and HSGPA benchmarks). More startlingly, 45% of these students would have registered a middle-school index value low enough to predict with 99% confidence that, absent any intervention, they would not be college-ready by the end of high school. Patterns like these suggest educators could use some help more efficiently identifying students who are off track. Our findings therefore have implications for school systems, but they also have limitations and generate additional questions for future research. This section is parsed according to those topics.

Implications

The first question that should naturally arise from a readiness diagnosis in middle school is simple: what's next? Answering that question requires more than a single number from the middle-school index. It requires diagnoses specific to a student's achievement, behavior, motivation, and social engagement. To that end, we introduce a middle-school indicator summary in Figure 1, which communicates overall readiness classifications along with factor-specific information for five NELS students. Note that despite their influence on college readiness, family circumstances, and school characteristics are not included in Figure 1. Students, parents, and teachers have little control over these factors, so they are of limited use in determining appropriate next steps for a student who is off track.

In Figure 1, the sizes of the circles in each column represent the relative importance of each factor, based on eigendecomposition results presented in Table 1. In addition, overall index values and factor values have been converted to four discrete ordinal categories—*well prepared*, *prepared*, *partially prepared*, and *inadequately prepared*. For the purposes of this example the key category threshold is the one separating *prepared* and *partially prepared* students. The former are predicted to meet college-readiness benchmarks by the end of high school, and the latter are not. Student 2, for example, is well on her way to college readiness, with solid indicators across all dimensions. Student 4, on the other hand, is decidedly off track, and will require improvement in multiple dimensions.

[5]Both the math and verbal sections of the SAT were included in these predictions, and ACT predictions use the composite score. NELS Grade 8 assessments include mathematics, reading, history, and science.

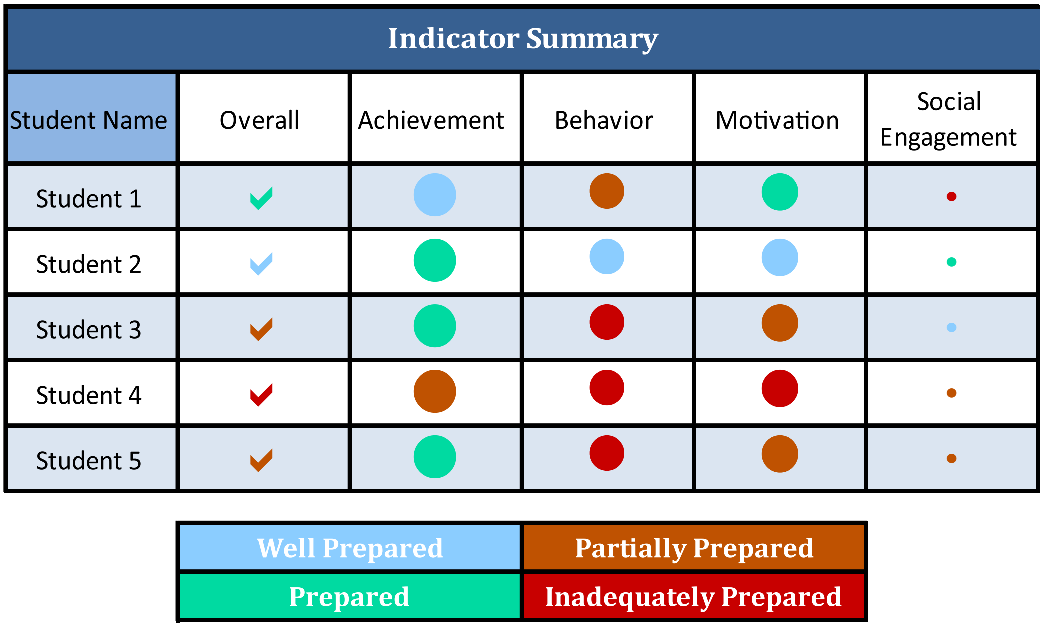

FIGURE 1. Example middle-school indicator summary.

Students 3 and 5 represent slightly different cases—they are predicted not to meet college-readiness benchmarks in high school, but targeted interventions in the areas of behavior and motivation could help them correct course. For example, Student 3 has had multiple discipline referrals and absences. If he could cut his absences in half and avoid discipline referrals and suspensions altogether, he would be on track to college readiness, even absent any change on any other indicator. Student 5, on the other hand, could get back on track by focusing on her studies outside of school. She reported spending less than an hour per week on homework. If she could spend one hour each week on each of four subjects (mathematics, English, science, and social studies), she too would be on track to college readiness—again without any change in her relative position on any other indicator.

More detailed diagnoses like these may be useful for parents and teachers seeking to pinpoint and address students' areas of weakness. Early warnings related to academic achievement (e.g., "Your low math score now suggests low math scores in the future") are not without value, but might not represent "actionable intelligence" for educators. Motivation and behavior dimensions, on the other hand, are composed of concrete and changeable attitudes and behaviors, empirically demonstrated to influence college readiness as measured by SAT, ACT, and HSGPA. The finding that motivation and behavior contribute significantly to college readiness is not unprecedented, but this study represents the first attempt to quantitatively compare the contribution of these factors to more commonly researched measures like achievement and socioeconomic status.

This study adds to the research literature not only by confirming middle-school information can be useful for researchers and practitioners interested in developing early-warning measures, but also by shifting the focus of those early-warning systems from reducing the risk of dropout (a laudable goal but certainly not the ultimate goal of K-12 education) to promoting college readiness. Demonstrating college readiness is a function of a complex set of interdependent attitudes and behaviors—not just cognitive ability and economic circumstance—may empower educators to intervene early and appropriately when students fall off track.

Limitations

The weaknesses in this research relate primarily to the data set and measures that underlie our statistical models. First, the data: NELS includes a considerable array of indicators collected on multiple dimensions (achievement, attitudes, and so on) at multiple levels (students, parents, teachers, and schools) across multiple years. To that end, our estimates may not be readily applicable in the field. We recognize few schools and school districts will have collected the diversity of variables available in NELS. Nor should the NELS variables represent the last word in college-readiness predictors. Indeed, the National Research Council's Committee on Defining Deeper Learning and 21st Century Skills (2012) lists numerous attributes (e.g., adaptability, self-reflection, grit) that are not available in NELS yet may be amenable to measurement (Duckworth & Quinn, 2009). Therefore, we hope this article offers a process, and not a fixed algorithm—a blueprint for developing quantitative middle-school college-readiness indicators using whatever data school systems have the capacity to collect.

A second NELS weakness is the age of the data. Students in this study were in eighth grade 26 years ago. It is reasonable to suspect some of the relationships we estimate between middle-school factors and high-school outcomes have changed in the past quarter century. One obvious example is social engagement, and this relates to both the age of the NELS data and measures it employs. Most of the variables that comprise the social engagement factor are binary (e.g., participation in the drama club or not). Statistically speaking, binary measures offer less predictive power than continuous measures, all else equal. It may not be surprising, then, that we found social engagement explained comparatively little variance in college readiness. Historically speaking, social engagement in 2014—influenced by the Internet and social media—probably looks a bit different than it did in 1988. Do middle-school data from 1988 fairly reflect middle-school realities in 2014? Moreover, will our 2014 estimates hold 26 years from now? We will not know the answers to these questions without a sustained national program of longitudinal data collection. More contemporary data employing sophisticated academic and affective measures is a *sine qua non* for rigorous college-readiness research moving forward.

Future Directions

While examining the predictive power of middle-school data and decomposing variance explained in college readiness are useful exercises from a research perspective, two additional steps should make this indicator system more helpful for end users. First, interpreting raw middle-school index values is difficult without an understanding of how those values relate to the likelihood of future success. A single cut score differentiating on-track and off-track middle-school students would be a step in the right direction, but multiple college-readiness performance levels such as those shown in Figure 1 would represent a more dramatic improvement over the binary classifications (college-ready versus not) currently available via ACT and SAT. As such, we employed ROC analysis to set cut scores along the middle-school index scale and define successive categories of college readiness. Each category has a conceptual definition and an empirical definition focused on the probability students in that category will reach college-readiness benchmarks in high school. We hinted at this ROC-based classification method in Figure 1. We will elaborate it further in future work.

Finally, extensions of this middle-school indicator system should focus on false negatives: students who are identified as off track in eighth grade, but end up succeeding in high school. These students may illuminate the steps required to get back on track. The more we learn about their paths to college readiness, the better equipped we will be to design targeted interventions that stand the best chance of supporting postsecondary access and success.

Appendix

NELS Observed Variables by Middle-School Factor

Label*	Mean	SD	Min	Max	Loading	% Missing
Achievement (PCA Variance Explained in Observed Variables = 16.3%)						
HISTORY/CIT/GEOG STANDARDIZED SCORE	51.08	10.09	15.7	80.8	.33	8.8%
MATHEMATICS STANDARDIZED SCORE	51.43	10.27	17.5	82.8	.37	8.4%
READING STANDARDIZED SCORE	51.23	10.08	17.1	79.6	.34	8.5%
SCIENCE STANDARDIZED SCORE	51.21	10.08	7.8	85.6	.33	8.5%
8TH GRADER SKIPPED KINDERGARTEN	.01	.08	−.3	3.7	.01	11.4%
8TH GRADER SKIPPED FIRST GRADE	.00	.06	−3.8	1.0	.01	11.4%
8TH GRADER SKIPPED SECOND GRADE	.00	.05	−.2	2.0	.00	11.4%
8TH GRADER SKIPPED THIRD GRADE	.00	.04	−.1	2.0	.01	11.4%
8TH GRADER SKIPPED FOURTH GRADE	.00	.04	−.2	1.2	.01	11.4%
8TH GRADER SKIPPED FIFTH GRADE	.00	.04	−.1	1.9	.00	11.4%
8TH GRADER SKIPPED SIXTH GRADE	.00	.05	−.2	2.4	−.01	11.4%
8TH GRADER SKIPPED SEVENTH GRADE	.00	.03	−1.3	1.0	−.01	11.4%
IN ADVANCED, ENRICHED, ACCELERATED ENGLISH	.33	.47	−1.5	2.0	.13	9.6%
IN ADVANCD, ENRICHD, ACCELERTD SOC.STUDIES	.25	.43	−1.4	2.1	.08	10.2%
IN ADVANCD, ENRICHED, ACCELERATED SCI	.27	.45	−1.4	2.1	.10	10.1%
IN ADVANCD, ENRICHED, ACCELERATED MATH	.42	.49	−1.8	2.1	.20	9.4%
ATTEND ALGEBRA AT LEAST ONCE A WEEK	.38	.49	−1.5	2.1	.26	15.7%
ENROLLED IN CLASSES FOR GIFTED STUDENTS	.19	.40	−1.7	1.6	.21	8.8%
EVER REPEAT KINDERGARTEN	.02	.15	−.6	1.0	−.04	9.2%
EVER REPEAT GRADE 1	.04	.20	−.7	1.0	−.09	9.2%
EVER REPEAT GRADE 2	.03	.16	−.5	1.0	−.08	9.2%
EVER REPEAT GRADE 3	.02	.14	−.5	1.0	−.07	9.2%
EVER REPEAT GRADE 4	.01	.11	−.4	1.0	−.06	9.2%
EVER REPEAT GRADE 5	.01	.11	−.4	1.0	−.07	9.2%
EVER REPEAT GRADE 6	.01	.11	−.4	1.0	−.06	9.2%
EVER REPEAT GRADE 7	.01	.11	−.4	1.0	−.07	9.2%
EVER REPEAT GRADE 8	.01	.11	−.4	1.0	−.06	9.2%
ENGLISH GRADES FROM GRADE 6 UNTIL NOW	1.99	.92	−1.2	6.3	−.27	7.2%
MATH GRADES FROM GRADE 6 UNTIL NOW	2.01	.97	−1.2	5.8	−.24	7.3%
SCI GRADES FROM GRADE 6 UNTIL NOW	2.12	1.01	−2.0	5.8	−.30	7.9%
SOC. STUDIES GRDS FRM GRADE 6 UNTIL NOW	2.10	1.04	−2.3	6.2	−.30	8.3%

(*Continued*)

Behavior (PCA Variance Explained in Observed Variables = 20.9%)						
TALK TO COUNSELOR ABOUT DISCIPLINE PROBS	.13	.33	−1.1	1.5	.21	8.4%
TALK TO TEACHER ABT DISCIPLINE PROBLEMS	.20	.40	−1.2	1.9	.18	8.6%
TALK TO OTHER ADULT ABT DISCIPLINE PROBS	.27	.44	−1.3	2.1	.19	8.3%
SENT TO OFFICE FOR MISBEHAVING	.35	.61	−1.7	2.8	.28	6.2%
# OF TIMES LATE FOR SCHOOL PAST 4 WEEKS	.51	.82	−2.4	4.0	.15	8.7%
TIME SPENT ON MATH HOMEWORK EACH WEEK	1.99	1.49	−3.6	8.7	−.35	8.7%
TIME SPENT ON SCI HOMEWORK EACH WEEK	1.52	1.26	−4.0	7.0	−.32	8.9%
TIME SPENT ON ENGLISH HOMEWORK EACH WEEK	1.69	1.29	−4.0	7.3	−.34	9.1%
TIME SPENT ON SOC STUDIES HOMEWK EACH WK	1.71	1.34	−4.3	10.2	−.32	9.2%
TIME SPENT ON ALL OTH SUBJECTS EACH WEEK	1.77	1.46	−4.1	7.1	−.29	9.0%
STUDENT RARELY COMPLETES HOMEWORK (T1)	.16	.37	−11.8	1.7	.22	14.8%
STUDENT IS FREQUENTLY TARDY (TCHR 1)	.05	.21	−3.5	5.1	.15	15.8%
STUDENT RARELY COMPLETES HOMEWORK (T2)	.17	.38	−1.3	11.3	.23	15.0%
STUDENT IS FREQUENTLY TARDY (TCHR 2)	.05	.22	−.9	9.7	.16	15.7%
HOW MANY TIMES SUSPENDED FROM SCHOOL	.09	.35	−1.0	4.0	.18	6.0%
TEEN EVER BEEN SUSPENDED FROM SCHOOL	.14	.34	−1.2	1.7	.23	13.7%
NUMBER OF DAYS ABSENT, 88–89	8.81	10.92	−348.4	487.4	.17	49.0%
Motivation (PCA Variance Explained in Observed Variables = 10.2%)						
SELF CONCEPT NELS v1	.00	.73	−3.5	2.5	.25	5.5%
SELF CONCEPT NELS v2	.00	.65	−2.9	2.2	.27	5.5%
NO. OF YRS 8TH GRADER AT PRESENT SCHL	2.98	1.41	−15.3	21.7	.02	11.3%
NO. OF TIMES 8TH GRADER CHANGED SCHOOLS	1.10	1.61	−5.3	120.1	−.03	11.4%
8TH GRADER SKIPPED KINDERGARTEN	.01	.08	−.3	3.7	.01	11.4%
8TH GRADER SKIPPED FIRST GRADE	.00	.06	−3.8	1.0	.01	11.4%
8TH GRADER SKIPPED SECOND GRADE	.00	.05	−.2	2.0	.01	11.4%
8TH GRADER SKIPPED THIRD GRADE	.00	.04	−.1	2.0	.00	11.4%
8TH GRADER SKIPPED FOURTH GRADE	.00	.04	−.2	1.2	.01	11.4%
8TH GRADER SKIPPED FIFTH GRADE	.00	.04	−.1	1.9	−.01	11.4%
8TH GRADER SKIPPED SIXTH GRADE	.00	.05	−.2	2.4	.00	11.4%
8TH GRADER SKIPPED SEVENTH GRADE	.00	.03	−1.3	1.0	.00	11.4%
HOW FAR IN SCH DO YOU THINK YOU WILL GET	4.63	1.25	−.3	9.2	.24	5.7%
IN ADVANCED,ENRICHED,ACCELERATED ENGLISH	.33	.47	−1.5	2.0	.14	9.6%
IN ADVANCD,ENRICHD,ACCELERTD SOC.STUDIES	.25	.43	−1.4	2.1	.12	1.2%
IN ADVANCD,ENRICHED,ACCELERATED SCI	.27	.45	−1.4	2.1	.14	1.1%
IN ADVANCD,ENRICHED,ACCELERATED MATH	.42	.49	−1.8	2.1	.16	9.4%
MATH WILL BE USEFUL IN MY FUTURE	1.70	.75	−1.4	4.6	−.17	8.6%
ENGLISH WILL BE USEFUL IN MY FUTURE	1.85	.77	−1.5	6.1	−.18	8.7%
SOC. STUDIES WILL BE USEFUL IN MY FUTURE	2.35	.86	−2.3	6.0	−.17	9.2%
SCI WILL BE USEFUL IN MY FUTURE	2.14	.89	−1.1	5.8	−.20	9.3%
EVER REPEAT KINDERGARTEN	.02	.15	−.6	1.0	−.03	9.2%
EVER REPEAT GRADE 1	.04	.20	−.7	1.0	−.07	9.2%
EVER REPEAT GRADE 2	.03	.16	−.5	1.0	−.04	9.2%
EVER REPEAT GRADE 3	.02	.14	−.5	1.0	−.05	9.2%
EVER REPEAT GRADE 4	.01	.11	−.4	1.0	−.05	9.2%
EVER REPEAT GRADE 5	.01	.11	−.4	1.0	−.06	9.2%
EVER REPEAT GRADE 6	.01	.11	−.4	1.0	−.05	9.2%
EVER REPEAT GRADE 7	.01	.11	−.4	1.0	−.06	9.2%
EVER REPEAT GRADE 8	.01	.11	−.4	1.0	−.05	9.2%
TIME SPENT ON MATH HOMEWORK EACH WEEK	1.99	1.49	−3.6	8.7	.30	8.7%
TIME SPENT ON SCI HOMEWORK EACH WEEK	1.52	1.26	−4.0	7.0	.26	8.9%
TIME SPENT ON ENGLISH HOMEWORK EACH WEEK	1.69	1.29	−4.0	7.3	.28	9.1%
TIME SPENT ON SOC STUDIES HOMEWK EACH WK	1.71	1.34	−4.3	10.2	.26	9.2%
TIME SPENT ON ALL OTH SUBJECTS EACH WEEK	1.77	1.46	−4.1	7.1	.24	9.0%
STUDENT PERFORMS BELOW ABILITY (TCHR 1)	.22	.42	−7.2	10.8	−.15	15.3%
STUDENT PERFORMS BELOW ABILITY (TCHR 2)	.22	.42	−18.2	3.0	−.14	15.1%
LOCUS OF CONTROL NELS v1	.04	.71	−2.7	2.8	.28	5.6%
LOCUS OF CONTROL NELS v2	.03	.60	−2.5	2.3	.30	5.6%
MAGNET SCHOOL	.00	.02	.0	1.0	.00	9.2%

(*Continued*)

Social Engagement (PCA Variance Explained in Observed Variables = 15.4%)						
TALK TO TEACHER ABOUT H.S. PROGRAMS	.42	.49	−1.6	2.3	.14	6.2%
TALK TO TEACHER ABOUT COURSES AT SCHOOL	.46	.50	−1.5	2.2	.14	7.1%
TALK TO TEACHER ABOUT STUDIES IN CLASS	.66	.47	−.9	2.8	.13	7.0%
STUDENTS IN CLASS SEE ME AS POPULAR	2.01	.58	−.3	4.3	−.14	8.2%
PARTICIPATED IN SCOUTING	1.16	.42	−.6	3.0	.11	12.8%
PARTICIPATED IN RELIGIOUS YOUTH GROUPS	1.38	.54	−.8	3.7	.18	12.9%
PARTICIPATED IN NON-SCHOOL TEAM SPORTS	1.39	.53	−.7	3.3	.18	13.3%
PARTICIPATED IN SUMMER PROGRAMS	1.21	.43	−.9	3.0	.24	13.5%
PARTICIPATED IN ANY OTHER ACTIVITIES	1.49	.57	−1.0	3.7	.20	14.6%
PARTICIPATED IN SCIENCE FAIRS	.00	.47	−1.6	2.0	.17	12.8%
PARTICIPATED IN VARSITY SPORTS	.00	.57	−2.5	2.2	.19	12.6%
PARTICIPATED IN INTRAMURAL SPORTS	.00	.54	−2.3	2.7	.21	13.1%
PARTICIPATED IN BAND OR ORCHESTRA	.00	.46	−1.8	1.8	.14	13.5%
PARTICIPATED IN CHORUS	.00	.47	−1.8	2.4	.17	13.3%
PARTICIPATED IN MATH CLUB	.00	.27	−1.1	1.9	.26	13.7%
PARTICIPATED IN SUBJECT MATTER CLUB	.00	.35	−1.5	1.9	.27	13.8%
PARTICIPATED IN DEBATE TEAM	.00	.27	−1.0	1.9	.28	13.8%
PARTICIPATED IN DRAMA CLUB	.00	.32	−1.2	1.9	.25	13.9%
PARTICIPATED IN ACADEMIC HONORS SOCIETY	.00	.40	−1.7	1.9	.25	14.0%
PARTICIPATED IN STUDENT NEWSPAPER	.00	.39	−1.6	2.0	.25	13.9%
PARTICIPATED IN STUDENT YEARBOOK	.00	.42	−1.6	2.2	.24	13.9%
PARTICIPATED IN STUDENT COUNCIL	.00	.47	−1.8	2.0	.25	14.2%
PARTICIPATED IN RELIGIOUS ORGANIZATION	.00	.42	−1.6	1.9	.25	14.3%
Family Circumstances (PCA Variance Explained in Observed Variables = 6.3%)						
YEARLY FAMILY INCOME	9.75	2.60	−6.5	72.2	.36	13.4%
FAMILY COMPOSITION	1.75	1.33	−3.0	7.3	−.11	6.1%
NO. OF TIMES 8TH GRADER CHANGED SCHOOLS	1.10	1.61	−5.3	120.1	.02	11.4%
PARENTS' HIGHEST EDUCATION LEVEL	3.08	1.27	−13.5	28.7	.42	5.6%
CURRENT LANGUAGE = GREEK	.00	.01	.0	1.0	−.01	5.2%
CURRENT LANGUAGE = POLISH	.00	.01	.0	1.0	.08	5.2%
CURRENT LANGUAGE = PORTUGESE	.00	.01	.0	1.0	−.01	5.2%
CURRENT LANGUAGE = OTHER	.00	.05	.0	1.0	.00	5.2%
CURRENT LANGUAGE = SPANISH	.01	.11	.0	1.0	−.13	5.2%
CURRENT LANGUAGE = CHINESE	.00	.04	.0	1.0	−.01	5.2%
CURRENT LANGUAGE = JAPANESE	.00	.01	.0	1.0	−.03	5.2%
CURRENT LANGUAGE = KOREAN	.00	.02	.0	1.0	.00	5.2%
CURRENT LANGUAGE = FILIPINO	.00	.03	.0	1.0	.02	5.2%
CURRENT LANGUAGE = ITALIAN	.00	.02	.0	1.0	−.01	5.2%
CURRENT LANGUAGE = FRENCH	.00	.03	.0	1.0	−.01	5.2%
CURRENT LANGUAGE = GERMAN	.00	.02	.0	1.0	.00	5.2%
ANY OTHER LANGUAGE SPOKEN IN HOME	.22	.41	−1.0	1.4	−.12	5.2%
HOME LANGUAGE = GREEK	.00	.03	.0	1.0	−.01	5.2%
HOME LANGUAGE = POLISH	.00	.03	.0	1.0	.03	5.2%
HOME LANGUAGE = PORTUGESE	.00	.03	.0	1.0	−.01	5.2%
HOME LANGUAGE = OTHER	.02	.13	.0	1.0	.02	5.2%
HOME LANGUAGE = SPANISH	.07	.25	.0	1.0	−.24	5.2%
HOME LANGUAGE = CHINESE	.01	.09	.0	1.0	.01	5.2%
HOME LANGUAGE = JAPANESE	.00	.03	.0	1.0	−.01	5.2%
HOME LANGUAGE = KOREAN	.00	.06	.0	1.0	.04	5.2%
HOME LANGUAGE = FILIPINO	.01	.08	.0	1.0	.03	5.2%
HOME LANGUAGE = ITALIAN	.00	.06	.0	1.0	−.02	5.2%
HOME LANGUAGE = FRENCH	.00	.07	.0	1.0	−.01	5.2%
HOME LANGUAGE = GERMAN	.00	.05	.0	1.0	.01	5.2%
NUMBER OF SIBLINGS	2.26	1.56	−3.4	8.5	−.20	5.5%
NUMBER OF OLDER SIBLINGS	1.26	1.48	−3.9	6.8	−.17	6.0%
FATHERS' HIGHEST LEVEL OF EDUCATION	3.18	1.91	−3.5	76.8	.41	19.0%
MOTHERS' HIGHEST LEVEL OF EDUCATION	2.98	1.72	−51.4	47.3	.38	15.9%
FAMILY HAS A COMPUTER	.42	.50	−1.5	2.1	.24	8.5%
HOW FAR IN SCHL FATHER WANTS ME TO GO	5.04	1.21	.3	10.3	.20	12.1%
HOW FAR IN SCHL MOTHER WANTS ME TO GO	5.01	1.16	.0	9.4	.20	11.0%

(*Continued*)

NO. OF HOURS WORKED FOR PAY PER WEEK	1.20	1.10	−2.5	5.0	.00	6.3%
WORK = LAWN WORK	.13	.33	.0	1.0	.03	6.3%
WORK = OTHER	.08	.27	.0	1.0	−.04	6.3%
WORK = WAITER/WAITRESS	.01	.10	.0	1.0	−.02	6.3%
WORK = NEWSPAPER ROUTE	.05	.22	.0	1.0	.01	6.3%
WORK = BABYSITTING	.41	.49	.0	1.0	.03	6.3%
WORK = FARM WORK	.04	.20	.0	1.0	−.04	6.3%
WORK = OTHER MANUAL LABOR	.03	.18	.0	1.0	.00	6.3%
WORK = STORE CLERK	.02	.13	.0	1.0	.00	6.3%
WORK = OFFICE/CLERICAL	.01	.09	.0	1.0	.02	6.3%
WORK = ODD JOBS	.05	.21	.0	1.0	.00	6.3%
FIRST LANGUAGE = GREEK	.00	.03	.0	1.0	−.01	5.2%
FIRST LANGUAGE = POLISH	.00	.02	.0	1.0	.05	5.2%
FIRST LANGUAGE = PORTUGESE	.00	.03	.0	1.0	−.01	5.2%
FIRST LANGUAGE = OTHER	.02	.13	.0	1.0	.01	5.2%
FIRST LANGUAGE = SPANISH	.06	.24	.0	1.0	−.23	5.2%
FIRST LANGUAGE = CHINESE	.01	.10	.0	1.0	.01	5.2%
FIRST LANGUAGE = JAPANESE	.00	.04	.0	1.0	.00	5.2%
FIRST LANGUAGE = KOREAN	.00	.07	.0	1.0	.04	5.2%
FIRST LANGUAGE = FILIPINO	.00	.07	.0	1.0	.02	5.2%
FIRST LANGUAGE = ITALIAN	.00	.05	.0	1.0	−.01	5.2%
FIRST LANGUAGE = FRENCH	.00	.05	.0	1.0	.01	5.2%
FIRST LANGUAGE = GERMAN	.00	.05	.0	1.0	.01	5.2%
School Characteristics (PCA Variance Explained in Observed Variables = 15.1%)						
THE SCHOOL IS A SAFE PLACE	1.90	.68	−16.8	19.1	−.14	12.7%
COMPOSITE STUDENT-TEACHER RATIO	17.71	5.07	−1.7	39.0	−.02	6.2%
I DON'T FEEL SAFE AT THIS SCHOOL	3.27	.71	.4	5.8	.09	7.1%
% OF AMERICAN INDIAN,ALASKAN 8TH GRADERS	1.09	7.06	−24.1	100.0	−.03	6.7%
% OF ASIAN,PACIFIC ISLANDER 8TH GRADERS	2.47	6.62	−21.3	92.0	−.03	6.7%
% OF HISPANIC 8TH GRADERS	9.52	20.74	−49.9	112.5	−.17	6.7%
% OF BLACK NON-HISPANIC 8TH GRADERS	10.58	19.54	−61.5	100.0	−.15	6.7%
% OF WHITE NON-HISPANIC 8TH GRADERS	76.36	29.12	−52.4	186.0	.23	6.7%
DEGREE STUDENT TARDINESS IS A PROBLEM	2.80	.74	−.1	5.7	.26	6.5%
DEGREE STUDENT ABSENTEEISM IS A PROBLEM	2.91	.80	−.1	5.7	.29	6.6%
DEGREE STUDENT CLASS CUTTING IS A PROB	3.48	.67	1.0	5.8	.31	6.2%
DEGREE STUDENT PHYS CONFLICTS ARE A PROB	3.10	.68	.3	5.7	.28	6.3%
DEGREE ROBBERY OR THEFT IS A PROBLEM	3.26	.62	.6	6.0	.25	6.2%
DEGREE VANDALISM IS A PROBLEM	3.32	.64	.9	5.6	.28	6.2%
DEGREE STUDENT ALCOHOL USE IS A PROBLEM	3.37	.71	.5	6.3	.16	6.2%
DEGREE STUDENT ILLEG DRUG USE IS A PROB	3.39	.66	.8	5.9	.22	6.2%
DEGREE STUDENT WEAPONS ARE A PROBLEM	3.80	.48	1.0	5.4	.26	6.3%
DEGREE PHYS ABUSE OF TEACHERS IS A PROB	3.92	.34	1.0	5.2	.22	6.4%
DEGREE VERBAL ABUSE OF TEACHRS IS A PROB	3.47	.61	1.0	6.0	.27	6.4%
DAYS ABSENT DURING FIRST SEMESTR THIS YR (T1)	2.28	1.15	−3.3	55.9	−.05	14.3%
DAYS ABSENT DURING FIRST SEMESTR THIS YR (T2)	2.27	1.14	−41.7	7.4	−.06	13.9%
% OF STUDENTS ELIGIBLE FOR FREE LUNCH	22.30	22.57	−65.1	121.9	−.21	6.7%
% OF STUDENTS IN REMEDIAL READING	.10	.12	−.3	1.0	−.19	6.4%
% OF STUDENTS IN REMEDIAL MATH	.07	.10	−.3	1.0	−.17	6.4%
% OF TEACHERS WITH A GRADUATE DEGREE	.47	.25	−.6	1.5	.01	8.8%
CHORUS OR CHOIR AVAILABLE	.00	.33	−1.2	1.2	.05	6.3%
COMPUTER CLUBS AVAILABLE	.00	.49	−2.1	1.6	.03	6.4%
DRAMA CLUBS AVAILABLE	.00	.48	−1.7	2.1	.03	6.3%
SERVICE CLUBS AVAILABLE	.00	.49	−1.8	2.0	.01	6.3%
MATH CLUB AVAILABLE	.00	.47	−2.0	1.7	.04	6.4%
OTHER SUBJ MATTER CLUB AVAILABLE	.00	.48	−1.9	1.9	.02	6.6%
STUDENT NEWSPAPER AVAILABLE	.00	.48	−1.6	1.7	.01	6.3%
STUDENT YEARBOOK AVAILABLE	.00	.45	−1.6	2.0	.02	6.2%
FOREIGN LANGUAGE CLUBS AVAILABLE	.00	.40	−1.5	1.6	.04	6.2%
ORCHESTRA AVAILABLE	.00	.47	−1.7	1.8	.00	6.3%
RELIGIOUS ORGANIZATIONS AVAILABLE	.00	.35	−1.2	1.3	.10	6.2%
DEBATE AND SPEECH TEAM AVAILABLE	.00	.44	−1.6	1.4	.01	6.2%
INTERSCHOLASTIC SPORTS AVAILABLE	.00	.36	−1.2	1.5	.03	6.3%

*Note: Negatively worded items are italicized and binary items are bolded.

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