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A Multidimensional Perspective of College Readiness:

Relating Student and School Characteristics to Performance on the ACT®

Daniel M. McNeish
University of Maryland

Justine Radunzel, PhD
ACT

Edgar Sanchez, PhD
ACT

Daniel M. McNeish is a PhD candidate in the Measurement, Statistics, and Evaluation Program at the University of Maryland College Park and interned at ACT during the summer of 2014.

Justine Radunzel, a principal research scientist in the Statistical and Applied Research Department at ACT, works on postsecondary outcomes research and validity evidence for the ACT® test.

Edgar Sanchez, a research scientist in the Statistical and Applied Research Department at ACT, works on predictive modeling of student educational outcomes such as enrollment, persistence, and graduation.

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Abstract

This study examined the contributions of students' noncognitive characteristics toward explaining performance on the ACT® test, over and above traditional predictors such as high school grade point average (HSGPA), coursework taken, and school characteristics. The sample consisted of 6,440 high school seniors from 4,541 schools who took the ACT in the fall of 2012 and completed an online questionnaire about their high school experience, study and work habits, parental involvement, educational and occupational plans and goals, and college courses taken and/or credits earned in high school. Twelve percent of the total sample responded and met the study inclusion criteria.

A blockwise regression model with cluster-robust standard errors was used to assess the relationships between cognitive and noncognitive characteristics with ACT scores. The total variance in ACT scores accounted for by available student and school characteristics ranged from 44% (reading) to 61% (Composite). HSGPA explained the most variance (20% to 31%), high school coursework taken explained an additional 8% (reading) to 17% (mathematics), and high school characteristics accounted for an additional 7% to 9% of the variance in ACT scores. After accounting for these traditional predictors, students' noncognitive factors explained between 4% and 7% of the variance in ACT scores. These noncognitive characteristics included indicators of needing help in improving subject-related academic skills, educational plans, parental involvement, perceptions of education, and taking the ACT test prior to senior year. Socioeconomic status and other demographic characteristics accounted for less variance in ACT scores (4% or below), after adjusting for other student and school characteristics. Moreover, adjusted mean score differences among racial/ethnic, family income, and parental education groups were substantially reduced, compared to unadjusted group differences. Students' noncognitive characteristics were also highly related to HSGPA. Study findings suggest that noncognitive characteristics affect ACT scores directly as well as through their impact on HSGPA.

In light of the growing interest for evaluating both cognitive and noncognitive measures of college readiness, the results from this study may help to provide better context and guidance for the interpretation of college readiness measures. These findings also contribute to a more holistic understanding of college readiness. This perspective is important in order to better understand the multidimensional nature of college and career readiness and subsequent success.

Introduction

To meet their admission goals, four-year postsecondary institutions often rely on academic measures to help determine the likelihood that a student will be successful in college (Clinedinst, 2015). Academic measures often include grades in college preparatory courses, strength of high school curriculum, standardized test scores (the ACT or SAT), and high school grade point average (HSGPA), because these measures have been found to be useful in identifying students who are ready for college and predicting students' eventual success in college (Kobrin, Patterson, Shaw, Mattern, & Barbuti, 2008; Radunzel & Noble, 2012; Sawyer, 2010).

Recently, there has been an increased interest in taking a more holistic approach to evaluating students' college readiness levels to better equip students with the knowledge, skills, and support they need to succeed in college (Farrington, Roderick, Allensworth, Nagaoka, Keyes, Johnson, & Beechum, 2012; Mattern, Burrus, Camara, O'Connor, Hanson, Gambrell, Casillas, & Bobek, 2014). This interest stems from the growing body of research that suggests that other noncognitive characteristics can improve college success predictions beyond those based on academic measures alone.[1] For example, in a meta-analysis of factors predicting college outcomes, Robbins, Lauver, Le, Davis, Langley, and Carlstrom (2004) argued that noncognitive characteristics can help to account for some of the remaining variability unaccounted for by academic measures. Specifically, the authors found that noncognitive factors such as motivation, academic goals, and academic self-efficacy[2] were significantly related to college grades and retention, even after controlling for socioeconomic status (SES), HSGPA, and ACT/SAT scores. Other noncognitive characteristics that have been found to be useful for predicting various measures of academic success in K–12 and/or college include: academic and social integration (Milem & Berger, 1997; Tinto, 1993), parental involvement (Flint, 1992; Henderson & Mapp, 2002), study attitudes (Zimmerman, Parks, Gray, & Michael, 1977), personality (Ridgell & Lounsbury, 2004), student involvement (Astin, 1993), problem-solving (Le, Casillas, Robbins, & Langley, 2005), student engagement (Lee & Shute, 2009), behavioral learning strategies (Lee & Shute, 2009), and conscientiousness (Poropat, 2009).

In a recent study, Gaertner and McClarty (2015) conducted an investigation of both cognitive and noncognitive factors affecting a college readiness index derived from students' HSGPA and ACT/SAT scores. Using data from the National Education Longitudinal Study of 1988, these researchers predicted their college readiness index from six component scores identified from a principal components analysis. These components, derived from 140 middle school variables, included: academic achievement, motivation and commitment, behavior, social engagement, family circumstances, and school characteristics. They found that about one third of the variability in their college readiness index was accounted for by the motivation, social, and behavior components; nearly 70% was explained by all six components.

[1] The definition of noncognitive characteristics (sometimes referred to as psychosocial or non-academic characteristics) can vary widely, but in general, the term has become a catchall phrase used to describe any factors beyond standardized test scores, HSGPA, coursework taken, class rank, and student demographics (Sommerfeld, 2011).

[2] According to Robbins et al. (2004), the construct definition for academic self-efficacy is a "self-evaluation of one's ability and/or chances for success in the academic environment."

Additional prior research has shown that high school grades and coursework are related to standardized achievement scores. For example, Noble, Davenport, Schiel, and Pommerich (1999a, 1999b) found that HSGPA accounts for nearly 40% of the variance in ACT Composite scores. Specific coursework taken in high school accounted for 9% of the variability in ACT Composite scores above that explained by HSGPA (Noble et al., 1999a, 1999b). This, however, leaves more than half of the variability in ACT scores unaccounted for.

Noble et al. (1999a, 1999b) also found that although HSGPA and ACT scores are related and have some noncognitive predictors in common, there are some noncognitive predictors related to HSGPA that are not directly related to ACT scores. Moreover, the two variables measure different aspects of academic achievement. ACT scores are reported on a scale that maintains the same meaning across years and across high schools; for this reason, these scores are not affected by differential grading standards. The scores reflect the level of educational achievement at a moment in time, often at the end of a student's junior year or beginning of the senior year in high school. HSGPA, in contrast, reflects performance in courses over the duration of high school. Some research on HSGPA indicates that teachers explicitly consider behavior and other noncognitive characteristics in assigning grades (Campbell, 2011). In this way, HSGPA is not only affected by level of content mastery, but also by the courses taken and a student's personal behaviors, such as whether the student is prudent about taking good notes, putting forth effort and participating in class, completing homework assignments, and preparing well for course exams.

In addition to student characteristics, previous research has shown academic performance to vary as a function of school characteristics. For example, past studies have found substantial variability among schools in the academic achievement levels of their students (as measured by ACT scores), even after accounting for differences in their students' characteristics (Sawyer, 2008). Moreover, relationships have been documented between academic outcomes (e.g., HSGPA, standardized tests, high school dropout) and school-level characteristics such as percentage of students on free/reduced lunch (Swanson, 2004), public school status (Lubienski, Lubienski, & Crane, 2008), wealth of the community (Kim & Sunderman, 2005), and racial/ethnic composition of the school (Cook & Evans, 2000). Measures of school culture and climate, such as those related to college-going expectations/aspirations and teacher quality, have also been suggested to be informative in studying student achievement (MacNeil, Prater, & Busch, 2009; Oseguera, 2013). Other studies have reported that schools that serve high proportions of low-income and racial/ethnic minority students often find it challenging to retain effective teachers due to poor work environments where effective teaching and learning are not supported (Johnson, Kraft, & Papay, 2012).

Average ACT scores also substantially differ among racial/ethnic and family income groups and by parental education level (ACT, 2014a; ACT & Council for Opportunity in Education, 2013; ACT & National Council for Community and Education Partnerships, 2013). For example, for the ACT-tested graduating class of 2014, average ACT Composite scores for Hispanic and African American students are over 3.0 and 5.0 scale score points lower than that for White students (18.8, 17.0, and 22.3, respectively). However, differences also exist among these demographic groups in average HSGPA and in the mathematics and science courses typically taken in high school (Radunzel, 2015).

Given the desire to have all students graduate from high school prepared for college or the workforce, more research is needed to understand the multitude of characteristics that foster readiness among students so that we can better prepare them for future success. As such, the primary purpose of this study is to explore the effects of noncognitive factors and student demographic characteristics on ACT test scores above and beyond HSGPA, high school coursework taken, and aspects of students' school environment, with an emphasis on noncognitive measures related to academic goals, behaviors, self-perceptions, and parental involvement. This study will build upon the work of Noble et al. (1999a, 1999b) and Gaertner and McClarty (2015) by using more proximal measures of academic preparation for a more recent cohort of high school students. Second, we will examine how mean differences in ACT scores among demographic groups (e.g., race/ethnicity, parental education, family income, gender) change after other cognitive, school-related, and noncognitive characteristics are taken into account. Third, to better understand differences in factors related to HSGPA and standardized test scores, we will investigate the extent to which noncognitive characteristics influence HSGPA, a traditional predictor of ACT scores. Fourth, from a methodological perspective, this study illustrates applications of statistical techniques that are not commonly used in educational research.

Data

Data Collection

Sampling Frame

The sampling frame consisted of the registration records of all US high school seniors from the 2013 high school graduating class who registered for the October or December 2012 national test dates of the ACT. Individuals were removed from the sampling frame if they did not provide a valid email address. Additionally, students who had been selected for participation in other recent ACT projects or studies were also removed from the sampling frame. The final sampling frames for the October and December 2012 test administrations included 296,890 and 279,148 high school seniors, respectively.

Sampling Procedure

For each of the two test dates, 28,000 registrants were randomly sampled from the sampling frame using simple random sampling as the sample selection method—that is, every student in the sampling frame had an equal probability of selection and sampling was without replacement. This resulted in the selection of 56,000 registrants. Student characteristics were found to be similar between the random sample and the sampling frame.

Next, emails were sent to the sampled registrants inviting them to complete an online questionnaire on the Monday after the date of the ACT test administration (which took place on Saturday for both administrations). Reminder emails to non-respondents were sent four and ten days after the initial contact. A third reminder email was also sent to the non-respondents from the December sample.

A total of 8,447 registrants responded to the online questionnaire (15%). Of these respondents, 1,222 (14%) did not take the ACT test that they registered for. Of the 7,225 registrants with ACT test scores, 785 (11%) either responded to only the first item on the questionnaire about whether they took the ACT in October or December 2012, or did not indicate plans of enrolling in college and therefore were not administered all of the remaining questionnaire questions. The final sample for the study included 6,440 college-bound high school seniors from the 2013 ACT-tested high school graduating class (12% of the initial sample).

Instruments

Data for this study were taken from two sources: the ACT, and an online questionnaire developed to collect information about students' academic engagement, parental involvement in college planning, and students' own college intentions, plans, expectations, commitments, and financial concerns.

The ACT

The ACT is a curriculum-based educational achievement test taken by nearly two million students each year. It consists of four academic tests in English, mathematics, reading, and science, and an optional writing test. The tests are designed to measure skills that are acquired in high school and that are important for success in the first year of college (ACT, 2013).[3] The ACT Composite score is the arithmetic average of the scores for the four academic tests (English, mathematics, reading, and science). Scores are reported on a scale of 1 to 36. The ACT English, mathematics, reading, science, and Composite scores were used as the dependent variables (outcome measures) for the study. A brief description of the four academic tests is provided below.

- The English test is a 75-question, 45-minute test, covering usage/mechanics (such as punctuation, grammar and usage, and sentence structure) and rhetorical skills (such as strategy, organization, and style).
- The mathematics test is a 60-question, 60-minute test designed to measure the mathematical skills students have typically acquired in courses taken by the end of 11th grade. It covers six content areas: Pre-Algebra, Elementary Algebra, Intermediate Algebra, Coordinate Geometry, Plane Geometry, and Trigonometry.
- The reading test is a 40-question, 35-minute test that measures reading comprehension. The reading test is based on four types of reading selections: social studies, natural sciences, literary narrative or prose fiction, and humanities.
- The science test is a 40-question, 35-minute test that measures the skills required in the natural sciences: interpretation, analysis, evaluation, reasoning, and problem solving.

At the time students register to take the ACT, they are asked to complete a Course Grade Information Section (CGIS) and a Student Profile Section (SPS). The CGIS provides information about students' coursework and grades in 30 specific high school courses. Students are asked to indicate whether they have taken or are currently taking a particular course, or whether they plan to take it prior to graduating from high school. For courses already completed, students are also asked to indicate the letter grade they received (A–F). Prior studies have shown that students report high school coursework and grades with a high degree of accuracy relative to information provided in their transcripts (Sanchez & Buddin, 2015; Shaw & Mattern, 2009). From the information provided on the CGIS, HSGPA was calculated from 23 specific courses taken in English, mathematics, social studies, and science. Subject-specific GPAs were also calculated.

Course information from the CGIS was also used to examine specific course taking patterns in mathematics and science that have been outlined in previous studies (ACT, 2004; Noble &

[3] These first-year college expectations are summarized in the ACT College and Career Readiness Standards™ (available at www.act.org/standard).

Schnelker, 2007). Course patterns are constructed such that the incremental benefit of specific courses could be determined. In mathematics, the course sequence patterns include:

- Less than Algebra I, Algebra II, and Geometry (labeled as Less AAG)
- Algebra I, Algebra II, and Geometry (AAG)
- Algebra I, Algebra II, Geometry, and other advanced math course (AAGO)
- Algebra I, Algebra II, Geometry, and Trigonometry (AAGT)
- Algebra I, Algebra II, Geometry, Trigonometry, and other advanced math course (AAGOT)
- Algebra I, Algebra II, Geometry, Trigonometry, and Calculus (AAGTC)
- Algebra I, Algebra II, Geometry, Trigonometry, Calculus, and other advanced course (AAGOTC)
- Other sequence of 3 or more years of mathematics courses (Other-High)
- Other sequence of fewer than 3 years of mathematics courses (Other-Low)

Sequences in science courses are:

- Less than Biology or other sequence of less than 3 years
- Biology
- Biology and Chemistry
- Biology, Chemistry, and Physics
- Other sequence of 3 years

Courses in social studies were also considered but did not follow a clear-cut sequence as in science and mathematics. Consequently, Government, Economics, Geography, Psychology, and History (other than American or World) were considered individually. English course information was also obtained from the CGIS; however, nearly all students reported taking English 9, English 10, English 11, and English 12. As a result of the low variability, high school English courses were not included in the analysis.

From the CGIS course information, indicators were developed for whether students had taken a core curriculum in English, mathematics, science, and social studies as well as for all subjects. A core curriculum was defined as four years of English and three years each of mathematics, science, and social studies. The number of years students studied a foreign language was also calculated from the CGIS.

The SPS includes noncognitive information such as students' expected educational attainment (a measure of academic goals; Allen, 1999; Cabrera & La Nasa, 2001; Eppler & Harju, 1997; Robbins et al., 2004) and whether they indicate needing help in improving their skills in a variety of subject areas. The SPS also collects demographic and background information as well as information about students' interests, accomplishments, career plans, and perceived need for help with their study skills and their educational and occupational plans.

Online Questionnaire

The questionnaire consisted of 48 items asking students to self-report information on areas such as their high school experience, study and work habits, parental involvement, educational and occupational plans and goals, perceptions of their future college experience, and college courses taken (dual-credit coursework) and/or credits earned in high school. All item response options were discrete and consisted of five or six-point Likert-type items evaluating respondents' general level of agreement or frequency of partaking in a particular behavior or action.

Variables from the online questionnaire featured noncognitive characteristics that have been found to be predictive of academic performance in other contexts. Students were asked about their effort and preparedness in school (academic commitment; Gaertner & McClarty, 2015; Robbins, Allen, Casillas, Peterson, & Le, 2006), expected educational outcomes and perceptions of college (commitment to college, academic goals; Allen, 1999; Ramist, 1981; Robbins et al., 2004), study and work habits (Cooper, Robinson, & Patall, 2006; Le et al., 2005; Singh, 1998), parental involvement (Comer, 2005; Flint, 1992; Gaertner & McClarty, 2015; Henderson & Mapp, 2002; Lee & Bowen, 2006), and whether they were challenged in high school.

High School Characteristics

Students indicated their high school attended at the time they registered for the ACT. School characteristics were obtained from the National Center for Educational Statistics' (NCES) Common Core of Data (CCD) for years 2010 to 2012 and Market Data Retrieval (MDR) files. Variables from these sources included the school type (public vs. non-public), the percentage of students eligible for free/reduced lunch (FRL), and percentage of minority students (the latter two available only for public schools). The median household income for the zip code associated with school location was obtained from readily available US 2000 Census data. In addition, the following measures were calculated for each high school based on the 2011, 2012, and 2013 ACT-tested high school graduating classes: mean ACT scores, the percentage of students taking mathematics coursework beyond Algebra II, the percentage of students intending to earn a post-baccalaureate degree, the percentage of students taking the ACT test, and the percentage of students immediately enrolling in college the fall following high school graduation (enrollment data obtained from the National Student Clearinghouse). For schools with fewer than 25 ACT-tested students, district-level means were used instead. The high school characteristics calculated for the 2011 through 2013 ACT-tested graduating classes were used as proxy measures of a college-going culture that has been found to promote students' college aspirations (Corwin & Tierney, 2007).[4]

[4] School demographics characteristics were included in this study as possible proxies for information related to school resources, school environment, and quality of education. The school-level characteristics that were calculated for the ACT-tested population were the only variables readily available to try to capture other aspects of the school climate/culture. See the Introduction and Discussion sections for a more detailed discussion on the relevance of these school-level characteristics.

Method

Weighting

The sample of respondents differed from the population of interest in terms of key characteristics (see Table 1). For example, there were fewer male respondents in the sample than among all seniors who tested in the 2012–13 academic year. Therefore, weights were applied to the sample to account for the overrepresentation of certain student groups. Students' responses were weighted on a combination of four different variables: gender, HSGPA, race/ethnicity, and ACT Composite score.[5] HSGPA was dichotomized into "high" (3.50 or above) and "low" (below 3.50); ACT Composite score was categorized into five groups: 1 to 16, 17 to 19, 20 to 22, 23 to 25, and 26 or higher.[6] The weights ranged from 0.51 for minority females with a high HSGPA and ACT Composite score of 26 or above to a weight of 2.24 for other/unknown ethnicity males with a low HSGPA and ACT Composite score of 16 or below. These weights were used throughout the rest of the analyses presented in this report.

Table 1. Unweighted Descriptive Statistics of Study Sample Compared to 2012–13 ACT-Tested Seniors

		Sample (n = 6,440)		2012–13 HS Seniors (n = 975,702)	
Student Characteristic		n	%	n	%
Race/Ethnicity	White	3,505	54%	537,967	55%
	African American	917	14%	151,325	16%
	Hispanic	1,023	16%	147,918	15%
	Asian	432	7%	45,021	5%
	Other	563	9%	93,471	10%
Gender	Male	2,206	34%	429,101	44%
	Female	4,234	66%	546,601	56%
ACT Composite Score	1–16	970	15%	197,455	20%
	17–19	1,204	19%	198,374	20%
	20–22	1,326	21%	208,465	21%
	23–25	1,251	19%	172,870	18%
	26–36	1,689	26%	198,538	20%
HSGPA	< 3.50	3,072	48%	472,832	56%
	≥ 3.50	3,368	52%	370,978	44%

Note: Percentages may not sum to 100% due to rounding. Percentages for HSGPA for 2012–13 ACT-tested seniors are conditional on a response being given; the percentage of missing responses is 14%. For the sample and the population, the Other racial/ethnic category included 3% and 5%, respectively, of students who did not provide their race/ethnicity.

[5] Weights were normalized so that the sum of the weights would equal the number of students included in the sample.

[6] For the weight calculations, race/ethnicity was categorized into the following three categories: White or Asian, minority (African American, Hispanic, American Indian, and Pacific Islander), and Other/Unknown. In other analyses, race/ethnicity was categorized into the following five categories: White, Asian, African American, Hispanic, and Other/Unknown.

Missing Data

Some students did not respond to all of the SPS, CGIS, and/or the online questionnaire items. In general, the percentage of missing values per item was low, but it did vary across items. One of the higher missing rates was for family income at 19%. Apart from two other sets of items to be discussed below, the remaining items used in this study were missing for at most 10% of the students, with an overwhelming majority of items missing for at most 5% of the students. A few of the items that had nearly a 10% missing rate included: parental education level (10%) and HSGPA (8%). Multiple imputation (SAS PROC MI) was used to estimate missing values for these items. Five data sets were imputed. Final models were estimated for all five imputed data sets; no differences of practical significance in the regression coefficients and significance levels were found across the data sets. Consequently, the results reported here are based only on the initial imputed data set.[7]

There were two sets of questions of interest asking non-sensitive information that had much higher levels of missingness (over 50%). The first set asked students to indicate whether they had taken any advanced, honors, or accelerated courses in five different subject areas. The second set asked students to indicate whether they needed help improving their skills in five different areas. Missing values were not imputed for these items. Instead, given that more than 90% of students with a non-missing response indicated that they took the course or needed help, omitted responses were considered as a "have not taken the course" or "no help needed" response.

Principal Components Analysis of the Online Questionnaire

Because many items on the online questionnaire addressed somewhat related areas, a principal components analysis (PCA)[8] was used as a data reduction technique to produce a smaller, more manageable set of components that would also serve to reduce collinearity concerns. Most, but not all, of the items from the online questionnaire were included in this analysis; individual items that were of particular interest as potential predictors of ACT test scores based on prior research studies were excluded from the PCA. All items on the online questionnaire were discrete, with most being Likert-type items (which often violate assumptions of traditional PCA); therefore, the PCA was run on a polychoric correlation matrix that assumed a latent normal distribution as recommended by Kolenikov and Angeles (2009). To determine the number of components to retain, Horn's Parallel Analysis (Horn, 1965) was used.[9] Using an orthogonal varimax rotation,[10] nine components were extracted and accounted for 60% of the variance of the original set of variables.

Of the nine extracted components, only two were deemed to be relevant as possible predictors for the outcomes of interest in this study. The first consisted of items related to how engaged students

[7] Although it is typically important to take the multiple imputations into account so that standard errors are not biased towards zero (Little & Rubin, 1989), given the categorical nature of the variables used in this study and the relatively low missing rates, analyzing only one of the imputed datasets should not lead to any downward bias in standard error estimates (Schafer, 1999). In general, categorical variables experience less random variation between imputations because they can only take on discrete values. Therefore, the between-imputation variance (which accounts for random variation between imputations) will be rather small, especially given the relatively low missing rates for most study variables.

[8] Although an exploratory factor analysis (EFA) may also have been a method for this purpose, EFA is more useful for discerning latent constructs underlying a set of variables. With the online questionnaire, dimension reduction was the more salient intention compared to uncovering the underlying latent structure, thus PCA was the selected technique.

[9] Horn Parallel Analysis (HPA) is a resampling procedure that generates multiple artificial datasets of the same sample size and number of variables as the PCA of interest, but all variables are generated such that they are completely independent of one another. A PCA is run on each generated dataset and the eigenvalues are saved. The mean eigenvalue for each component is then calculated across all replicated data sets. If the eigenvalue from the analysis exceeds the value from HPA, then, based on HPA, the component should be retained. This method is related to Kaiser's Rule, which retains components with eigenvalues greater than 1.0.

[10] An oblique rotation was initially considered but only two component correlations had magnitudes greater than 0.20.

were with their academics in high school such as being prepared for assessments and turning in assignments on time. This component, labeled as the academic commitment component, had a Cronbach's α of 0.73. The second component was related to students' perceptions of education—such as college being worth the cost, and completion of a college degree being a priority. The perceptions of education component had a Cronbach's α of 0.44. Specific items that loaded highly on each of these components can be found in Table A-1 of Appendix A.

For two other PCA components, the individual items were considered to be of greater interest and more interpretable than the overall component on which they loaded. For example, one component consisted of items pertaining to indicators of whether students had taken dual-credit coursework in high school in five different subject areas, as well as an overall item concerning total college credits earned while in high school. We were more interested in relating the subject-specific dual-credit course information to performance on the corresponding ACT subject test than using an overall aggregate measure of any dual-credit coursework. The other component was comprised of three parental involvement items. Two items were closely related and pertained to parental involvement in post-high school plans. The third item addressed a different aspect of parental involvement by asking students how often their parents check that they have completed their schoolwork. We were interested in evaluating the effects of these two different aspects of parental involvement separately. Therefore, individual items from these latter two PCA components were evaluated as possible predictors of performance on the ACT tests.

The other five PCA components were deemed to be more relevant for predicting college outcomes (e.g., who is likely to enroll in college, who is likely to persist in college) than for predicting performance on the ACT. These components were related to students' (1) uncertainty in setting career and educational goals (e.g., it is difficult deciding what occupation fits me best), (2) participation in college planning activities (e.g., I have taken steps to learn about scholarship opportunities), (3) college financial concerns (e.g., I am concerned about how I am going to pay for my education after high school), (4) likely college behaviors (e.g., I will likely take at least one term off after enrolling but before graduating), and (5) exploration of college options (I have attended a college fair).

Clustered Nature of the Data

Although students were sampled through a simple random sample, they were naturally clustered within both schools and states. Although clustered data often necessitate methods that account for clustering, it is important first to assess whether the clustering is meaningful. The primary method used to address this concern is the intraclass correlation (ICC). While no strict cutoffs exist for determining what values correspond to being meaningfully clustered, ICC values above 0.05 or 0.10 typically require methods to account for clustering to avoid downwardly biased standard errors and, consequently, inflated type-I error rates (Hox, 1998).

For this study, ICCs ranged from 0.20 (mathematics and reading) to 0.23 (Composite and science).[11] These are fairly large ICC values and are in line with what Hedges and Hedberg (2007) found in a review of ICC values for math and reading scores in high school students (0.17 for 12th grade reading, 0.24 for 12th grade math). The ICC estimates suggest that modeling the data with a single-

[11] It is also important to note that the ICCs may be slightly inflated as Clarke (2008) and McNeish (2014) found that sparse data structures (often defined by an average cluster size below 5) tend to overestimate the variance of the intercept random effect.

level model that does not account for clustering might lead to downwardly biased standard errors and inflated type-I error rates. States were also considered as a third level of clustering; however, ICCs at the state-level were less than 0.05 for all ACT tests and, consequently, only clustering within schools was considered in subsequent analyses.

It is worth noting that there were three groups of students who were not traditionally clustered within schools: home-schooled students (*n* = 86), students working on completing a GED (*n* = 8), and students who could not locate or provide a high school code (*n* = 5). In estimating the ICC, these students were accounted for in different ways, but ICC values were very similar between these methods.[12] Therefore, in all subsequent analyses, each of these three groups of students was treated as a cluster (i.e., all home-schooled students comprised a single cluster).[13]

Modeling Technique

In this study, students were clustered within schools, but very sparsely as there were 4,541 different schools and only 6,440 students. Most schools were comprised of only a single student (weighted mean = 1.4 students per school, weighted median = 1.1). Previous studies used fixed effects models where dummy-coded indicators for different schools were entered into the model (Noble et al., 1999a, 1999b) to account for the variability attributable to high school attended. For the current study, however, a more parsimonious approach was desired.

Furthermore, model-based methods typically utilized for clustered data in education (e.g., hierarchical linear models) may be of questionable utility when the clusters exhibit such a high level of sparseness (Clarke, 2008; Clarke & Wheaton, 2007; McNeish, 2014). Specifically, problems arise when estimating random effects based on highly sparse clusters. As a result, the variance components have been found to be overestimated with sparse clusters, which can propagate throughout the model and potentially lead to biased standard errors and possibly biased fixed-effect point estimates as well (Primo, Jacobsmeier, & Milyo, 2007). However, McNeish (2014) showed that design-based methods (DBMs) that account for clustering were far less affected by sparsely clustered data and performed well in simulation conditions with an ICC of 0.20; 200 clusters; and an average cluster size of 1.5. This design closely mirrors the attributes of the current dataset. Therefore, DBMs were used to account for clustering in this study.

Specifically, a blockwise regression model with cluster-robust standard errors (CR-SEs; Huber, 1967; White, 1984; White, 1980) was used to assess the relation between noncognitive characteristics with ACT scores over and above HSGPA, high school coursework, and characteristics of the high school attended. A blockwise approach means that sets of predictor variables were entered into the model together. Changes in R^2 (the percentage of variation explained by the block of predictors) were germane to the research question. Fortunately, parametric DBMs (e.g., cluster-robust standard errors, also called sandwich or empirical estimators) are able to preserve R^2 such that it is asymptotically equivalent to what would be obtained with ordinary least squares (OLS) regression (Hayes & Cai, 2007). Specifically, because cluster-robust standard errors account for the clustering through a statistical correction rather than by including random effects, as is done in multilevel models, comparing the reduction in the residual variance of a target model compared to

[12] The three approaches included: (1) treating each group as a cluster, (2) excluding these students from the analyses, and (3) coding each student as a cluster of size one.

[13] Similar regression coefficients and p-values from the final models were obtained when these students were excluded from the analyses.

an intercept-only model can be shown to be algebraically equivalent to an OLS R^2 calculation. This cannot be said of multilevel models because the expected mean square is formulated differently when random effects are present.[14]

ACT Score Models

Five separate regression models were developed, one for each of the five ACT scores (Composite, English, mathematics, reading, and science). Relevant candidate predictor variables obtained from the previously described instruments or PCA results were placed into seven different blocks based on the nature of the variables. The candidate predictors and their corresponding block and block category assignments are shown in Table 2. To simplify presentation of some of the results, blocks were further categorized into the following four "block categories": high school academic factors, school characteristics, noncognitive characteristics, and demographics. By design, blocks containing high school student academic factors (grades, coursework) entered the model first so that the incremental effect of noncognitive characteristics could be evaluated.

Table 2: Variables Included in Each Block of Predictors

Block Category	Block Name and Associated Variables
HS Student Academic Factors	**Block 1: High School Grades Earned**
	23-Course HSGPA or Subject-Specific HSGPA (Based on higher R^2)[1]
	Block 2: Course Information
	Core Curriculum Indicators (English, Math, Social Science, Natural Science, Overall)
	Math Course Sequence Taken (AAG is referent)
	Science Course Sequence Taken (Biology is referent)
	Social Studies Courses Taken (Government, Economics, Geography, Psychology, Other History)
	Years of Foreign Language
	Block 3: Advanced Coursework Indicators
	Accelerated, Advanced, Honors, and/or Dual-Credit English Course Taken
	Accelerated, Advanced , Honors, and/or Dual-Credit Math Course Taken
	Accelerated, Advanced , Honors, and/or Dual-Credit Natural Science Course Taken
	Accelerated, Advanced , Honors, and/or Dual-Credit Social Science Course Taken
	Number of College Credits Earned in High School (0; 1–6; 7 or more)

[14] A more detailed discussion of both model-based and design-based methods to account for clustering is provided in Appendix B.

Block Category	Block Name and Associated Variables
High School Characteristics	**Block 4: High School Characteristics**
	Median Income for High School Zip Code[2] (< \$35,421; \$35,421-\$47,852; > \$47,852)[3]
	Percent Anticipating Graduate Degree[4] (Mean = 42%)[1]
	Percent Enrolling in College[4] (Mean = 71%)[1]
	Percent Free/Reduced Lunch (FRL)[5] (≤ 24%; 25%–50%; ≥ 51%)[3]
	Percent of High School Taking the ACT test[4] (Mean = 62%)[1]
	Percent Minority[5] (≤ 8%; 9%–36%; ≥ 37%)[3]
	Non-Public School Indicator
Noncognitive Characteristics	**Block 5: Noncognitive Characteristics**
	Academic Commitment Component (from PCA) [and quadratic term]
	Expected Education Level (Below Bachelor's, Bachelor's, Beyond Bachelor's)
	Hours spent studying per week outside of class (0–5; 6–10; 11 or more)
	Hours spent working for pay per week (0; 1–10; 11 or more)
	My parent/guardian is involved in my post-HS plans[6] Strongly Agree, Moderately Agree, Slightly Agree, Slightly Disagree, Moderately Disagree, Strongly Disagree
	My parent/guardian checks to make sure I have completed assignments[6] Always, Usually, About Half the Time, Occasionally, Never
	My school challenges me to perform to the best of my ability[6] Always, Usually, About Half the Time, Occasionally, Never
	Need Help Math Skills Indicator
	Need Help Reading Skills Indicator
	Need Help Educational/Occupational Plans Indicator
	Need Help Study Skills Indicator
	Need Help Writing Skills Indicator
	Perception of Education Component (from PCA)
	Plan to discuss postsecondary plans with counselor Have Done So, Have Not but Plan to, Have Not and Will Not
	Plan to find out what education is necessary for desired job Have Done So, Have Not but Plan to, Have Not and Will Not
	Self-Reported College Prep High School Curriculum Indicator
	Tested with the ACT in Junior Year Indicator

Block Category	Block Name and Associated Variables
Demographics	Block 6: SES-Related Demographics
	English Spoken at Home Indicator
	Family Pre-Tax Annual Income (< $36,000; $36,000–$80,000; > $80,000)
	Highest Parental Education Level (No College, Some College, Bachelor's Degree, Graduate-Level Degree)
	Block 7: Gender and Ethnicity
	Female Gender Indicator
	Race/ethnicity (Asian, African American, Hispanic, Other/More than two ethnicities, White (referent))

Note: Italics indicates a binary variable.

[1] Variable was grand-mean centered.

[2] Based on 2000 US Census data. The median US household income in 2000 was $42,148 (US Census Bureau, 2014) and the 2012 inflation-adjusted value was $55,030 (Noss, 2013). Year 2012 inflation-adjusted range categories include: ≤ $46,246; $46,246–$62,476; ≥ $62,476. The median US household income in 2012 was $51,371 (Noss, 2013).

[3] Categories based on sample tertiles.

[4] Variable was calculated for the ACT-tested population only (i.e., 2011, 2012, and 2013 ACT- tested high school graduating classes).

[5] Available for public schools only.

[6] Variable was treated as continuous in regression models since there were more than five response categories.

Predictor Variable Selection

Variables were considered for inclusion in the model after a screening process was applied that was similar to that used by Noble et al. (1999a, 1999b). To be considered in the modeling process, variables needed to have a bivariate correlation of at least 0.05 with at least four of the five outcome variables (unless the variable was specific to a certain subject test, in which case it only had to have a 0.05 correlation with the corresponding subject test). Based on this criteria, the variables that were eliminated from consideration as predictors in the model included: taking an American Government course, taking an Economics course, taking a Geography course, taking a core curriculum in English, taking a core curriculum in social studies, the school percentage of students taking the ACT test, planning to discuss college plans with a high school counselor, and parents being involved with college plans.[15]

Using the remaining possible predictors, a stepwise selection procedure was employed within each block using a significance level threshold of 0.01 to determine the relevant predictors. Once a predictor was included based on statistical significance, it was retained in the model regardless of whether the statistical significance changed after subsequent blocks were added.

All analyses were conducted using the SAS 9.2 software package. To circumvent software limitations for stepwise selection with CR-SEs, a two-step procedure that takes advantage of the known property that the standard errors for OLS regression will be consistently downwardly biased (underestimated) was used. For each block, an OLS stepwise regression was conducted to identify predictors (or multi-parameter factors) that were significant at the 0.01 (two-tailed) level

[15] The academic commitment component was hypothesized to have a quadratic component, so the linear correlation may not have been appropriate and it was therefore retained in the model even though it did not meet the initial inclusion criteria.

prior to accounting for clustering. Then, the predictors that were significant from the OLS model were modeled employing CR-SEs to correct the standard errors for clustering. Variables that were significant at the 0.01 level after using the CR-SEs were kept in the model.

Comparing Differences in ACT Scores among Student Demographic Groups

To evaluate whether other student and school characteristics—such as academic preparation, course grades, and behaviors—help to explain demographic group differences in ACT scores, unadjusted and adjusted mean differences in ACT scores were compared using the following student demographic characteristics: race/ethnicity (White vs. African American and White vs. Hispanic), gender, annual family income ($36,000 to $80,000 vs. < $36,000; and > $80,000 vs. < $36,000), and parental education level (some college vs. no college; bachelor's degree vs. no college; and graduate degree vs. no college).

Relating Noncognitive Variables and HSGPA

In order to examine the possibility that noncognitive characteristics may influence ACT scores through HSGPA, HSGPA was predicted from the noncognitive variables that were included in Block 5. For further information, see Table 2 (Blocks 1 through 4 were not entered into the model). Automatic selection procedures were used to decide which predictors to include in the final model. First, stepwise selection using a 0.01 *p*-value threshold was used. Since the HSGPA model was not a blockwise model, selection was compared to the more modern hybrid Least Angle Regression selection/least squares estimation method (LARS; Belloni & Chernozhukov, 2013; Belloni, Chernozhukov, & Hansen, 2014; Efron, Hastie, Johnstone, & Tibshirani, 2004). This was done to evaluate the extent to which the results from the ACT score models might depend on the stepwise method used. Interested readers should see Appendix C for more details about LARS. Because the ratio of sample size to candidate predictors is high, results are expected to be similar between the two selection methods.

Results

Descriptive Statistics

Table 3 shows the demographic information for the study sample (n = 6,440) and for all high school seniors who took the ACT during the 2012–13 academic year (n = 975,702). For the sample, raw frequencies and weighted percentages are reported. Across all variables, the weighted percentages were very close to the percentages observed for all high school seniors nationally who took the ACT in 2012–13. The largest differences in the percentages between the sample and population were associated with students' self-reports on the various needing help indicators. In addition, average HSGPA and ACT Composite and subject scores were similar between the sample and population of high school seniors (see Table 4).

Table 3. Student Characteristics for the Study Sample and High School Seniors Nationally Who Took the ACT in 2012–13

		Sample		2012–13 HS Seniors	
Characteristic	Categories	n	Weighted %	n	%
Race/Ethnicity	White	3,505	54%	537,967	55%
	African American	917	15%	151,325	16%
	Hispanic	1,023	15%	147,918	15%
	Asian	432	7%	45,021	5%
	Other	563	9%	93,471	10%
Gender	Female	4,234	57%	546,601	56%
	Male	2,206	43%	429,101	44%
Family Income	< $36,000	2,128	35%	239,214	33%
	$36,000 to $80,000	2,348	36%	247,166	34%
	> $80,000	1,964	29%	239,261	33%
Math Course Sequence	Less AAG	199	4%	49,450	5%
	Other-Low (< 3 years)	76	1%	14,329	1%
	AAG	1,352	23%	247,191	26%
	AAGO	1,540	25%	220,788	23%
	AAGT	745	12%	121,365	13%
	AAGOT	883	13%	119,184	12%
	AAGTC	431	6%	48,312	5%
	AAGOTC	1,048	14%	113,459	12%
	Other-High (≥ 3 years)	166	2%	24,276	3%
Science Course Sequence	Less than Biology	96	2%	15,352	2%
	Biology	554	10%	103,913	11%
	Biology & Chemistry	2,783	44%	428,589	45%
	Biology, Chemistry, Physics	2,825	42%	380,457	40%
	Other 3-year sequence	182	3%	29,846	3%

		Sample		2012–13 HS Seniors	
Characteristic	Categories	n	Weighted %	n	%
Advanced English[1]	Yes	3,342	46%	412,169	42%
	No	3,098	54%	563,533	58%
Advanced Math[1]	Yes	2,882	39%	349,953	36%
	No	3,558	61%	625,749	64%
Advanced Soc. Studies[1]	Yes	2,827	39%	357,411	37%
	No	3,613	61%	618,291	63%
Advanced Science[1]	Yes	2,788	38%	343,109	35%
	No	3,652	62%	632,593	65%
Expected Education	Below Bachelor's Degree	297	6%	54,663	6%
	Bachelor's Degree	3,011	50%	461,687	52%
	Beyond Bachelor's Degree	3,132	44%	377,504	42%
Parent Education	No College	1,327	21%	175,340	21%
	Some College	2,087	33%	241,694	29%
	Bachelor's Degree	1,640	25%	227,018	28%
	Graduate Degree	1,386	21%	179,392	22%
Need Help—Occ./Educ.	Yes	3,280	51%	432,129	44%
	No	3,160	49%	543,573	56%
Need Help—Math Skills	Yes	2,319	38%	322,409	33%
	No	4,121	62%	653,293	67%
Need Help—Reading	Yes	1,831	30%	235,558	24%
	No	4,609	70%	740,144	76%
Need Help—Study Skills	Yes	2,887	47%	407,515	42%
	No	3,553	53%	568,187	58%
Need Help—Writing Skills	Yes	1,639	26%	201,787	21%
	No	4,801	74%	773,915	79%

Note: Percentages may not sum to 100% due to rounding. Percentages for high school seniors nationally who took the ACT in 2012–13 were based on respondents only for the following characteristics: family income, math course sequence, science course sequence, expected education level, and highest parental education level. The percentages of missing responses for the population were as follows: 26% for family income, 2% for math course sequence, 2% for science course sequence, 8% for expected education level, and 16% for highest parental education level. For the sample and the population, the Other racial/ethnic category included 3% and 5%, respectively of students who did not provide their race/ethnicity.

[1] Advanced coursework variables included accelerated, advanced placement, and honors courses; they did not include dual-credit courses in these analyses since this information was not available for the population.

Table 4. Average HSGPA and ACT Scores for the Study Sample and High School Seniors Nationally Who Took the ACT in 2012–13

		Sample	2012–13 HS Seniors
Mean HSGPA (SD)	Overall HSGPA (0.00-4.00)	3.31 (0.55)	3.29 (0.57)
Mean ACT Score (SD)	Composite	21.3 (5.0)	21.1 (5.0)
	English	20.8 (6.3)	20.6 (6.2)
	Mathematics	21.1 (5.1)	21.0 (5.1)
	Reading	21.6 (6.0)	21.4 (6.0)
	Science	21.2 (5.0)	20.9 (5.0)

Note: The percentage of students from the population missing HSGPA was 14%. Weighted statistics are reported for the sample.

ACT Score Models

Regression coefficients from the final blockwise regression models are provided in Table 5. The incremental percentage of the variation explained by each block is also provided. Next, results are described block by block, including interpretation of some of the significant regression coefficients. All coefficients are to be interpreted as conditional on all other predictors in the model.

Table 5. Blockwise Regression Model Results

Block	Predictor	Composite Reg. Coeff.	Composite ΔR²	English Reg. Coeff.	English ΔR²	Mathematics Reg. Coeff.	Mathematics ΔR²	Reading Reg. Coeff.	Reading ΔR²	Science Reg. Coeff.	Science ΔR²
	Intercept	19.80		17.73		20.14		20.59		20.45	
1	High School Grades Earned		0.31		0.28		0.29		0.20		0.23
	Overall HSGPA	2.18		2.74		2.05		2.16		1.83	
2	High School Course Information		0.08		0.05		0.13		0.04		0.08
	Math Course Sequence										
	Less than AAG	-0.38†		-0.41		-0.39		-0.25		-0.69	
	AAG (referent)										
	AAGO	0.59		0.58		0.71		0.57		0.56	
	AAGT	0.54		0.64		0.82		0.40		0.41	
	AAGOT	1.33		1.57		1.63		1.10		1.21	
	AAGTC	2.04		2.04		2.62		1.68		2.01	
	AAGOTC	2.32		2.37		3.02		1.86		2.21	
	Other (≥3 yrs)	0.99		0.94		1.59		0.50		1.18	
	Other (<3 yrs)	0.56		0.58		0.77		0.38		0.28	
	Science Course Sequence										
	Less than Biology††	0.48		0.58		0.78		---		0.40	
	Biology (referent)										
	Biology, Chemistry	0.27		0.39		0.34		---		0.18	
	Biology, Chemistry, Physics	0.53		0.39		0.82		---		0.60	
	Other 3-year sequence	0.12		-0.08		0.55†		---		0.07	
	Years of Foreign Language	---		0.10		---		---		---	
3	Advance High School Coursework		0.04		0.05		0.04		0.04		0.03
	Advanced English	0.54		1.13		-0.15		0.99		---	
	Advanced Math	0.66		---		1.30		---		0.68	
	Advanced Nat Science	0.49		0.67		0.63		0.42		0.64	
	Advanced Social Studies	0.69		1.10		0.30		1.12		0.40	
	College Credits Earned in HS										
	0 (referent)										
	1–6	-0.04		-0.12		0.26*		-0.09		-0.03	
	7 or more	0.39		0.26		0.60		0.42*		0.44	

Block	Predictor	Composite Reg. Coeff.	Composite ΔR²	English Reg. Coeff.	English ΔR²	Mathematics Reg. Coeff.	Mathematics ΔR²	Reading Reg. Coeff.	Reading ΔR²	Science Reg. Coeff.	Science ΔR²
4	High School Characteristics		0.09		0.08		0.07		0.07		0.07
	Median Zip Code Income										
	Low (referent)										
	Middle	0.48		0.41		0.46		0.47		0.53	
	High	0.67		0.60		0.70		0.53		0.72	
	% College Enrollment	---		---		0.01		---		0.01	
	% Free/Reduced Lunch										
	Low (referent)										
	Middle	-0.27		-0.27		-0.37		-0.28		-0.15	
	High	-0.51		-0.59		-0.59		-0.44		-0.33	
	% Intending Graduate Degree	0.03		0.03		0.02		0.03		0.01*	
	Quadratic	< 0.01		< 0.01		< 0.01		< 0.01		< 0.01	
	% Minority										
	Low (referent)										
	Middle	-0.16		-0.15		-0.23		-0.14		-0.09	
	High	-0.87		-0.87		-0.78		-0.93		-0.78	
	Non-Public School Indicator	-0.13		0.70		-0.76		0.15		-0.69	
5	Noncognitive Characteristics		0.06		0.07		0.04		0.07		0.04
	College Prep Course Curriculum	0.34		0.41		---		0.47		0.28*	
	Expected Ed. Attainment										
	Below Bachelor's (referent)										
	Bachelor's Degree	0.34		0.50		0.24		0.29		0.28	
	Beyond Bachelor's Degree	1.08		1.34		0.81		1.21		0.92	
	Need Help—Educ./Occu. Plans	---		0.38		---		---		---	
	Need Help—Writing Skills	---		-0.26		---		---		---	
	Need Help—Study Skills	---		-0.34*		---		---		---	
	Need Help—Reading Speed and Comp.	-1.33		-1.69		---		-2.39		-0.94	
	Need Help—Math Skills	-0.52		---		-1.49		---		-0.69	
	Parents Check Assignments	-0.31		-0.41		-0.24		-0.35		-0.23	
	Perception of Educ. Component	0.13		---		0.16		---		0.19	
	Student Challenged by School	-0.39		-0.41		-0.27		-0.49		-0.36	
	Tested in Junior Year	0.77		1.35		0.58		0.64		0.74	

Block	Predictor	Composite Reg. Coeff.	Composite ΔR^2	English Reg. Coeff.	English ΔR^2	Mathematics Reg. Coeff.	Mathematics ΔR^2	Reading Reg. Coeff.	Reading ΔR^2	Science Reg. Coeff.	Science ΔR^2
6	SES-Related Demographics		0.01		0.01		<0.01		0.01		0.01
	English Spoken at Home	0.70		0.99		---		0.91		0.68	
	Family Income										
	< $36,000 (referent)										
	$36,000 to $80,000	0.24		0.37*		0.16		---		0.22	
	> $80,000	0.39		0.61		0.46		---		0.26	
	Highest Parental Education Level										
	No College (referent)										
	Some College	0.36		0.56		0.15		0.54		0.21	
	Bachelor's Degree	0.61		0.91		0.35		0.89		0.34	
	Graduate Degree	0.73		1.14		0.35		1.11		0.44	
7	Gender and Race/Ethnicity		0.02		0.02		0.03		0.01		0.03
	Female	-0.64		---		-1.14		---		-1.19	
	Race/Ethnicity										
	Asian	-0.57		-1.24		0.85		-1.43		-0.58	
	African American	-2.04		-2.28		-1.67		-2.13		-2.07	
	Hispanic	-1.53		-1.98		-1.11		-1.66		-1.41	
	Other	-0.44		-0.71		-0.28		-0.32		-0.43	
	White (referent)										
Final R^2		0.61		0.56		0.60		0.44		0.49	
Root Mean Square Error		3.13		4.22		3.21		4.47		3.54	

--- indicates that the predictor was not significant for the particular outcome variables

† indicates a *p*-value between 0.010 and 0.015 upon entry to the model

* indicates a *p*-value between 0.010 and 0.015 in the final model

†† sample size for the less than Biology course sequence was relatively small (< 100 students)

Note: Grey shading indicates that the predictor was not statistically significant upon entry but was retained as part of a factor. Orange shading indicates that the predictor was statistically significant upon entry but was no longer significant in the final model. Weighted analyses were used.

High School Academic Factors

Overall HSGPA accounted for the largest proportion of variance of any predictor in the model—20% (reading) to 31% (Composite). Although both overall and subject-specific HSGPAs were considered, overall HSGPA accounted for more variation across all ACT scores and was thus the measure of HSGPA retained in the models. Conditional on all other predictors in the final model, a one-point increase in overall HSGPA above the grand-mean was predicted to increase ACT scores by 1.8 to 2.7 points, on average.

Block 2 accounted for between 4% (reading) and 13% (mathematics) of additional variance in ACT scores beyond the variance accounted for by Block 1. Taking higher-level mathematics courses was predicted to increase ACT scores in every subject area and for the Composite score. Figure 1 shows the adjusted average ACT mathematics score for specific mathematics course sequences. Compared to students who took Algebra I, Geometry, and Algebra II, students who took mathematics courses beyond Algebra II had higher ACT mathematics scores by 0.7 to 3.0 points, on average.

Science coursework entered the model for all tests except in reading. However, some of the specific science course sequence indicators were not significant predictors of performance on the ACT tests once additional blocks of variables entered the models, especially for the English test. Specifically, the Biology, Chemistry, and Physics course sequence indicator remained statistically significant for predicting ACT science, mathematics, and Composite scores only once all blocks had entered the models. The average ACT science score was 0.6 point higher for students who took Biology, Chemistry, and Physics than for those who only took Biology.

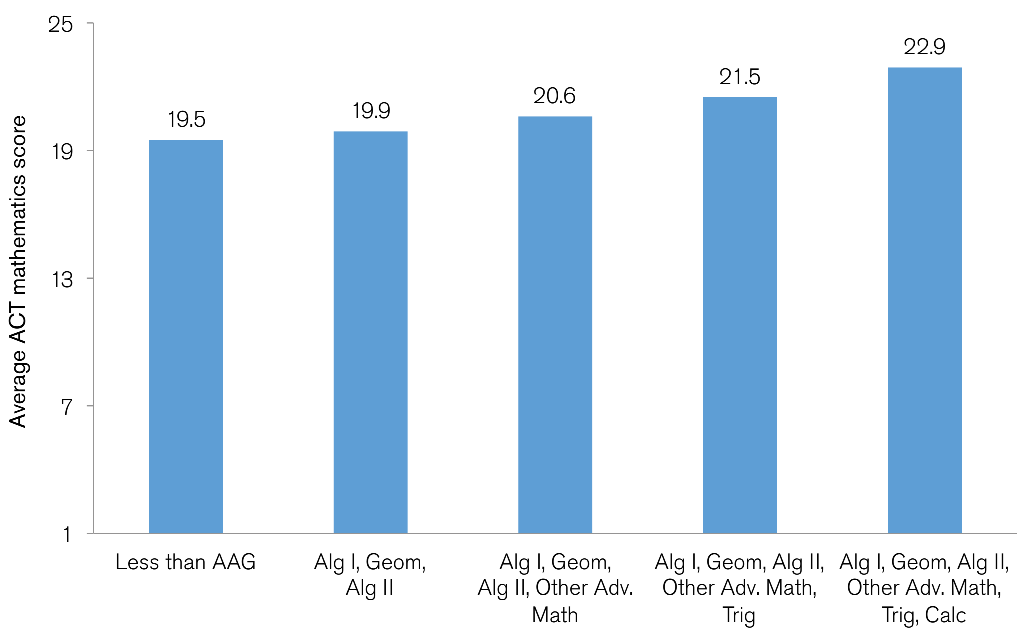

Figure 1: Adjusted average ACT mathematics score by mathematics course sequence.

The number of years of foreign language taken entered the model only for the English test, but was not a significant predictor in the final model. The social studies courses (e.g., Psychology and other history) and core curriculum indicators (e.g., overall and in mathematics and science) did not enter any of the models after the math and science course sequences had entered. In general, these courses either had very high or very low participation rates or were found to be related to the mathematics and science course sequences.

The variables in Block 3 accounted for between 3% and 5% of additional variance beyond that accounted for by Blocks 1 and 2. In general, students who took accelerated advanced, honors, and/or dual-enrollment coursework in high school had higher ACT scores than those who did not. The advanced coursework regression coefficients for the different subject areas did vary though, depending on which ACT score was being modeled. For example, students taking accelerated, advanced, honors, and/or dual-enrollment courses in English were predicted to score about 1.0 to 1.1 points higher on the ACT reading and English tests, on average. In contrast, performance on the ACT mathematics and science scores was not related to whether a student took advanced coursework in English. Additionally, for all tests except in English, students expecting to earn seven or more college credits while in high school were predicted to score between 0.4 and 0.6 point higher than students expecting to earn zero college credits. In total (for Blocks 2 and 3), the coursework taken by students in high school accounted for between 8% (reading) and 17% (mathematics) of the variance in ACT scores, beyond that accounted for by HSGPA.

High School Characteristics

The high school characteristics in Block 4 accounted for between 7% and 9% of additional variance in ACT scores beyond the factors included in Blocks 1 through 3. All of the high school characteristics that met the initial screening process entered at least one of the models. Two of the significant characteristics were proxy measures for school and neighborhood poverty. Students who attended schools located in zip code areas associated with mid and high values for median household income were predicted to score, on average, between 0.4 and 0.5 point and between 0.5 and 0.7 point higher respectively than students from neighborhoods with low values for median household income. Moreover, ACT English, mathematics, and Composite scores were negatively related to school percentages of FRL-eligible students. Students in schools with higher FRL-eligible percentages were typically predicted to score 0.5 to 0.6 point lower than students from schools with lower FRL-eligible percentages. On average for ACT mathematics scores, students from schools with percentages of FRL-eligible students in the middle range were predicted to score 0.4 point lower than students from schools with lower FRL-eligible percentages.

School characteristics related to the college-going culture of the high school attended were also found to be related to performance on the ACT. For example, the school percentage of ACT-tested students enrolling in college the fall following high school graduation was significantly related to ACT mathematics and science scores. Additionally, the percentage of ACT-tested students at a school aspiring to earn a graduate degree had a significant, positive quadratic term in relation to ACT scores (see Table 5), meaning that this school characteristic was non-linearly related to performance on the ACT tests. For instance, as illustrated in Figure 2, the average ACT Composite score is almost 1.0 scale score point higher for students at schools with 62% of ACT-tested students aspiring to a graduate degree, compared to students at schools with a corresponding percentage of 42% (the sample mean). The predicted increase in ACT Composite score was positive for students from schools with more than 41% of students at the school aspiring to a graduate degree.[16]

Students in schools that had a higher percentage of racial/ethnic minority students were predicted to score about 0.8 to 0.9 point lower, on average, than students from schools with a lower percentage of racial/ethnic minority students. In the final model, there was not a significant difference in average ACT scores between students from schools that had percentages of racial/ethnic minority students in the middle and lower ranges. Lastly, compared to students attending non-public schools, those attending public schools generally scored about 0.8 and 0.7 point higher on ACT mathematics and science tests, respectively.

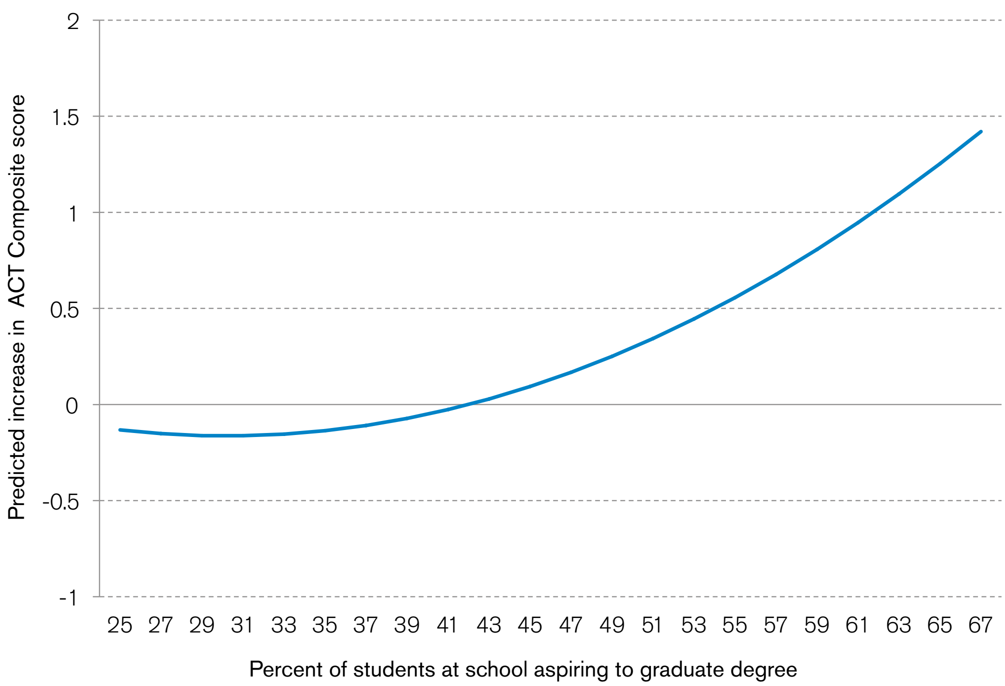

Figure 2: Predicted increase in ACT Composite score as a function of the percentage of students at school aspiring to earn a graduate degree.

[16] About 56% of schools had less than 41% of students at the school aspiring to a graduate degree.

Noncognitive Characteristics

The block of noncognitive characteristics accounted for between 4% and 7% of additional variance in ACT scores, beyond HSGPA, high school coursework taken, and school characteristics (Blocks 1 through 4). Several aspects of students' educational goals and values were positively related to performance on the ACT. First, students reporting plans to pursue a post-baccalaureate degree were predicted to score 0.8 (mathematics) to 1.3 (English) points higher, on average, than students intending to pursue a degree below a bachelor's degree (e.g., an associate's degree). Second, students with higher perceptions on the value of education tended to have slightly higher ACT mathematics, science, and Composite scores, compared to those with lower values on this component (by 0.1 to 0.2 point for each one-unit increase). Third, higher average ACT scores were found for students who had taken the ACT test prior to their senior year and for students who had described their high school coursework as a college preparatory curriculum, compared to those who did not (by 0.6 to 1.4 score points across all tests and by 0.3 to 0.5 point across all tests except in mathematics, respectively). Fourth, students who indicated needing help with their educational/occupational plans were predicted to score higher on the ACT English test (by 0.4 point).

The remaining significant predictors were negatively related to performance on the ACT. For instance, students indicating that they need help with certain academic skills were predicted to have lower ACT scores, on average. Specifically, students reporting that they need help on reading speed and comprehension scored lower on all tests except in mathematics (by 0.9 to 2.4 points), and students reporting that they need help with their math skills were predicted to have lower ACT mathematics, science, and Composite scores (by 0.5 to 1.5 points). In the final model, while indications of needing help with study skills remained related to ACT English scores, indications of needing help with writing skills did not. Additionally, ACT scores in all four subject areas were negatively related to the frequency at which students felt challenged by their high school coursework (by a one-unit incremental effect of 0.3 to 0.5).

Although parental involvement is often thought to positively influence student educational outcomes, one of the parental involvement predictors (parents involved in post-high school plans) did not enter any of the models and the other (parents check that my assignments are complete) was negatively related to ACT scores.[17] This latter result suggests that students whose parents more frequently check their assignments tended to score lower than those whose parents less frequently check their assignments (by a one-unit incremental effect of 0.2 to 0.4 point). The following noncognitive characteristics did not enter the ACT score models: academic commitment component, hours spent studying per week outside of class, hours spent working for pay per week, and plans to find out what education is necessary for desired jobs.

Demographic Characteristics

After accounting for HSGPA, high school coursework taken, school characteristics, and noncognitive student characteristics (Blocks 1 through 5), student demographic characteristics (Blocks 6 and 7) explained a fairly small proportion of the variance in ACT scores (2% to 4%). For the SES-related characteristics in Block 6, students with higher annual family incomes, higher parental education levels, and those from families where English is the primary language spoken at home tended

[17] This result was consistent with the bivariate relationship between the frequency with which parents check assignments and ACT scores. More elaboration is provided in the discussion.

to score higher on ACT tests, as compared to their corresponding peers. However, these results varied by subject area. In the final models, English being the primary language spoken at home was related to all ACT scores except mathematics. Average ACT Composite, English, and mathematics scores significantly differed among income groups; average ACT Composite and mathematics scores differed between higher- and lower-income students only. Even after accounting for all other predictors in the model, as parental education level increased, so did average ACT Composite, English, and reading scores.

Gender and racial/ethnic differences in average ACT scores were also found (Block 7). Compared to male students, female students tended to score 1.1 to 1.2 points lower on ACT mathematics and science; no gender differences were found in average ACT English and reading scores. The adjusted gender difference in average ACT Composite scores was 0.6 point. Lastly, African American and Hispanic students generally scored lower than White students across all tests by 1.7 to 2.3 points and 1.1 to 2.0 points, respectively. Asian students tended to score 0.9 point higher than White students, on average, on the mathematics test, but they typically scored 1.4 and 1.2 points lower on the reading and English tests, respectively.

To evaluate the impact of including both student- and school-level demographic characteristics in the models, additional models were estimated that excluded certain school-level characteristics. For example, compared to the regression coefficients from the final models (Table 5), only small changes were observed in regression coefficients for the student-level racial/ethnic categories when the school-level minority percentage was removed from Block 4; they tended to increase in magnitude by at most 0.4 point across all tests. Similarly, the student-level income coefficients (in Block 6) increased by at most 0.1 point across all tests, when the school-level income-related predictors were removed from Block 4.

Summary of Final Models

In summation, the total amount of variance explained across all five ACT scores ranged from 44% (reading) to 61% (Composite). Figure 3 shows the percentage of variance explained by each block of predictors. High school academic factors, such as HSGPA and high school coursework taken (Blocks 1 through 3) accounted for the greatest proportion of explained variance in all five ACT test scores (R^2 = 0.28 to 0.46). These three blocks alone comprised 64% to 77% of the total variance explained by the models. Figure 4 shows the percentage of variance accounted for by each major block category: high school academic factors, school characteristics, noncognitive student characteristics, and student demographic characteristics.

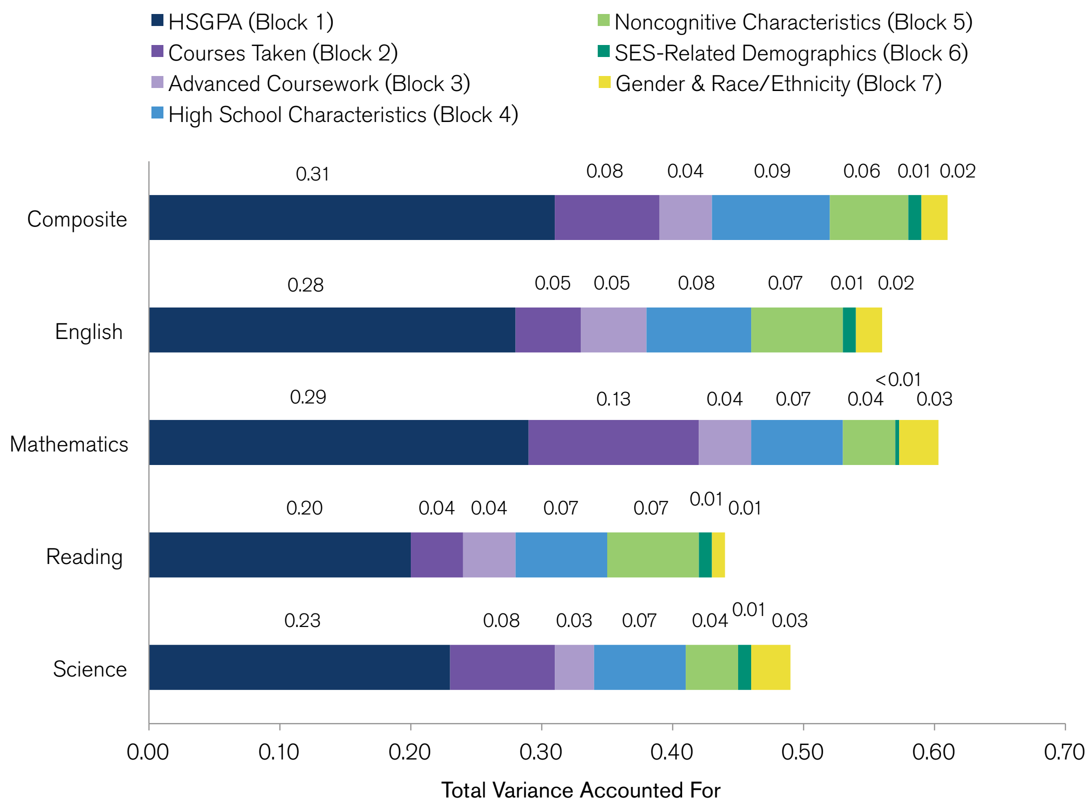

Figure 3: Proportion of variance in ACT scores explained by each block of predictors.

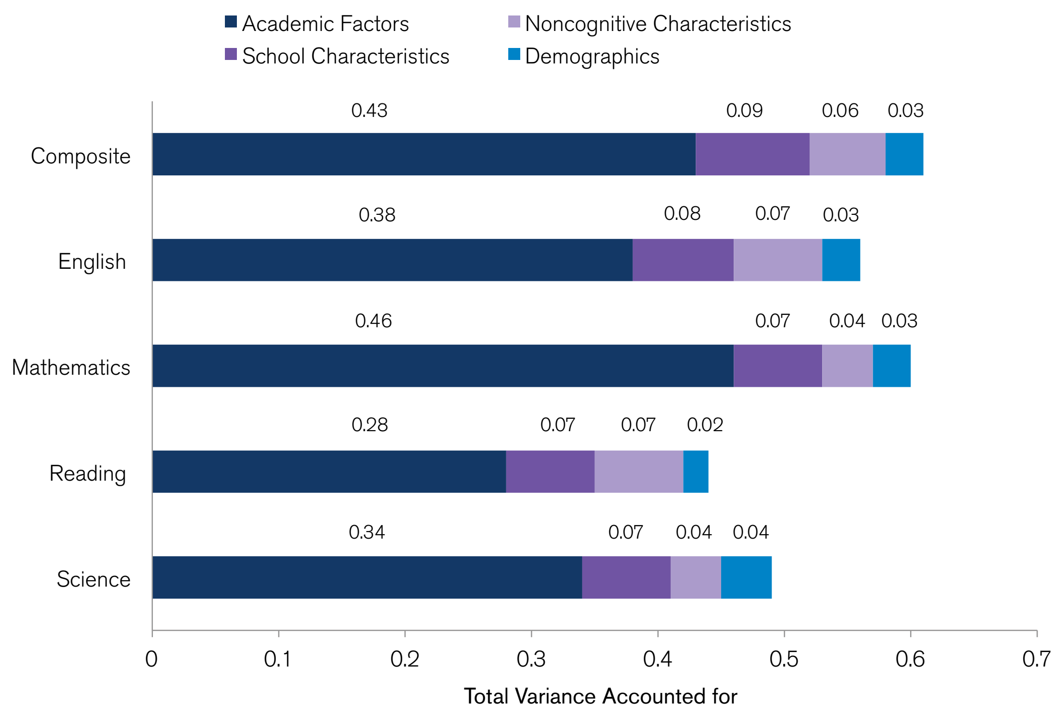

Figure 4: Proportion of variance in ACT scores explained by overall block categories.

Unadjusted and Adjusted Mean Differences by Student Demographic Characteristics

To evaluate the extent to which other student and school characteristics explain differences observed in mean ACT scores among student demographic groups, unadjusted and adjusted mean differences among these groups were compared. These comparisons were examined for the following student demographic characteristics: race/ethnicity, gender, annual family income, and parental education level.

Race/ethnicity. Unadjusted mean differences in ACT scores between White and African American students ranged from 4.2 points (mathematics) to 5.6 points (English). Similarly, unadjusted mean differences between White and Hispanic students were rather large, ranging from 2.7 points (mathematics) to 4.9 points (English). However, after accounting for HSGPA, high school coursework taken, school characteristics, noncognitive student characteristics, and other student demographics, mean differences were reduced by nearly 60% and ranged from 1.7 to 2.3 points for White and African American students and ranged from 1.1 to 2.0 points for White and Hispanic students (see Figure 5).

Gender. Unadjusted mean ACT scores were 1.1 score points higher in mathematics and science for male students than for female students, and were 0.3 to 0.4 point lower in reading and English for males. Even after accounting for the other student and school characteristics, differences persisted in mean ACT mathematics and science scores between male and female students. The adjusted mean ACT English and reading scores did not significantly differ between male and female students.

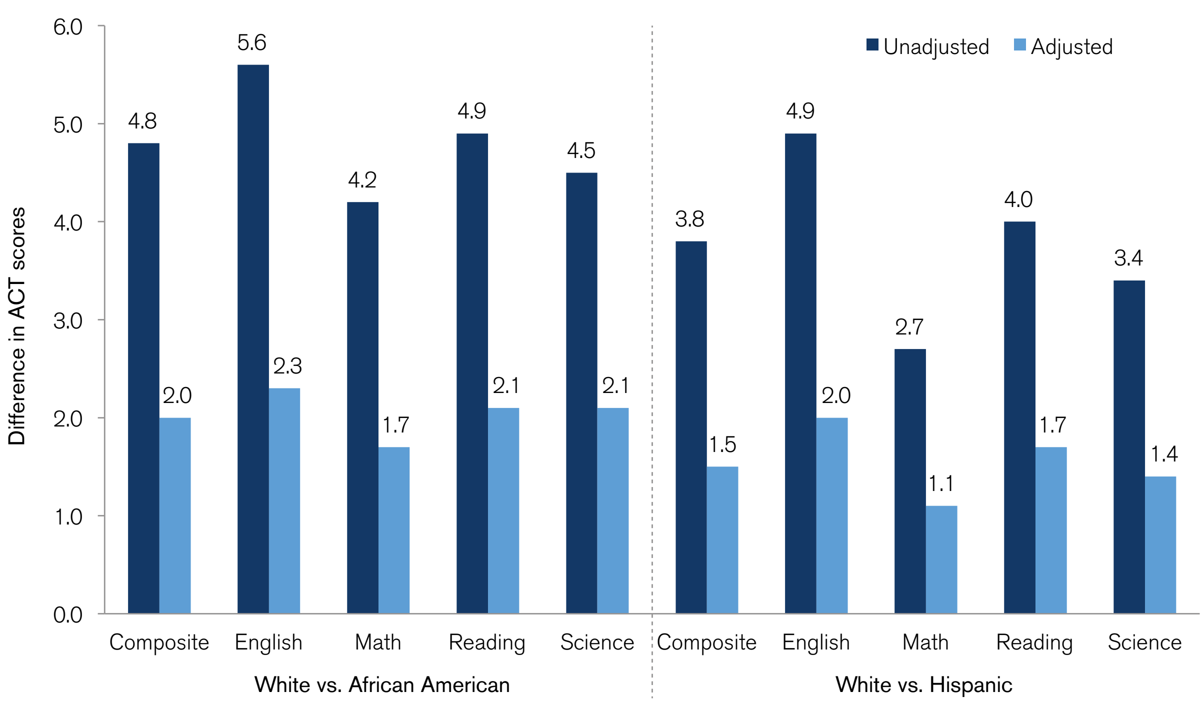

Figure 5: Unadjusted and adjusted mean differences in ACT scores by race/ethnicity.

Family income. Unadjusted mean differences in ACT scores ranged between 2.0 points (mathematics) and 3.1 points (English) between middle- and lower-income students and from 3.7 points (science) and 5.3 points (English) between higher- and lower-income students. After accounting for the other student and school predictors in the final regression models, the mean differences were reduced by between 87% and 95% (see Figure 6). For example, the unadjusted mean difference in average ACT reading scores between higher- and lower-income students was reduced from 4.3 points to 0.2 point, after other student and school characteristics were taken into account.

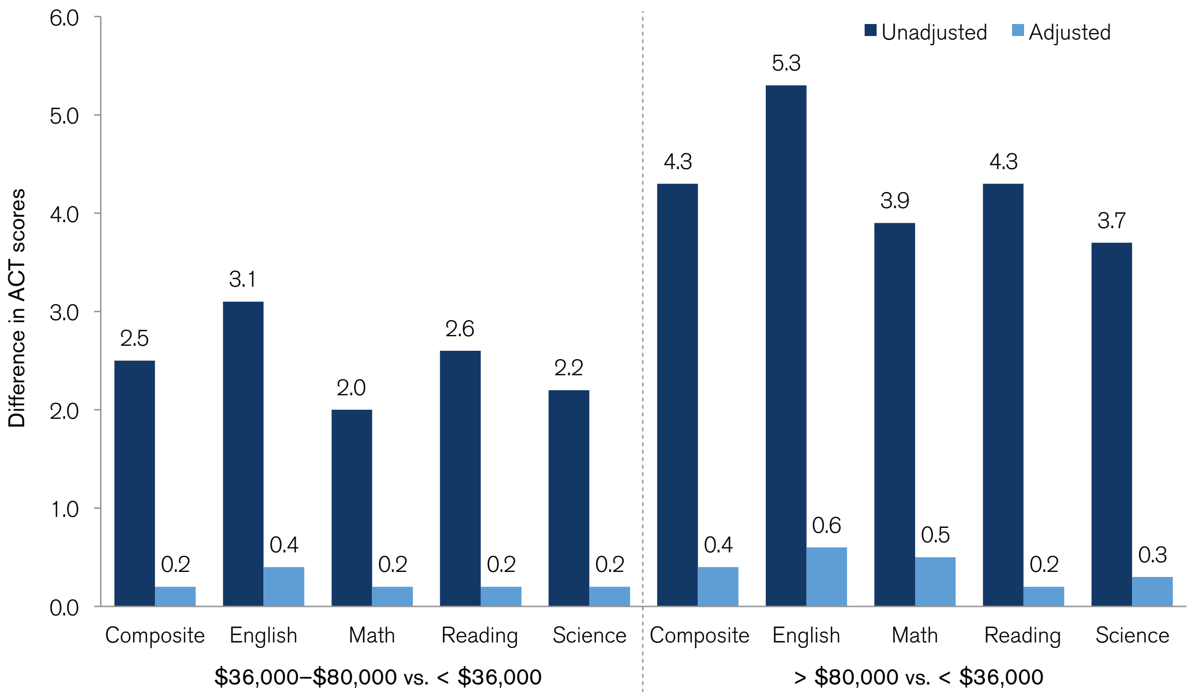

Figure 6: Unadjusted and adjusted mean differences in ACT scores by family income.

Parental Education. Compared to students whose parents had no college experience (first-generation students), the unadjusted means in ACT scores were 1.1 points to 2.3 points higher for students whose parents had some college experience, 2.9 points to 4.6 points higher for students whose parents completed a bachelor's degree, and 4.2 points to 6.3 points higher for students whose parents completed a graduate-level degree. Adjusted mean differences in ACT scores between these groups were substantially smaller (reduced by at least 74%; see Figure 7), after other student and school characteristics were taken into account (Table 5). The largest adjusted mean difference across ACT test scores and parental education level was 1.1 scale score points.

HSGPA Predicted from Noncognitive Student Characteristics

Table 6 shows the noncognitive student characteristics that were found to be significantly related to HSGPA based on stepwise and LARS selection procedures. For both selection methods, the noncognitive predictors accounted for 29% of the variance in HSGPA. In comparison to the final models presented in Table 5, the following noncognitive predictors were positively related to HSGPA but were not significantly related to ACT scores: hours spent studying per week outside of class, hours spent working for pay per week, and the academic commitment component. Moreover, students indicating that they need help with their study skills were predicted to have lower HSGPAs than students who did not indicate needing such help. In contrast, this predictor was significantly related to ACT English scores only (Table 5).

The remaining predictors of HSGPA were also found to be significantly related to ACT scores and they were related in the same direction. These findings suggest that noncognitive student

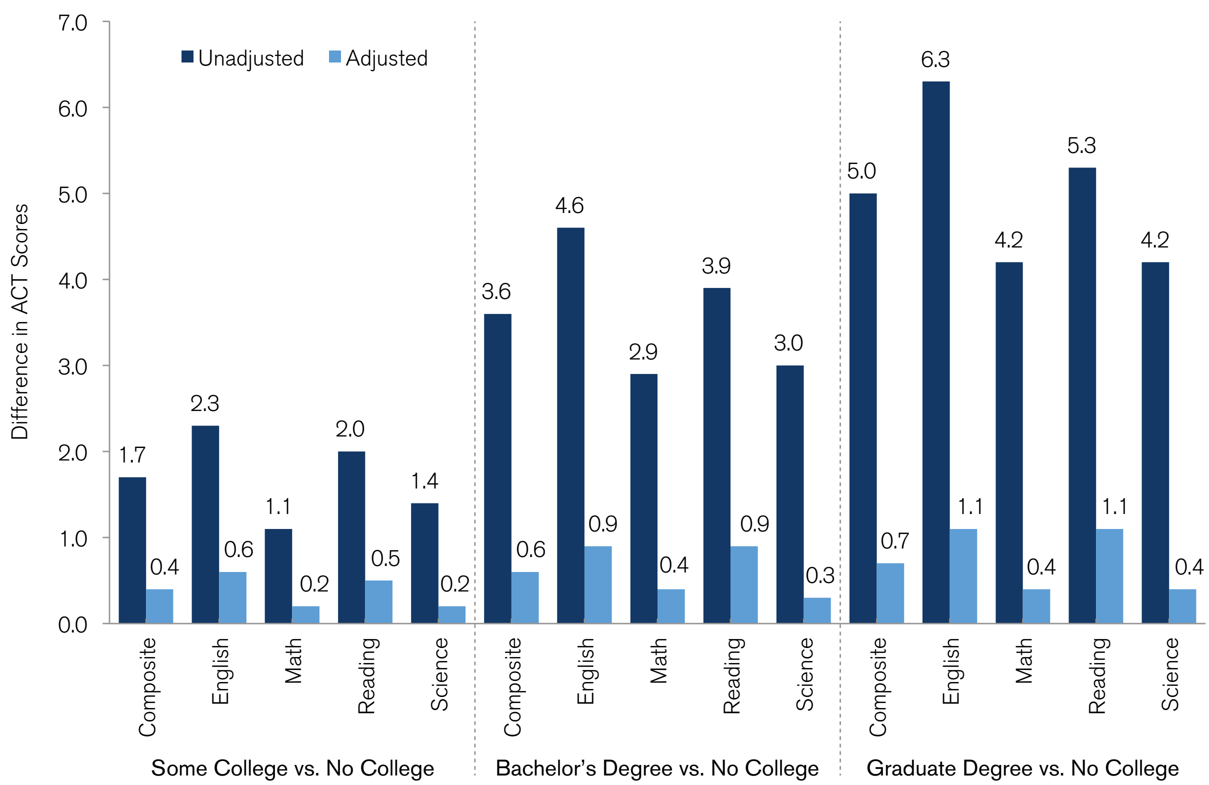

Figure 7: Unadjusted and adjusted mean differences in ACT scores by parental education level.

characteristics, such as academic commitment and hours spent studying, are also indirectly related to performance on the ACT through their effects on HSGPA.

Differences in the selected predictors and their coefficients were rather small between the stepwise selection procedure using p-values and the LARS procedure. The same predictors were selected by the two procedures with the exceptions of the following variables not being selected by the LARS procedure: students indicating that they need help with their educational and occupational plans and that they are challenged by their high school coursework. Results for these two methods were compared and presented to help address the question of whether the use of a traditional stepwise selection procedure would lead to vastly different final models than alternative selection procedures that did not rely upon p-values. These findings suggest that there are minimal concerns with the use of a stepwise selection procedure for the ACT models in this study.

Table 6. Stepwise Selection Results for Predicting HSGPA from Noncognitive Factors

Variable	Stepwise Estimates	LARS Estimates
Intercept	3.09	3.06
Academic Commitment Component	0.13	0.12
College Prep Curriculum	0.14	0.14
Educational Perception Component	0.04	0.03
Expected Education Attainment		
Below Bachelor's (referent)		
Bachelor's	0.20	0.20
Beyond Bachelor's	0.39	0.37
Find High School Challenging	-0.04	---
Hours Spent Studying per Week		
0–5 Hours (referent)		
6–10 Hours	0.07	0.06
11 or More Hours	0.13	0.12
Hours Spent Working per Week		
0 Hours (referent)		
1–10 Hours	0.07	0.07
11 or More Hours	0.03*	0.02*
Need Help—Educ./Occ. Plans	0.05	---
Need Help—Math Skills	-0.19	-0.18
Need Help—Study Skills	-0.13	-0.11
Parents Check Assignments	-0.02	-0.03
Took ACT Junior Year	0.12	0.13
R^2	0.29	0.29
Root Mean Square Error	0.46	0.46

Note: All variables are significant at the 0.01 level unless noted with an asterisk (*).

Discussion

Similar to the results from two prior studies conducted in 1999 (Noble et al., 1999a, 1999b) on the relationships between noncognitive characteristics and ACT scores, this study on a more recent cohort of students found that between 44% and 61% of the variance in ACT scores can be explained by HSGPA, coursework taken, school characteristics, noncognitive student characteristics, and demographic characteristics. Over and above HSGPA, coursework taken, and school characteristics, noncognitive variables accounted for between 4% and 7% of the variance in ACT scores. This percentage was slightly higher than that for advanced coursework (between 3% and 5%) and slightly lower than that for school-level characteristics (between 7% and 9%), conditional on variables entering the model in previous blocks. It is important to note that the noncognitive characteristics available in this study do not represent the universe of noncognitive factors; this could have affected the percentage of variance explained by the noncognitive characteristics.

In contrast to the current study, the Gaertner and McClarty study (2015) found a much larger percentage of variance accounted for by noncognitive factors related to students' behaviors, motivation, and social engagement (32% vs. 4% to 7% in this study). However, it should be noted that their college readiness index included both HSGPA and ACT/SAT test scores while this study used HSGPA as a predictor of ACT test scores. Moreover, their academic achievement and noncognitive predictors were measured from when students were in middle school. This study used more proximal measures of academic preparation (HSGPA and high school coursework taken) and noncognitive characteristics for a sample of high school seniors in the midst of the college planning process. In this study, when ACT Composite score was regressed solely on the available noncognitive characteristics, the percentage of the variance in scores accounted for by these predictors was 33%, a value more in line with the findings of Gaertner and McClarty (2015). The focus of this study, however, was to evaluate the incremental variance explained in ACT scores by noncognitive characteristics beyond the traditional predictors.

Academic Factors

The rigor or academic intensity of the high school curriculum (especially in mathematics) has been shown to be a key indicator for whether a student is ready for and will succeed in college (Achieve, 2008; Adelman, 2006). Therefore, given the content and purpose of the ACT tests, it is not surprising that ACT scores have a strong relationship with both the courses taken in high school and the grades earned in these courses. The level of the coursework taken in high school was found to be strongly related to performance on the ACT, even after accounting for high school grades. Specifically, taking higher-level mathematics and science coursework was associated with higher ACT scores in most subject areas (by up to 3.0 scale score points). This is not to say that other courses taken, including English and social studies courses, were unrelated to ACT performance. In general, some of these other courses had limited variability (either most taken or not taken). This study also found that taking advanced, accelerated, honors, and/or dual credit coursework in specific subject areas was associated with higher ACT scores, by at most 2.9 scale score points if a student took advanced coursework in English, mathematics, natural science, and social studies. Beyond these effects, students expecting to earn seven or more college credit hours typically had higher ACT scores than those not expecting to earn any college credit hours while in high school (by 0.4 to 0.6 point).

School Characteristics

The percentage of variance accounted for by the school-level variables was consistent with what has been found in previous studies. Specifically, although Gaertner and McClarty (2015) had nearly 40 different school-level characteristics that comprised an overall school-level factor and Noble et al. (1999a, 1999b) included fixed effects for each school, this study found a similar percentage of variance accounted for by school-level characteristics using fewer school characteristics (7% to 9% versus 7.5% and 5% to 7%, respectively). The specific school demographic and climate/culture-related characteristics used in this study have also been found to be related to student achievement in other studies (Swanson, 2004; Kim & Sunderman, 2005; Cook & Evans, 2000; Oseguera, 2013). School demographic characteristics were included in this study as possible proxies for information related to school resources, school environment, and quality of education (Alliance for Excellent Education, 2013; Comer, 2005). Some studies have suggested that the demographic composition of schools and school working conditions have a high impact on where higher-performing teachers are employed, even beyond teacher salary (Baugh & Stone, 1982; Hanushek, Kain, & Rivkin, 1999; 2004; Hanushek & Luque, 2000).

After controlling for other student and school characteristics, the finding that public schools outperformed non-public schools on the ACT mathematics and science tests may initially seem counterintuitive. However, this finding in mathematics has been noted previously by Lubienski et al. (2008); the authors used the 2003 National Assessment of Educational Progress (NAEP) data set that included fourth and eighth graders. The explanation provided for this finding was that public schools tend to employ more certified mathematics teachers and utilize more reform-oriented mathematics teaching practices, which include using calculators, non-number emphasis, and discovery learning, with less emphasis on rote learning and routine procedures.

School-level characteristics are often considered factors that students cannot change, including the quality of education that they receive. Because the school climate and culture can influence students' aspirations, engagement, academic behaviors, and achievement (Akey, 2006; O'Brennan & Bradshaw, 2013), school-level characteristics were included in the models prior to noncognitive student characteristics. However, the overall results of the study did not significantly change when these blocks (4 and 5) were reversed in the models.[18] Unfortunately, school characteristics analyzed were necessarily limited to those available for all schools, especially in terms of those measuring school climate and culture.

Noncognitive Characteristics

In this study, we found that higher educational plans and perceptions of education were associated with higher ACT scores, even after accounting for academic factors and school characteristics. One possible explanation for these findings is that these students may be more motivated and engaged in their learning because of their academic goals and values. Higher levels of student engagement have been found to be related to higher levels of academic achievement (Heller, Calderon, & Medrich, 2003; Lee & Shute, 2009).

Given that a majority of the students included in this study were from states whose ACT-tested population represents college-bound students, the interpretation of the finding that students who

[18] If the noncognitive characteristic block was specified to enter the model prior to the school-level characteristics, then the variance accounted for by the noncognitive characteristics remained in a similar range (4% to 9%).

took the ACT earlier during their junior year tended to have higher test scores might also be related to motivation. Students who have a stronger desire to enroll in college may take the test earlier to better understand their college options, gauge their college readiness, or to allow ample time to retest if they believe they can score better on subsequent attempts.[19] Other ACT studies have found retesting to be associated with similar score gains (Schiel & Valiga, 2014).

In this study, indicating a need for help with reading and mathematics skills and the frequency with which students were challenged by their high school coursework were both negatively related to ACT scores. The results for the need for help in certain academic skills were consistent with those reported in the earlier studies by Noble et al. (1999a, 1999b). ACT English scores were more strongly related to indicating a need for help in reading than in writing. This finding could be due to these two variables being moderately related ($r = 0.45$). ACT science scores were related to indicating a need for help in both reading and mathematics; students were not asked about their need for help in science. In general, students appear to have a good idea about those areas in which they need additional help. Unfortunately, we do not know whether study respondents acted upon their indications of needing help after receiving their ACT score reports. Future studies might consider following such students to further examine this issue.

Parents checking completion of homework assignments more frequently was negatively related to performance on the ACT. This finding seems counterintuitive because parental involvement has generally been found to positively influence student achievement (Comer, 2005; Henderson & Mapp, 2002). However, in a review of the literature, Henderson and Mapp (2002) cited a couple of studies that found parental at-home involvement to be negatively related to test scores and grades. The authors indicated that the findings suggested that more at-home help was provided for struggling students than for those not struggling academically. In this study, there was not a statistically significant interaction effect between HSGPA and parents checking completion of homework assignments on ACT scores. However, the association of this parental involvement factor with ACT scores was in the same direction in unadjusted and adjusted analyses.

The number of hours spent studying per week outside of class and the academic commitment component were not found to be related to ACT scores. These factors were, however, related to HSGPA. These findings agree with another study (Allen, Robbins, Casillas, & Oh, 2008) that found that students' level of academic discipline (as measured by ACT Engage®) was statistically related to HSGPA, but was not related to ACT scores. Motivational processes, self-efficacy, and education plans likely factor into coursework selection and grades earned.[20] Considering that HSGPA and noncognitive characteristics were shown to be fairly highly related and that HSGPA entered the model first, any overlap in variance accounted for in ACT scores by HSGPA and noncognitive characteristics would be attributed to HSGPA.

The modeling techniques used in this study were not able to detect mediation effects that may be present. This was why we also evaluated the relationships between the noncognitive characteristics and HSGPA. A study by Noble, Roberts, and Sawyer (2006), using structural equation modeling, found that ACT scores were directly influenced only by academic achievement in high school

[19] At the time of data collection, eight states administered the ACT to all public high school juniors. These states accounted for 19% of the study sample. Within these states, 91% of respondents had taken the ACT as a junior compared to only 48% of students from all other states.

[20] For example, in Gaertner and McClarty (2015) study, participation in advanced and accelerated courses loaded on both their achievement and motivation components.

as measured by grades earned and coursework taken. Education-related accomplishments and activities and perceptions of self and others (other noncognitive characteristics) had only indirect effects on ACT scores through their academic achievement measure. Their findings may help explain why the noncognitive characteristics accounted for a small percentage of the variance in ACT scores beyond the traditional predictors.

Student Demographics

Despite ample contrary evidence (Mattern, Patterson, Shaw, Kobrin, & Barbuti, 2008; Radunzel & Noble, 2013; Sanchez, 2013), some researchers have suggested that standardized test scores like the ACT test unfairly disadvantage underrepresented minority and lower-income students in the college admissions process (Soares, 2012). Others contend that standardized test scores simply capture SES (Colvin, 1997; Guinier & Torres, 2002; Kohn, 2001). However, Sackett, Kuncel, Arneson, Cooper, and Waters (2009) largely dispelled this latter claim by showing that the relation between standardized achievement test scores and college grades—when partialing out the effect of SES—is nearly identical to the zero-order relation ($r = 0.44$ vs. 0.47), which indicates that nearly all of the variability between college grades and standard achievement test scores is independent of SES.

Results from this study suggest that differential performance on the ACT among student demographic groups is largely attributable to differential academic preparation. Specifically, after accounting for HSGPA, high school coursework taken, school characteristics, and other noncognitive student characteristics, SES and other demographic characteristics (including parental education level, race/ethnicity, and gender) accounted for a small percentage of the variance in ACT scores (4% or below). Additionally, differences in ACT scores among racial/ethnic, family income, and parental education level groups were substantially reduced when students' academic preparation and achievement levels were taken into account.[21] Other research (Sawyer, 2008) suggests that differential performance on test scores starts early, and that improved high school coursework and grades benefits students with greater prior achievement more than those with lower prior achievement. School-level demographic characteristics, along with other school-level characteristics, were included in the models to account for high school attended. In subsequent analyses, when the school-level demographic factors were excluded, student-level racial/ethnic and income regression coefficients were only slightly higher, by at most 0.4 point, than those reported from the final models.

Even though gender did not contribute much to the percentage of variation in ACT scores beyond that explained by other student and school characteristics, mean gender differences in ACT mathematics, science, and Composite scores persisted in the final models (by 1.1, 1.2, and 0.6 points, respectively). Future research should explore factors related to gender differences in ACT scores. One such area might include evaluating gender differences in students' academic self-concept in mathematics and science—that is, their belief that they can do well in these subject areas (Rosen, 2010). In this study, female students were more likely than male students to indicate that they need help with improving their mathematics skills (41% vs. 34%). This finding held even among students scoring higher on the ACT mathematics test.[22]

[21] ACT score differences among these demographic groups would likely have been even smaller if standardized measures of prior achievement had been included in the multiple regression models.

[22] For both male and female students, the average ACT mathematics score was lower for those who indicated that they need help in mathematics than for those who did not indicate needing such help.

Application for Alternative Statistical Techniques

This study applied statistical techniques for sparsely clustered data and model selection that are not commonly used in educational research, but that have been shown to be effective either in simulation studies or in other disciplines. A DBM approach using CR-SEs was the regression method used to account for students being sparsely clustered within schools. Differences in regression coefficients and standard errors estimated from OLS versus CR-SE methods were not large. However, across all predictors and outcome variables, the standard errors estimated by OLS were about 10% smaller, on average, than those estimated from CR-SE. This finding is roughly in line with what would be expected from the design effect (Kish, 1965). Additionally, since many selected variables were highly significant and the design effect was fairly small,[23] predictors that were on the boundary of significance were the most affected by the clustering with about three or four variables per model changing significance between OLS and CR-SE (always in the direction of being significant with OLS but non-significant with CR-SE).

Stepwise selection regression was the method used to identify predictors related to performance on the ACT. A common argument against using stepwise selection procedures is that R^2 values and regression coefficients can be upwardly biased and lead to model overfitting (Thompson, 1995, 2001). Modern selection methods, such as LARS or the related least absolute shrinkage and selection operator (LASSO), overcome these concerns, but are not able to accommodate order restrictions (i.e., requiring certain predictors to be in the model before other predictors are considered) that are needed in a blockwise analysis. As a result, these methods were not a viable option for the ACT score models in this study (Hesterberg, Choi, Meier, & Fraley, 2008). However, when comparing the results between the hybrid LARS and stepwise selection procedures for the HSGPA model, very few differences were found in the predictors selected, and the R^2 and regression coefficients were similar between these two methods. Moreover, with over 300 observations per candidate predictor, overfitting concerns are likely to be small for the models in this study (Babyak, 2004).

Limitations and Future Research

The relatively high non-response rate of greater than 80% associated with the online questionnaire may limit the generalization of the results because those who responded may differ from those who did not. In fact, respondents may represent a more motivated group of students. The sample was weighted to account for important demographic and academic differences between respondents and the population. Weighting, however, does not address potential unobserved differences between respondents and non-respondents. When high school coursework, grades, student demographics, and the needs help indicators between the weighted sample and the entire population (i.e., variables available for both groups) were compared, no major differences were found in the distributions for these variables.

Moreover, even though a considerable percentage of the variability in ACT scores was explained, a fair amount remained unaccounted for by the student and school characteristics included in this study—from 39% (Composite) to 56% (reading). While part of the unexplained variance is due to

[23] The design effect is calculated by $1+(m-1)\rho$ where m is the average cluster size and ρ is the ICC. The design effect gives an estimate of the ratio of the sampling variance with clustering compared to the sampling variance assuming independence. The design effect for this study was 1.08 to 1.09, which means that the sample variance is 1.08 to 1.09 times bigger than it would be if the study data was based on the same sample size under independence among students.

measurement error in the subject tests (average standard error of measurement is about 2.0 scale score points; ACT, 2014b), most of the remaining unexplained variance is likely due to the limited number of noncognitive and school characteristics available.[24] For instance, the online questionnaire focused more on students' college planning activities, intentions, and financial concerns—characteristics that did not seem to be relevant for performance on the ACT. Future studies should incorporate a more extensive list of noncognitive characteristics, including using instruments designed to measure specific constructs such as motivation, self-regulation, and academic self-efficacy. Future studies might also consider accounting for measurement error in the variables studied. Moreover, one could investigate relationships of postsecondary outcomes (e.g., enrollment, persistence, and first-year grades in college) with ACT scores and the other student and school characteristics included in this study.

Implications

The implications of the study findings are similar to those outlined fifteen years ago by Noble et al. (1999a). First, in order for students to achieve higher ACT scores, and thus be better prepared academically for college, they need to focus on taking rigorous courses in high school and earning good grades. In particular, taking mathematics courses beyond Algebra II, science coursework that includes a Physics course, and/or advanced, accelerated, honors, or dual-credit coursework in multiple subject areas appears to benefit students. Research by others suggests that students also need to develop strong academic behaviors and study skills early on, even before entering high school, to succeed in college (Conley, 2007).

Second, counselors and teachers can support students by encouraging them to do well in school, to have high aspirations and perceptions on the value of education, and to seek help when they need it. Students appear to have a good idea about those areas in which they need additional help, such as in reading and mathematics. Counselors and teachers can provide these students with the support and resources they need to improve their academic skills.

Third, although not directly measured in this study, all students need to be provided with a challenging, quality education, including equal access to rigorous high school coursework and the opportunity to earn college credits while in high school (Clinedinst, 2015; Gagnon & Mattingly, 2015; Handwerk, Tognatta, Conley, & Gitomer, 2008). This responsibility falls to administrators, teachers, and counselors, as well as the parents and communities that support the school system. Research by others suggests that positive school climates featuring high-quality academic instruction and high levels of academic expectations, student engagement, and parental involvement can contribute to improved student achievement and increased college aspirations and access (Alliance for Excellent Education, 2013; Heller et al., 2003; O'Brennan & Bradshaw, 2013; Oseguera, 2013). ■

[24] The amount of explained variance is capped by the reliability of the individual subject scales (typical estimates range from 0.83 in science to 0.92 in English; ACT, 2014b).

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Appendix A

Table A-1. Items that loaded with magnitude above 0.40 on components

Component	Item	Loading
Academic Commitment		0.73[1]
	I turn in assignments on time.	0.81
	I am well-prepared for in-class activities (e.g., discussion, pop quizzes, etc.).	0.81
	I put forth my best effort in my schoolwork.	0.81
	It will be difficult to discipline myself to keep my academic commitments in college, such as attending classes and being prepared for them.	-0.42
Perception of Education		0.44[1]
	It is important to take mathematics and/or science classes during my senior year of high school.	0.67
	The benefits of earning a college degree are well worth the costs.	0.71
	Regardless of the obstacles or hardships I face in college, I am committed to completing a college degree.	0.62

[1] The loading column for the component row is the internal consistency reliability (as measured by Cronbach's α) of the items loading with magnitude above 0.40 on the component.

Appendix B

Additional Detail on Model-Based and Design-Based Methods to Account for Clustering

Model-Based Methods

Model-based methods account for clustering by specifically incorporating the clustered data structure in the model through random effects and/or a particular within-cluster residual covariance matrix. The predominant model-based method is multilevel models (MLMs; also called hierarchical linear models, random coefficient models, mixed models). Using Laird and Ware (1982) notation, MLMs for continuous outcomes can be written as $\mathbf{Y}_j = \mathbf{X}_j\boldsymbol{\beta} + \mathbf{Z}_j\mathbf{b}_j + \boldsymbol{\varepsilon}_j$, where $\mathbf{Y}_j$ is a vector of responses for cluster j, $\mathbf{X}_j$ is a design matrix for the fixed effects of cluster j, $\boldsymbol{\beta}$ is a vector of fixed effects, $\mathbf{Z}_j$ is a design matrix for the random effects of cluster j, $\mathbf{b}_j$ is a vector of random effects for cluster j where $E(\mathbf{b}_j) = \mathbf{0}$ and $Cov(\mathbf{b}_j) = \mathbf{G}$, and $\boldsymbol{\varepsilon}_j$ is a matrix of residuals of the observations in cluster j where $E(\boldsymbol{\varepsilon}_j) = \mathbf{0}$ and $Cov(\boldsymbol{\varepsilon}_j) = \mathbf{R}_j$. MLMs produce cluster-specific inferences such that the mean of the outcome is conditional on both the values of the predictor variables and the values of the random effects (i.e., $E[\mathbf{Y}_j \mid \mathbf{X}_j, \mathbf{b}_j]$ for $\mathbf{Y}_j$ a vector of outcomes for cluster j, $\mathbf{X}_j$ a matrix of predictors for cluster j, and $\mathbf{b}_j$ a vector of random effects).

MLMs are implemented when there is an explicit interest in modeling both the mean and the covariance of the outcome such that $E[\mathbf{Y}_j \mid \mathbf{X}_j, \mathbf{b}_j] = \mathbf{X}_j\boldsymbol{\beta}$ and $Var(\mathbf{Y}_j) = \mathbf{Z}_j\mathbf{G}\mathbf{Z}^{\mathrm{T}}_j + \mathbf{R}$. Because $Var(\mathbf{Y}_j)$ is of explicit interest, the covariance structures for $\mathbf{G}$ and $\mathbf{R}$ must be properly specified. Otherwise, standard error estimates and point estimates may be estimated with bias.

Design-Based Methods

Design-based methods (DBMs) account for the clustering through statistical corrections to address violations of single-level model assumptions rather than through incorporating aspects of the clustering directly into the model which is often accomplished through random effects. The two common DBMs are (1) the semi-parametric generalized estimating equations (GEEs, Liang & Zeger, 1986) which are estimated with quasi-likelihood and (2) the parametric cluster-robust estimators (CR-SEs, also called sandwich or empirical estimators) which are typically estimated with ordinary least squares (OLS) or likelihood methods.

Standard OLS regression is formulated by $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ for $\mathbf{Y}$, an $n \times 1$ vector of outcomes, $\mathbf{X}$, an $n \times p$ design matrix, and $\boldsymbol{\varepsilon}$, an $n \times 1$ vector of residuals assumed to be distributed $N^{i.i.d.}(0,\sigma^2)$. Under OLS, the regression coefficients have a closed form solution such that $\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$. The standard errors of the regression coefficients are taken from the square root of the diagonal elements of variance of $Var(\hat{\boldsymbol{\beta}})$ which is most generally calculated by $Var(\hat{\boldsymbol{\beta}}) = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}\mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$. Assuming independently and identically distributed residuals, $\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ can be summarized by the average squared residuals $\sigma^2 = (n-p)^{-1}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ which results in a block diagonal matrix $\sigma^2\mathbf{I}$ where σ^2 is the residual variance. The estimate of $Var(\hat{\boldsymbol{\beta}})$ then simplifies to $(\sigma^2)(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$, and given that $(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{X} = \mathbf{I}$, $Var(\hat{\boldsymbol{\beta}}) = \sigma^2(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$ if residuals are independently and identically distributed. However, when the independence assumption is violated, summarizing $\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ with $(n-p)^{-1}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ is not appropriate and results in estimates of $Var(\hat{\boldsymbol{\beta}})$ being too small, meaning that the standard errors are underestimated and, consequently, type I errors are inflated (Cameron & Miller, 2013).

When data are dependent through clustering, the residuals of observations within clusters are likely related, meaning that the assumption of independently and identically distributed residuals is unlikely to be upheld. Robust standard errors (perhaps more appropriately called empirical or heteroskedasdicity-corrected covariance estimators) address this problem by replacing the average of squared residuals $(n-p)^{-1}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ with the squared residual $\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ which does not require diagonal elements to be identical. After this substitution, $\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}$ can no longer be summarized by $\sigma^2\mathbf{I}$ and thus the variance of the regression coefficients is equal to its original formulation as $Var(\hat{\boldsymbol{\beta}}) = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}\mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$ (White, 1980).

To address violations of the residuals being independently distributed, $\mathbf{X}^{\mathrm{T}}\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathrm{T}}\mathbf{X}$ is calculated for each cluster individually and then summed across all clusters, $\sum_{j=1}^{J}\mathbf{X}_j^{\mathrm{T}}\boldsymbol{\varepsilon}_j\boldsymbol{\varepsilon}_j^{\mathrm{T}}\mathbf{X}_j$. This quantity is then pre and post multiplied by $(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$ to obtain the standard errors that account for clustering (i.e., cluster robust standard errors) such that $Var^{\mathrm{CR}}(\hat{\boldsymbol{\beta}}) = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\sum_{j=1}^{J}(\mathbf{X}_j^{\mathrm{T}}\boldsymbol{\varepsilon}_j\boldsymbol{\varepsilon}_j^{\mathrm{T}}\mathbf{X}_j)(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$ (White, 1984). For non-linear models and/or models estimated with maximum likelihood, the same principles can be applied except that the residuals will be calculated differently and estimates will not have closed form solutions.

The square root of the diagonal elements of $Var^{\mathrm{CR}}(\hat{\boldsymbol{\beta}})$ provides standard errors for the regression coefficients that account for the dependency in the data due to the clustering of observations. Note that the clustering was accounted for without any random effects that are required in MLMs—the residuals are used to assess the degree of dependence and then to correct $Var(\hat{\boldsymbol{\beta}})$ accordingly. As a result, CR-SEs (as well as GEEs) are population-averaged models, meaning that estimates apply to the average over all clusters rather than being cluster-specific as with MLMs (i.e., $E[\mathbf{Y}_j \mid \mathbf{X}_j]$ in DBMs (Cameron & Miller, 2013)). This interpretation is identical to a single-level model which makes sense since a CR-SE model is essentially a single-level model with a statistical correction for clustered observations. That is, DBMs are useful when the regression coefficients are of interest and partitioning the variance within and between levels is not relevant nor are inferences for specific clusters. Although DBMs and MLMs are representative of different quantities, cluster-specific and population-averaged estimates can be shown to be equivalently interpreted with continuous (but not discrete) outcomes (Fitzmaurice, Laird, & Ware, 2012).

More conceptually, in DBMs, the clustering is considered a nuisance that has to be dealt with and prevents one from fitting a single-level model. In contrast, clustering in MLMs is a substantively interesting part of the research question to be explicitly modeled and tested to determine how the variance is partitioned between and within cluster levels. In DBMs, neither the random effects nor their covariance structure need to be specified. In place of random effects, clustering is alternatively accounted for indirectly through the effect of clustering through the residuals, which are affected when assumptions are violated. DBMs use the information from the residuals to statistically correct standard errors to account for the clustering of the data. The variance is not partitioned between levels, no random effects are estimated, and no variance components are output. The resulting output resembles a standard single-level regression (e.g., OLS for metric outcomes) except the standard errors have accounted for the clustered nature of the data.

Appendix C

More Detail on Least Angle Regression (LARS)

LARS is a forward selection algorithm that encompasses a variety of regularization methods as special cases or extensions. Regularization methods are used to account for overfitting by applying a penalty term in the estimation process (e.g., the loss function in OLS; see McNeish, 2015, for an overview of regularization as relevant to behavioral sciences). LARS uses the correlation between candidate predictors and the residual to select relevant predictors as opposed to *p*-values or R^2 that are commonly used in stepwise procedures. LARS can select and estimate coefficients by itself or can also be implemented as a more general, computationally efficient method to obtain least absolute shrinkage and selection operator (LASSO) or ridge regression estimates. As a result of LARS, regularization methods can be estimated in the same amount of time as an equivalent OLS model (Efron, Hastie, Johnstone, & Tibshirani, 2004).

LARS and related methods improve upon traditional automatic selection methods that use *p*-values or R^2 by addressing concerns such as overfitting, inflated R^2 values, and over-selection of variables due to inflated type-I errors resulting from repeated testing (Flom & Cassell, 2007). These concerns are more prevalent when the ratio of sample size to candidate predictors is small, which is not the case in the current study (Babyak, 2004; Hesterberg, Choi, Meier, & Fraley, 2008).

Although LARS can output regression coefficients through LASSO (also known as ℓ_1 penalization) or its own estimation process, Efron et al. (2004) also outlined a hybrid method whereby the LARS algorithm selects relevant variables but least squares or another estimation method is used to estimate regression coefficients. Belloni and Chernozhukov (2013), Belloni, Chen, Chernozhukov, and Hansen (2012), and Belloni, Chernozhukov, and Hansen (2014) also discuss using LARS or related regularization methods to select predictors and then an alternative estimation method for the regression coefficients. The HSGPA model employed this hybrid method by obtaining estimates through CR-SEs once the LARS algorithm identified the relevant predictors.

Standard LARS operates on the full design matrix of predictors, so it was not a candidate selection procedure for the blockwise ACT score models because variables that were significant in earlier blocks would not be assured to be kept in the model when subsequent blocks of predictors were added (Hesterberg et al., 2008). There are grouped versions of LASSO, but these methods define group as multi-parameter factors rather than group as blocks of predictors. Grouped LARS would not be appropriate for blockwise regression since the regularization is applied to the group as a whole, which would not be desirable in the context of blockwise regression. Additionally, grouped methods are not currently available in SAS, the statistical software package that was used in this analysis.

LARS selection can be implemented in SAS through Proc GlmSelect using the Selection = LAR option in the Model statement. Due to the quickly expanding literature on these alternative methods and the open-source platform of the software program R, R has more advanced capabilities with LARS and related methods (LASSO in particular) than SAS does.

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