Skills That Pay: Subject-Specific Test Scores and Long-Run Outcomes*

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Abstract

Using linked administrative data from Maryland, we estimate earnings premiums and postsecondary outcomes associated with K–12 test scores and subscores across subjects and grades. Math scores—especially in middle school—carry the largest earnings premiums, while math and English scores similarly predict college enrollment and completion. Educational attainment explains nearly all of the English earnings premium and about half of the math premium. Subscores reveal substantial within-subject heterogeneity in skills and earnings premiums that composite scores mask. We further present findings for science and social studies, heterogeneity, non-linearities, and cross-subject complementarities.

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1 Introduction

Schools cultivate a wide range of academic skills that shape students' later postsecondary and labor market trajectories. Standardized test scores sit at the center of how educators, researchers, and policymakers measure these skills. However, existing evidence offers surprisingly little guidance on how test scores across different subjects and grades translate into long-run educational attainment and earnings. Even within a given subject, test scores provide only a coarse representation of students' underlying skills. For example, a top-line math score may conflate performance on routine calculations the ability to reason through unfamiliar problems—two skills with distinct applications in the labor market. Together, these limitations complicate efforts to assess how the skills emphasized in classrooms (and the measures used to capture them) map to later educational and labor market outcomes.

This paper uses longitudinal administrative data to link detailed test score data—including detailed subscore performance—across different subjects and grades to postsecondary outcomes (e.g., college-going, major choice, college completion) and earnings. We aim to provide accessible estimates of earnings premiums and postsecondary outcomes associated with test score performance across a wide variety of grades (from 3rd grade and beyond), subjects (math, English, science, and social studies), and subject-specific subscores. We envision these estimates serving as inputs into cost-benefit analyses of educational interventions, aiding the interpretation of test-score-based treatment effects, and facilitating comparisons across policies that shift achievement in different subjects or at different points in the schooling lifecycle.

Despite the simplicity of this exercise, we remain unaware of studies that link subject-specific test performance to long-run outcomes using longitudinal administrative data. Closely related work by Chetty et al. (2014b) uses administrative data and quasi-experimental variation in teacher value-added (TVA) to show that higher achievement (via higher quality teachers) raises college attainment and earnings. Their primary estimates focus on a subject-invariant TVA measure, leaving open how performance in specific subjects—or specific competencies within subjects—map to long-run outcomes.[1] Other related studies rely on survey data limited by small survey samples and self-reported outcomes.[2]

[1] In secondary analyses, the authors report subject-specific TVA effects for college quality only.

[2] Neal and Johnson (1996); Heckman et al. (2006); Lin et al. (2018) use the AFQT from the National Longitudinal

We use data from the Maryland Longitudinal Data System (MLDS) Center, which links K-12 academic records for public school students in Maryland to postsecondary outcomes and earnings. We begin by conducting descriptive regressions relating core math and English Language Arts (ELA) test scores, measured every year from grades 3-8, to postsecondary attainment, degree field, and earnings. We find that a one standard deviation (SD) increase in these test scores corresponds with increases in average earnings at ages 29-32 of approximately $8,100 (17 percent) for math and $2,200 (4.5 percent) for ELA. Both math and English Language Arts (ELA) test scores are predictive of broad educational attainment outcomes (a 7-10 p.p. increase in college enrollment and BA attainment per SD increase in test scores). Additionally, we find that degree choice aligns closely with students' performance on the corresponding subject. For example, math scores are substantially more predictive of earning a BA in a STEM field (7.7 percentage point/74% increase in STEM BA attainment for math and a 2.5 percentage point/24% increase for ELA).

We supplement these descriptive regressions with a teacher value-added (TVA) design exploiting quasi-random teacher assignment to estimate the causal effect of exposure to higher- versus lower-value-added teachers.[3] Our quasi-experimental estimates broadly align with our descriptive results. A one SD increase in teacher value-added raises on-time BA attainment by approximately 0.5 p.p. for both subjects. The same increase in math teacher value-added increases STEM degree receipt by 1.3 p.p. and earnings by roughly $184 (0.8 percent), with the latter effect marginally significant.

Beyond our estimates for core math and ELA test scores, we present results for high school subject exams, heterogeneity by grade and student characteristics, and earnings premiums at different ages in adulthood. We estimate earnings premiums for high school Algebra ($4,700), English ($841), Biology ($1,500), and Government ($2,800) test scores. We also find that the math-earnings relationship is stronger than the ELA-earnings relationship across all demographic subgroups, though these gaps shrink for students from disadvantaged groups, including low-income students, Black students, and students at the lower end of the achievement distribution. We further document that earnings premiums gradually increase as we progress from 3rd grade test scores to 8th grade test scores. Finally, we show that earnings premiums increase substantially as we progress across three

Survey of Youth (NLSY). Murnane et al. (1995, 2000) use U.S. Department of Education longitudinal surveys. Grogger and Eide (1995); Dougherty (2003); Deming (2017) use the NLSY. Hanushek et al. (2015) use international survey data from the Programme for the International Assessment of Adult Competencies (PIAAC).

[3] Prior research shows teacher value-added estimates represent unbiased estimates of teachers' causal effects on student outcomes (Chetty et al., 2014a; Jackson, 2018; Petek and Pope, 2023).

age group bins (22-24, 25-28, and 29-32).

We next use mediation techniques to assess the extent to which the relationship between test scores and earnings is explained by educational attainment and degree field. For ELA, most of the relationship between test scores and earnings is explained by educational attainment and degree field. In contrast, roughly half of the math-earnings relationship remains unexplained by these mediators. After controlling for these educational factors, a one SD increase in math scores is associated with an earnings increase of $3,700 (7.7 percent), compared to just $700 (1.5 percent) for ELA. In short, the earnings premium from higher English achievement can mostly be explained by higher educational attainment, whereas higher math achievement affects earnings substantially beyond the postsecondary education channel.

We also decompose top-line test scores into subscores (described in Tables A1 and A2) to capture finer dimensions of within-subject skills. We find substantial variation in the earnings premiums across these subscores. For example, the small earnings premium for high school English is almost entirely driven by the "Writing and Composition" subscore. Broadly, we find suggestive evidence that more general, cross-cutting skills tend to outperform knowledge-based, subject-specific skills. These subscore estimates highlight the value of disaggregated assessment data for identifying which abilities merit greater emphasis in the classroom, since aggregate math and reading scores alone provide little guidance for instructional priorities.

Finally, we examine nonlinearities and complementarities in the relationship between skills and outcomes. Earnings premiums rise roughly linearly with test scores, suggesting that incremental gains in achievement generally translate to steady economic returns. Some educational outcomes, however, display mild nonlinearities that manifest most clearly at opposite ends of the achievement distribution. We also find that math and English function as complements for later-stage earnings, but often as substitutes for earlier outcomes such as course-taking and college entry.

2 Data

We use data from the Maryland Longitudinal Data System (MLDS) Center from 2008 to 2024. The MLDS Center provides a centralized repository of linked student and workforce data stemming from a partnership among numerous state and non-profit entities. We use three key datasets: 1) K-

12 data from the Maryland State Department of Education (MSDE), 2) postsecondary data from the Maryland Higher Education Commission (MHEC) and the National Student Clearinghouse (NSC), and 3) workforce data from the Maryland Department of Labor Division of Unemployment Insurance (UI).

The K-12 data from MSDE include information on all students enrolled in Maryland public schools, including attendance and demographics, assessments, course enrollments, school information, and high school graduation.[4] For postsecondary data, MHEC provides information on all students enrolled in Maryland colleges, while NSC captures out-of-state enrollment for Maryland public high school graduates. The two sources substantially overlap, and we possess near-complete coverage of postsecondary outcomes for the cohorts for which these data are available.[5] The earnings data from the Maryland Division of UI cover wages for individuals who work for Maryland employers that report to the state UI. We highlight that the UI data do not capture wages for the following types of employees: federal, military, self-employed, private contractor, or out-of-state.[6] Consequently, we cannot distinguish whether an individual with missing earnings was non-employed versus a non-covered employee.

Analytic Samples. We use three different samples with varying structures depending on exam type and analytic task.

1. Elementary and middle school ("EMS") student sample containing all 3rd through 8th grade students from 2008-2019 with non-missing math and English Language Arts (ELA) test scores. Math and ELA were assessed annually for these grades and years.[7]

2. High school (HS) student sample including all students from 2008-2019 with non-missing Algebra I, English 10, Biology, and U.S. Government end-of-course HS test scores. These are one-time exams, though some students may retake an exam if they did not pass on their first attempt. In cases of multiple assessment attempts, we use the score from the first attempt.

[4] Course enrollment data begin in 2013.

[5] We are missing information on bachelor's degree field for less than 0.2 percent of observations, as shown in Table 1.

[6] In 2023, 5.9 percent of the Maryland workforce was employed in the federal government,(Maryland State Archives, 2025) compared to 1.8 percent of the U.S. population (BLS, 2025a,b).

[7] The math and ELA assessments from 2008-2014 were the Maryland School Assessments (MSA), and the assessments from 2015-2019 were assessments designed by the Partnership for Assessment of Readiness for College and Careers (PARCC). 5th and 8th graders were also assessed in science in 2008-2015 (MSA) and 2018-2019 (Maryland Integrated Science Assessments, MISA).

Although these are HS-level assessments, some students first take them in middle school, particularly for Algebra I.[8]

3. A teacher value-added (TVA) student sample. Includes student-year-subject level data for all Maryland 4th through 8th grade students from 2013-2019 with non-missing math or ELA test scores. The MLDS course data can be used to link students to their math and ELA classroom teachers each year. We link our student-year EMS data to course data to construct student-year-subject data for the relevant grades and years.[9] We impose five sample restrictions commonly used in the TVA literature (Chetty et al., 2014a; Jackson, 2018; Petek and Pope, 2023): 1) each observation must have non-missing observable covariates for compute TVA measures, especially lagged own-subject test score; 2) we omit observations when there is more than one subject area course observed for a student in an academic year; 3) we drop classrooms with over 40 percent of students identifying as special education (SPED); 4) we drop classrooms in which the assigned teacher is linked to 200 or more students in an academic year; 5) we drop classrooms with fewer than 7 students or 40 or more students.

All samples include students enrolled in Maryland regular public schools.[10] The EMS and HS samples also exclude outgoing transfer students who transfer from a Maryland public high school to a private or out-of-state high school.[11]

Key Explanatory Variables. The key explanatory variables are standardized test scores and standardized GPAs. For the EMS sample, the two main explanatory variables are math and ELA test scores, both standardized to have a mean of zero and a standard deviation of one. Other explanatory variables for this sample include annual GPA measures in math, ELA, science, and social studies (SS), also standardized to have a mean of zero and a standard deviation of one. For the HS sample, the four main explanatory variables are standardized test scores for Algebra I,

[8] The Algebra I and English 10 assessments from 2008-2014 were from Maryland's High School Assessments (HSA) and the assessments from 2015-2019 were PARCC. The Biology assessment from 2008-17 was HSA and for 2019 was HS MISA. The U.S. Government exam from 2008-2019 was HSA.

[9] We focus our TVA analysis on students in the EMS sample, where annual assessments in both math and ELA allow us to control for prior test scores, a key requirement for the TVA model. In contrast, HS assessments are administered only once, limiting our ability to implement the same approach.

[10] We include students enrolled in traditional, charter, and career and technical education schools and exclude students enrolled in special education, alternative, and other special program schools.

[11] We identify outgoing transfers using exit codes (MSDE, 2020). We include these students in the TVA sample to construct value-added measures although we are not able to observe long-term outcomes for outgoing transfer students.

English 10, Biology, and U.S. Government. This sample also includes standardized GPA measures in the four core subjects, though these GPA measures are cumulative based on grades earned throughout HS since this sample contains student-level data.

Student Outcomes. Our main outcome variables include measures of educational attainment, degree field, and earnings. First, we create binary indicators for educational attainment, including high school graduation within four years, on-time college enrollment, associate of arts (AA) degree receipt within four years, and bachelor of arts (BA) degree receipt within 6 years.[12] We classify degree fields using the STEM-designated degree list maintained by the Department of Homeland Security (DHS, 2023), along with the Classification of Instructional Programs (CIP) codes from the National Center for Education Statistics (NCES, 2020). Our degree field outcomes include indicators for BA completion within six years in the following categories: i) STEM; ii) mathematics, statistics, or computer science; iii) engineering or architecture; iv) life, physical, and environmental science; v) social science; vi) humanities; vii) health professions; viii) business; and ix) education.[13]

For workforce outcomes, our main outcomes are conditional average annual earnings at ages 22-24, 25-28, and 29-32. We create these measures in four steps: i) sum quarterly earnings for all employers over the calendar year, ii) convert to 2024 dollars using the CPI-U (Minneapolis Fed, 2025), iii) winsorize at the 99th percentile, and iv) take the average across the ages within each respective age range. Other workforce outcomes are employment and unconditional earnings. Employment is defined using a binary indicator for having positive earnings observed in Maryland UI data in each respective age range. Unconditional earnings measures impute zeros for those who are missing earnings.[14]

Descriptive Statistics. Table 1 provides summary statistics for both the EMS and HS samples. Overall, both samples are relatively similar and there is slight positive selection in the samples

[12]The timing of educational attainment outcomes are measured relative to the first year of observed enrollment in 9th grade in Maryland public schools. Thus high school graduation is within 4 years of 9th grade enrollment, on-time college enrollment is within 5 years of 9th grade enrollment, etc.

[13]There is substantial overlap in i) STEM majors and CIP categories ii)-iv). However, some DHS-designated STEM fields are outside the field categories determined using CIP codes in ii)-iv). Additionally, not all fields in ii)-iv) are DHS-designated STEM fields. Field categories defined using CIP codes ii)-ix) are defined to be mutually exclusive categories, although a small percentage of students may earn multiple degrees from different fields. The CIP major categories are not collectively exhaustive, but do comprise the most common majors.

[14]The largest sources of missingness in earnings data are non-employment and out-of-state migration. During the time period when earnings are measured in our study, the national prime-age employment to population ratio ranged from 75 to 81 percent (BLS, 2025c). This suggests that up to 25 percent of observations that are missing earnings are real zeros from non-employment.

due to the exclusion of specialized schools and the restriction to non-missing test scores. One of the main differences in the samples is that almost 42 percent of observations in the EMS sample are Free and Reduced-price Meals (FARMS) eligible while only about 36 percent of the HS sample is FARMS-eligible. Standardized test score means are all above zero. This suggests that conditioning the EMS sample on non-missing math and ELA test scores and the HS sample on non-missing test scores in the four core subjects induces some small positive selection in the samples. This sample restriction also reduces the variance of the test score and GPA variables. There is less evidence of positive selection on the GPA variables, which may be driven by students with non-missing test scores sorting into classrooms in which they are graded relative to a more positively selected group of peers. High school graduation rates are higher in the HS sample, which is likely driven by the fact that there is less high school dropout among students with non-missing high school test scores relative to the EMS sample which is conditional on non-missing test scores in earlier grades. However, BA receipt, STEM BA receipt, and earnings from ages 25-28 and 29-32 are higher in the EMS sample.

3 Empirical Strategies

We estimate the relationship between test scores and future outcomes in two ways: 1) a series of descriptive regressions, and 2) a quasi-experimental teacher value-added (TVA) framework.

3.1 Relationships Between Student Performance and Outcomes

Following Bettinger et al. (2013), we estimate the association between each composite test score and long-run outcomes conditional on other composite test scores and demographic covariates:

$$Y_i = \alpha + \sum_{k=1}^{K} \beta^k S_{it}^k + \gamma C_{it} + \epsilon_{it}, \tag{1}$$

Here, Y_i is an outcome (e.g. BA receipt or earnings) for student i; S_{it}^k is a composite test score variable for subject k in academic year t, standardized in the population to have mean zero and standard deviation one; C_{it} are demographic covariates including indicators for gender, race, gender-race interactions, FARMS, English-language learner (ELL), special education (SPED), and imputed values for demographic variables; and ϵ_{it} is an error term clustered at the student level. β^k estimates the relationship between a one standard deviation increase in composite test S_{it}^k conditional on other subject tests S_{it}^{k-1} and demographic covariates C_{it}. Equation (1) can be generalized to include only one composite test score ($K = 1$) in univariate models or to include standardized GPA variables in models that also estimate the conditional relationship between standardized GPA and outcomes.

This specification summarizes how long-run educational attainment and earnings vary with subject-specific test scores, conditional on observed demographics (and, in some specifications, GPAs). We interpret the resulting β^k estimates as descriptive associations rather than causal effects. Unobserved determinants of both test performance and later outcomes (e.g., family resources, school environments, non-cognitive skills) may remain correlated with S_{it}^k, so conditioning on the aforementioned observables does not remove all confounding. We therefore turn next to a TVA design that leverages quasi-random variation in teacher assignment to estimate causal effects.

3.2 Teacher Value-Added

We follow the TVA framework developed in Chetty et al. (2014a) and used widely in subsequent work (Jackson, 2018; Petek and Pope, 2023). The approach constructs teacher-specific measures of achievement gains after residualizing current-year student test scores on a rich set of covariates, including prior test scores and demographics. We estimate each teacher's value-added by predicting the average residual score of their students in a given year using residuals from students taught in other years. Identification requires that, conditional on controls, teacher assignment is uncorrelated with unobserved determinants of students' outcomes.

Our TVA strategy proceeds in three steps. First, we construct subject-specific TVA measures following Chetty et al. (2014a). Second, we estimate how these TVA measures affect educational attainment and earnings. Third, we report forecast bias diagnostics to assess the validity of our research design.

Estimating Test Score TVA. We construct subject-level TVA in two steps: i) residualize student test scores on a rich set of controls and ii) compute leave-year-out predictions of teacher effects using residuals from surrounding years. First, we residualize test score S_{ijt}^k by regressing it on a vector of controls X_{ijt} for student i taught by teacher j in academic year t for subject k. The control vector includes flexible functions of lagged student achievement, demographic characteristics, and the classroom environment. Specifically, the controls include: i) lags of a cubic polynomial in students' math and ELA test scores; ii) lags of a cubic polynomial in class- and grade-level means of those test scores; iii) the demographic controls used in our descriptive test score model; and iv) class- and grade-level means of those demographic variables. We interact each of these covariates with grade fixed effects, and we further include a control for class size.[15] We compute residualized test scores ν_{ijt}^k via following equation:

$$\nu_{ijt}^k = S_{ijt}^k - \hat{\Gamma} X_{ijt}. \tag{2}$$

This residualization partials out observed determinants of S_{ijt}^k, including prior achievement, demographics, grade level, and classroom composition. Next, we compute the mean residual across students by year for each teacher j:

$$\bar{\nu}_{jt}^k = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} \nu_{ijt}^k. \tag{3}$$

where N_{jt} is the number of students taught by teacher j in year t. We then predict test score TVA in year t with mean teacher test score residuals from surrounding years:

$$\hat{\nu}_{jt}^k = \sum_{s=t-a}^{t+a} \hat{\psi}_s \bar{\nu}_{js}^k \mathbb{1}[s \neq t]. \tag{4}$$

where $a = 6$ in our setting. Using data from surrounding years reduces exposure to transitory unobservables and shocks in year t that could affect both the mean teacher test score residual $\bar{\nu}_{jt}^k$ and test scores in year t. The weights $\hat{\psi}_s$, which vary by the number of years before or after t, are chosen to minimize the mean-squared prediction error of $\bar{\nu}_{jt}^k$ using residuals from surrounding years taught by the same teacher:

$$\Psi = \underset{\{\psi_{t-a},\ldots,\psi_{t+a}\}}{\arg\min} \sum_{j=1}^{J} (\bar{\nu}_{jt}^k - \sum_{s=t-a}^{t+a} \psi_s \bar{\nu}_{js}^k \mathbb{1}[s \neq t])^2 \tag{5}$$

This procedure yields leave-year-out jackknife TVA predictions which allow teacher quality to drift over time and incorporate Bayesian shrinkage toward the mean (Chetty et al., 2014a).

[15] When lagged scores in the other subject are missing, we set the other subject lagged score to zero and include an indicator for missing data in the other subject interacted with controls for lagged own-subject test scores.

Relating TVA to Long-Run Outcomes. We use the leave-year-out TVA measures $\hat{\nu}^k_{jt}$ to estimate how assignment to a higher-TVA teacher relates to long-run educational attainment and earnings. Our main specification is a multivariate TVA model which includes TVA from multiple subjects as follows:

$$Y_i = \alpha + \sum_{k=1}^{K} \delta^k \hat{\nu}^k_{jt} + \Gamma X_{ijt} + \eta_{ijt}, \tag{6}$$

where Y_i is a long-run outcome for student i, $\hat{\nu}^k_{jt}$ is our TVA measure for teacher j in academic year t and subject k, X_{ijt} is the same vector of controls from Equation (2),[16] and η_{ijt} is the error term. We cluster standard errors at the school level. δ^k is the coefficient of interest and represents how outcomes vary with a one standard deviation increase in TVA in subject k, holding fixed our control vector as well as TVA in other subjects. In practice, our main multivariate specification includes just two TVA measures: math TVA $\hat{\nu}^m_{jt}$ and ELA TVA $\hat{\nu}^e_{jt}$. We also report univariate models with $K = 1$.

Identification requires that, conditional on X_{ijt}, students are not systematically sorted to teachers on unobserved determinants of Y_i. The primary threat is residual non-random assignment (e.g., sorting based on unobserved ability, motivation, or family resources) that remains correlated with $\hat{\nu}^k_{jt}$ even after conditioning on prior achievement and classroom composition. Prior research suggests there is little bias in test score TVA estimates (Chetty et al., 2014a; Petek and Pope, 2023; Jackson, 2018), but we explore this threat further using forecast bias as a diagnostic.

Estimating Forecast Bias. We follow Chetty et al. (2014a) and estimate the relationship between residualized test scores ν^k_{ijt} and estimated TVA $\hat{\nu}^k_{jt}$:

$$\nu^k_{ijt} = \alpha + \lambda \hat{\nu}^k_{jt} + \xi_{ijt}. \tag{7}$$

Under random assignment of teachers, regressing test score residuals ν^k_{ijt} on $\hat{\nu}^k_{jt}$ yields a λ coefficient of 1 because $\hat{\nu}^k_{jt}$ is the best linear predictor of ν^k_{ijt}. The amount of forecast bias in test score TVA

[16] The controls include: i) lags of a cubic polynomial in students' math and ELA test scores; ii) lags of a cubic polynomial in class- and grade-level means of those test scores; iii) student demographics (gender, race, gender-race interactions, FARMS, ELL, SPED, and imputed values for missing demographics); and iv) class- and grade-level means of those demographic variables. All these covariates are interacted with grade fixed effects, and we include a control for class size. When lagged scores in the other subject are missing, we set the other subject lagged score to zero and include an indicator for missing data in the other subject interacted with controls for lagged own-subject test scores.

$\hat{\nu}^k_{jt}$ is $B(\hat{\nu}^k_{jt}) = 1 - \lambda$. The main idea is that the degree of forecast bias can be quantified by the extent to which students are sorted to teachers on unobservables.

Using our TVA sample, we present estimates of the relationship between estimated test score TVA and residualized test scores in Appendix Table A3. For math, we find that a one unit increase in current year test score TVA increases current year test scores by 1.12 standard deviations, with the confidence interval for the coefficient ranging from 1.06 to 1.17. For ELA, we find that a one unit increase in current year test score TVA increases current year test scores by 1.1 standard deviations, with the confidence interval for the coefficient ranging from 1.01 to 1.19. Plugging in our estimates for λ into the forecast bias equation, we find estimates of forecast bias in the range of -17 to -6 percent for math and -19 to -1 percent for ELA. This implies that our TVA estimates are downward biased and understate the true variance in teacher quality. The attenuation of our TVA estimates relative to the true values also implies that using our TVA measures to estimate impacts on long-term outcomes will lead to bias away from zero in the range of 6 to 17 percent for math and 1 to 19 percent for ELA. Given this, the magnitudes of the estimates for TVA impacts on long-term outcomes should be interpreted with caution.

4 Results

We begin by examining how test scores descriptively relate to long-term outcomes (Section 4.1). We then explore heterogeneity by FARMS status, race, achievement, grade, and age at which we measure earnings (Section 4.3). Next, we present TVA-based estimates (Section 4.4). We conclude with robustness checks (Section 4.5).

4.1 How test scores relate to long-term Outcomes

Univariate models: Table 2 reports univariate associations between test scores and outcomes. In the EMS sample, math and ELA scores relate similarly to educational attainment, with slightly larger coefficients for math. A one standard deviation (SD) increase in test scores corresponds to a 6 percentage point (p.p.) increase in on-time high school graduation for math versus 5.2 p.p. for ELA. A one SD increase in math and reading test scores also translates to a 14 p.p. increase in on-time college enrollment. For AA attainment within four years, the math coefficient is twice the

ELA coefficient (0.6 p.p./8.8 percent vs. 0.3 p.p./4.4 percent). Coefficients for BA receipt within 6 years are only slightly larger for math (17 p.p./53 percent vs. 15 p.p./47 percent). The same pattern holds for STEM BA receipt within 6 years (9.3 p.p./90 percent vs. 7.3 p.p./70 percent). Despite similarities for educational attainment, the earnings estimates differ more sharply. A one SD increase in math test scores corresponds to $9,500 higher earnings at ages 29-32 (20 percent), compared to about $7,000 (14 percent) for ELA. We also highlight the steep age gradient for earnings: a 1 SD increase in math scores correlates with about $917 higher annual earnings at ages 22–24, $5,376 at ages 25–28, and $9,500 at ages 29–32.

The HS sample shows similar patterns and also allows us to examine science (Biology) and social studies (U.S. Government) alongside math (Algebra I) and ELA (10th grade English). One difference is that our estimates for AA receipt within 4 years are considerably larger in this sample at roughly 1.5 p.p. (20 percent) for both math and ELA. For age 29-32 earnings, the ELA, science, and social studies coefficients are all similar in magnitude (each at least $6,200). The math coefficient is larger ($7,800), but smaller than the math coefficient in the EMS sample and comparatively less differentiated.

Multivariate models: Table 3 presents multivariate models that include multiple subject scores simultaneously. In the EMS sample, inclusion of both test scores in the same model attenuates coefficients substantially, but the relationships remain sizeable. Math remains modestly larger than ELA for most attainment outcomes besides STEM BA receipt. A one SD increase in test scores corresponds to increases in on-time college enrollment by 9.2 (14 percent) p.p. for math and 7.9 p.p. (12 percent) for ELA. The coefficients for BA receipt are 12 p.p. (37 percent) for math and 7.7 p.p. (24 percent) for ELA while the estimates for STEM BA receipt are 7.7 p.p. (74 percent) for math and 2.5 p.p. (24 percent) for ELA. For earnings, the multivariate estimate for math declines modestly relative to the univariate estimate, while the multivariate estimate for ELA drops sharply. The math earnings premium at ages 29-32 is roughly four times the ELA premium ($8,100/17 percent vs. $2,200/4.5 percent). The age-earnings gradient remains steep—and notably, we observe that the ELA earnings premium is *negative* for ELA at ages 22-24.

For the HS sample, we find that BA receipt increases by 5.9 p.p. for math, 6.4 p.p. for ELA, 3.6 p.p. for science, and 6.9 p.p. for social studies. However, these relative impacts reverse for STEM BA receipt: a one SD increase in test scores increases STEM BA receipt by 3 p.p. for math, 2 p.p. for ELA, 3.7 p.p. for science, and 2 p.p. for SS. Earnings patterns in the HS sample are similar to those in the EMS sample. Relative to the univariate relationships, math attenuates the least while ELA decline the most. At ages 29-32, a one SD increase in test scores corresponds to $4,700 higher earnings for math, $800 for ELA, $1,500 for science, and $2,800 for SS.

GPA vs. test scores: Table 4 adds subject GPAs as additional controls. Grades and test scores both proxy for subject mastery but capture different dimensions of student performance. Incorporating subject GPAs alongside test scores therefore helps distinguish between two sources of association in test-score regressions. In particular, grades are more likely to reflect sustained performance over the school year across repeated assignments, exams, and teacher evaluations. Grades, which show up on transcripts, also can directly influence postsecondary trajectories. On the other hand, test scores reflect exam-specific content mastery, the ability to access knowledge under time-limited and high-stakes conditions, test-taking skills, and idiosyncratic test-day variation. Test scores also remove teacher discretion in assigning grades, which might not always align with actual subject mastery.

Consequently, adding subject GPAs substantially attenuates many of the multivariate test-score coefficients. For math test scores, on-time high graduation attenuates to 11% of its value in Table 3; college enrollment attenuates to 31%, and BA attainment to 65%. For ELA, the attenuated coefficients are 19%, 65%, and 51%. These reductions appear similar for the HS sample. We note that the STEM BA attainment coefficient for math test scores remains approximately the same even after controlling for grades.

The especially sharp attenuation for on-time high school graduation is consistent with graduation hinging on transcript-based criteria so that once GPAs enter, test scores add relatively little additional information. The more moderate attenuation for college enrollment and BA receipt indicates that test scores retain some distinct association with longer-run attainment, but much of the relationship operates through the same underlying factors that generate higher grades. The stability of the math–STEM BA coefficient points to a different mechanism: math test performance appears to contain information about STEM-relevant competencies that grades may not fully summarize and that matter for persistence in STEM fields. In other words, conditional on grades, math test scores continue to differentiate students in ways that predict STEM completion, whereas grades largely subsume the test-score signal for more general attainment outcomes.

Earnings move in similar directions: in the EMS sample (ages 25-28),[17] the math coefficient falls from roughly \$4,900 to \$3,500, whereas the ELA coefficient drops from about \$800 to -\$900. In the HS sample (ages 29–32), the corresponding attenuations are \$4,700 to \$2,900 (math), \$800 to \$90 (ELA), \$1,500 to \$1,100 (science), and \$2,800 to \$2,400 (social studies). These attenuation patterns suggest that GPAs absorb much of the test-score variation that correlates with later earnings, especially in ELA where the earnings signal appears to operate primarily through sustained classroom performance. Math attenuates more modestly and remains economically meaningful in both samples, indicating that math performance on standardized exams captures dimensions of skill that grades do not fully summarize and that continue to relate to adult earnings.

The GPA coefficients themselves are large, and for broad educational attainment outcomes they often match or exceed the test-score coefficients once both enter the model. In the EMS sample for BA receipt, math test scores remain larger than math GPA (7.7 p.p. vs. 2.3 p.p.), while ELA flips in the other direction (3.9 p.p. vs. 6.0 p.p.). For earnings at ages 25–28, math test scores similarly remain large relative to math GPA (\$3,500 vs. \$800) whereas ELA again reverses (-\$900 vs. \$1,800). The HS patterns largely reinforce this contrast for math and ELA, while providing additional insights for science and social studies. For BA attainment, test scores fall far behind grades for both science (-0.6 p.p. vs. 4.1 p.p.) and social studies (2.7 p.p. vs. 7.1 p.p.). The same pattern holds for science earnings (\$1,125 vs. \$2,196) but not for social studies earnings (\$2,405 vs. \$2,280).

BA degree field: Table 5 relates subject test scores to BA degree field within 6 years. Overall, test scores in a given subject predict degree completion in closely related fields. In the EMS sample, the difference between math and ELA coefficients is largest for math/statistics/computer science and engineering/architecture fields while the difference between ELA and math coefficients is largest for social sciences and humanities fields. We also find that the math coefficient is considerably larger than the ELA coefficient for science and business fields.

Our results for the HS sample are similar but provide additional support for the link between test scores and degree fields because we estimate coefficients for all four core subjects. We find that among the four test scores, math coefficients are largest for math, engineering, and business fields;

[17] We are unable to observe earnings from ages 29-32 in our EMS sample with the inclusion of GPAs in the model because the course data to compute GPAs first begin in 2013.

the ELA coefficient is largest for humanities fields; the science coefficient is largest for science fields; and the social studies coefficient is largest for social science fields. Overall, these findings provide compelling evidence that students sort into degree fields that match their relative strengths across subject-specific skills.

4.2 Mediation analysis: How much of the earnings gradient is explained by educational attainment?

Table 6 examines the extent to which educational attainment and degree field mediate the relationship between test scores and age 29-32 earnings. Column (1) replicates our baseline multivariate earnings specification,[18] while columns (2) through (4) sequentially add controls for on-time college enrollment, BA receipt within six years, and major field of study (from Table 5).

These controls substantially attenuate the test score coefficients, especially for ELA. In the EMS sample, controlling for college enrollment reduces the math and ELA coefficients by 16 percent and 33 percent; adding BA attainment reduces them by 41 percent (math) and 84 percent (ELA); and including degree field controls yields total attenuation of 54 percent for math and 67 percent for ELA. Even in the fully controlled specification, a one SD increase in math test scores corresponds to $3,700 higher earnings at ages 29-32, compared to about $700 for ELA. The same patterns hold in the HS sample. With all controls included, the coefficients attenuate from $4,700 to $3,000 for math (36 percent), $830 to -$60 for ELA (107 percent), $1,500 to $550 for science (64 percent), and $2,800 to $1,200 for SS (56 percent). The estimates in the HS sample suggest that the ELA-earnings relationship is completely explained by educational pathways, while most of the math-earnings relationship is not explained by these mechanisms.

Taken together, our mediation results suggest that subject-specific achievement maps to earnings through different channels. For ELA, controlling for college enrollment, degree completion, and field of study largely eliminates the earnings gradient, suggesting that ELA achievement primarily operates through postsecondary educational attainment. For math, a substantial earnings association remains even after conditioning on these pathways, suggesting that math scores capture dimensions of skill that relate to labor market success beyond their role in shaping postsecondary

[18] The estimates in Table 6, column (1) are nearly identical to those in Table 3, column (8). Minor differences reflect sample restrictions due to missing degree field data in Table 6.

trajectories.

4.3 Heterogeneity

Heterogeneity by Socioeconomic Status, Race, and Achievement. Table 7 examines how the relationship between test scores and outcomes varies by FARMS status, race subgroups, and student achievement terciles. We focus on on-time college enrollment, BA attainment within six years, and earnings at ages 29-32.

For college enrollment, the test score coefficients are larger for historically disadvantaged subgroups including students who are FARMS, Black, Hispanic, or in the bottom two terciles of achievement. The achievement results are particularly striking: a one SD increase in math test scores corresponds to at least a 10 p.p. increase in college enrollment in the bottom two achievement terciles while the same increase only corresponds to a 3.5 p.p. increase in enrollment in the top tercile. The coefficients for ELA are at least 9.4 p.p. for the bottom and middle terciles, but only 2.5 p.p. for top tercile students.

This pattern reverses for BA attainment: coefficients are generally smaller for FARMS, Black, Hispanic, and bottom achievement tercile students. Across subgroups, test scores therefore predict college enrollment more strongly for disadvantaged students, but they predict on-time BA completion more weakly for those same students. One potential interpretation is that lower-achieving students may be more likely to attend less selective universities, where time to degree has been noticeably increasing (Bound et al., 2012). A second interpretation is that disadvantaged students—even those with higher test scores—simply face larger barriers to college completion (Bailey and Dynarski, 2011). Across terciles, the BA coefficients rise sharply from the bottom to the middle tercile and then decline somewhat at the top: for math, 4.9 p.p. (bottom), 14.9 p.p. (middle), and 10.2 p.p. (top); for ELA, 2.7 p.p., 10.0 p.p., and 6.0 p.p., respectively.

For earnings from ages 29-32, the heterogeneity combines elements of both patterns. Across all subgroups, math corresponds to higher earnings than ELA, but the math-ELA gap is smallest for disadvantaged students. For math, the coefficients for the achievement terciles from lowest to highest are are \$6,000, \$9,200, and \$8,500, respectively. For ELA, the coefficients for the achievement terciles from lowest to highest are are \$2,400, \$2,700, and \$1,000, respectively. Table 8 shows similar patterns in the HS sample: coefficients are relatively larger in the top two achievement terciles for math, science, and social studies, while ELA gradients are larger in the bottom two terciles.

Heterogeneity by Grade and Age of Earnings. Figure 1 shows estimates of the relationship between test scores and outcomes by grade level. Two broad takeaways stand out. First, the coefficients gradually increase from grades 3 through 8. The relationship substantially increases for the high school ELA assessment and *decreases* for the high school math assessment. Second, while the math coefficients are typically only modestly larger than the ELA coefficients for high school graduation, college enrollment, and AA receipt, they are considerably larger than the ELA coefficients for BA receipt, STEM BA attainment, and earnings from ages 25-28. The math-ELA gap for attainment and earnings outcomes is especially pronounced for 8th graders. A one SD increase in 8th grade math test scores corresponds to a 14 p.p. increase in BA attainment, a 10 p.p. increase in STEM BA receipt, and an earnings increase of over $5,000. By contrast, a one SD increase in 8th grade ELA scores corresponds to a 7.5 p.p. increase in BA attainment, a 1.5 p.p. increase in STEM BA receipt, and an earnings increase of about $1,000.

Figure 3 relates test scores to earnings by the age at which earnings are measured. Again, two clear patterns emerge. First, coefficients rise with age: earnings premiums increase when earnings are measured later in adulthood. Second, math consistently exceeds other subjects almost all ages when earnings are measured. For our EMS sample, we find that a one SD increase in math test scores corresponds to over a $2,000 (approximately 10 percent) increase in earnings at age 23 and about a $9,000 (approximately 20 percent) increase in earnings at age 30. In contrast, a one SD increase in ELA scores is associated with about a $500 (approximately 3 percent) decrease in earnings at age 23 and almost a $2,500 (approximately 6 percent) increase in earnings at age 30. For our HS sample, we observe similar patterns, although the coefficients are somewhat smaller, likely in part because the multivariate model includes test scores for science and SS in addition to math and ELA. Notably, the coefficients for science and SS are larger than those for ELA, suggesting that these variables may absorb variation that would otherwise be attributed to ELA in a more limited model.

In Figure 2, we also plot the relationship between GPAs and outcomes by grade level. Two patterns stand out. First, GPA gradients are relatively flat across grades, in contrast to the rising test-score gradients shown in Figure 1. Second, math GPA coefficients are consistently smaller than those for other subjects, reinforcing the finding that math test scores capture much of the relevant variation in outcomes. By contrast, ELA and social studies GPAs remain large across grades, and the ELA GPA coefficients appear comparable in magnitude to the corresponding ELA test-score coefficients. Estimates of the relationship between GPAs and earnings by age are similarly shown in Figure 4. Here, coefficients appear small across the board, and there is a slight and gradual increase in earnings coefficients as age increases.

4.4 Teacher value-added effects on long-term outcomes

We complement our descriptive results by estimating causal effects using test score TVA. Table 9 presents these estimates for the TVA sample. Panel A presents univariate models that include a single TVA measure (math or ELA), while Panel B reports multivariate models that include both simultaneously.

In the univariate results, test score TVA shows limited impacts on HS graduation, college enrollment, and AA degree receipt.[19] By contrast, a one SD increase in test score TVA increases BA receipt within four years by about 0.6 p.p. for both math and ELA. These estimates attenuate substantially for BA receipt within 6 years; the math TVA coefficient decreases substantially while the ELA TVA estimate remains the same but becomes less precisely estimated. A one SD increase in math TVA also boosts STEM BA receipt within six years by 1.3 p.p. and leads to a marginally significant increase in earnings from ages 22-24 of about \$160 (0.7 percent). ELA TVA shows no corresponding effect on STEM BA attainment and an insignificantly negative effect on earnings.

The estimates for the multivariate model follow the same pattern. Becausemath and ELA TVA are weakly correlated, including both measures leads to only modest attenuation. A one SD increase in TVA increases BA receipt within four years by about 0.56 p.p. for math and 0.4 p.p. for ELA. The estimates for BA attainment within six years closely mirror the estimates from the univariate model. For STEM BA receipt, the math TVA estimate is nearly identical to the univariate estimate while the ELA TVA estimate becomes insignificantly negative. The earnings estimates are also similar; the math TVA estimate increases to \$184 while the ELA TVA coefficient becomes slightly more negative.

[19] There is a small, negative, marginally significant coefficient for math TVA on HS graduation, but the decrease is not economically meaningful at 0.1 p.p.

Overall, we find some alignment between our descriptive and TVA-based analyses. Math and ELA TVA have comparable effects on general educational attainment, while math TVA has larger effects on STEM attainment and earnings. This correspondence supports the interpretation of our descriptive results when examined through a causal lens. However, two caveats remain. First, the TVA estimates should be interpreted with caution due to modest forecast bias (Appendix Table A3). Second, with the exception of math TVA effects on STEM BA attainment, the magnitudes are small, suggesting that causal effects of test-score gains on long-run outcomes are more limited than the descriptive associations imply.

4.5 Employment status and unconditional earnings

Thus far, we have focused on earnings conditional on obseved employment as the primary labor market outcome. We briefly show how two other common labor market measures (employment, unconditional earnings) lead to issues given the limitations of our data. We define employment as having positive earnings reported in the Maryland UI data. Unconditional earnings are calculated by imputing zero earnings for individuals who are missing UI earnings data, while conditional earnings include only those with observed positive earnings.

Table A4 presents estimates for both outcomes, as well as our baseline estimates for conditional earnings. Because the patterns are similar across age ranges, we focus on earnings measured at ages 29-32. In the EMS sample, a one standard deviation increase in either math or ELA test scores is associated with a roughly 3 p.p. decrease in employment. This negative association likely reflects selective out-migration: higher-achieving students are more likely to work outside of Maryland and therefore to be missing from the UI data. Similarly, imputing zeros for missing earnings likely biases unconditional earnings estimates downward. For example, a one SD increase in math scores corresponds to a $2,800 increase in unconditional earnings but an $8,100 increasThe same pattern holds for ELA, where a one SD increase predicts a $700 decrease in unconditional earnings but a $2,200 increase in conditional earnings. Estimates from the HS sample, including coefficients for science and social studies scores, show similar patterns.

Overall, these findings highlight the importance of conditioning on observed earnings when using UI data to study the relationship between achievement and labor market outcomes. Unconditional measures tend to substantially understate the strength of the relationship between test scores and earnings, while conditional earnings provide a more accurate measure of this correlation. Recent research suggests that even conditional earnings may be biased toward zero, if higher-achieving individuals (who would have higher earnings on average) are more likely to leave the state (Foote and Stange, 2022).

4.6 Subscore decomposition

To examine heterogeneity in skill content within subjects, we extend our baseline multivariate test score specification to incorporate subject-specific subscores. We begin from the composite-score model, which relates a long-run outcome Y_i (i.e. earnings and BA within 6 years) to standardized composite test scores in each subject and the full set of demographic controls:

$$Y_i = \alpha + \sum_{k=1}^{K} \beta^k S_{it}^k + \gamma' C_{it} + \epsilon_{it}, \tag{8}$$

where S_{it}^k denotes the composite score for subject k, standardized to have mean zero and standard deviation one. The coefficients β_k summarize the conditional association between subject-level test performance and the outcome, holding performance in other subjects and covariates fixed.

To unpack within-subject skill heterogeneity, we re-estimate this specification one subject at a time by replacing that subject's composite score with its full set of standardized subscores, while leaving all other subjects in composite-score form:

$$Y_i = \alpha + \sum_{m=1}^{M_k} \beta_{k,m} s_{it}^{k,m} + \sum_{\ell \neq k} \beta_\ell S_{it}^\ell + \gamma' X_{it} + \epsilon_{it}, \tag{9}$$

where $s_{it}^{k,m}$ denotes subscore m within subject k. In these specifications, the coefficients $\beta_{k,m}$ measure how outcomes vary with a one–standard deviation increase in a given subscore, conditional on the other subscores within the same subject, performance in other subjects, and covariates.

Because subscores within a subject are often strongly correlated, the estimated subscore coefficients need not sum to the corresponding composite-score coefficient. Instead, they capture differences in skill composition *within* a subject, highlighting which underlying competencies are most strongly associated with long-run educational and labor market outcomes.

Overall, we find that replacing composite scores with subscores reveals substantial heterogeneity in how underlying competencies relate to long-run outcomes. Figures 7 and 8 report subscore coefficients for BA attainment for the EMS and HS samples separately. In the EMS sample, all five math subscores load similarly in magnitude whereas ELA shows slightly more differentiation (with "General Reading Processes" being materially smaller). In the HS Sample, math again loads evenly across subscores, whereas ELA loads heavily on writing subskills. Science also loads relatively evenly (except for "Interdependence of Organisms in the Biosphere, which contributes negligibly), and Social Studies skews heavily toward "U.S. Government Principles" (whereas Economic Principles appears to matter little).

Figures 5 and 6 show subscore results for earnings. This time around, the math subscores load much more unevely. "Processes of Mathematics" carries the highest earnings premium in the EMS sample, whereas "Modeling Real World Situations" tops the list in the HS sample. The distribution is even more uneven for ELA, especially in the HS sample, where essentially the entire ELA coefficient is explained by "Writing: Composing". Science subscores load similarly for earnings as they do for BA attainment. For social studies, subscores load more evenly for earnings than they do for BA.

Our subscore decompositions also reveal potential distinctions between the skill content associated with BA attainment and that associated with earnings. BA attainment loads on a broader bundle of competencies within each subject, with many subscores contributing positively and relatively evenly, consistent with degree completion reflecting sustained academic proficiency across multiple domains. Earnings, by contrast, place greater weight on a narrower set of competencies, with within-subject associations concentrating in fewer subscores that tend to reflect more transferable or applied skills. Consequently, composite test scores may be blending subskills that primarily support educational progression with subskills that more directly relate to labor market outcomes. Consequently, the mapping from academic performance to economic

4.7 Non-linearities and complementarities

5 Conclusion

A growing body of research has examined how cognitive skills developed in school shape students' long-term economic outcomes.[20] Much of this literature relies on longitudinal survey data and finds that both general and subject-specific skills, particularly math, are predictive of earnings. However, prior research often uses small samples from survey data, self-reported outcomes, and limited causal identification strategies. This paper builds on and extends this literature by using population-level administrative data and quasi-experimental methods to provide new evidence on the link between specific academic skills and long-term economic outcomes.

Our findings show that both math and ELA test scores predict college attainment, but math scores are substantially more predictive of STEM degree completion and post-college earnings. We find that a one SD increase in test scores is associated with an increase in average annual earnings at ages 29-32 of approximately 17 percent for math and 4.5 percent for ELA. GPA also predicts earnings, potentially reflecting non-cognitive skills like effort and motivation that are not fully captured by test scores. Patterns across degree fields suggest that students tend to pursue majors aligned with their strongest academic subjects, consistent with comparative advantage. Mediation analysis reveals that most of the ELA test-earnings relationship operates through educational attainment and degree field, while a substantial portion of the math test-earnings link remains unexplained. Importantly, heterogeneity analyses show that math scores are more predictive of earnings than ELA scores across all student subgroups. However, compared to their more advantaged peers, historically disadvantaged students exhibit a weaker association between math scores and earnings and a somewhat stronger association between ELA scores and earnings. Finally, teacher value-added results corroborate the descriptive findings: math teacher value-added has larger impacts on both STEM attainment and earnings than ELA value-added.

Taken together, these findings offer novel insights into how different types of academic skills relate to long-run economic success. They suggest that policies aiming to promote economic mobility

[20] Neal and Johnson (1996); Heckman et al. (2006); Lin et al. (2018); Murnane et al. (1995, 2000); Grogger and Eide (1995); Dougherty (2003); Deming (2017); Hanushek et al. (2015) use longitudinal surveys to study the relationship between cognitive skills and earnings. Chetty et al. (2014b) uses administrative data and quasi-experimental teacher value-added methods to estimate impacts on postsecondary and earnings outcomes.

may have differential effects depending on which skills are targeted and which student subgroups are served. This underscores the need for a multi-faceted approach to improving outcomes and reducing inequality. Investing in more rigorous math requirements and instruction may be one important policy lever (Goodman, 2019). Complementing this with supports such as tutoring and mentoring for disadvantaged students can further enhance long-term outcomes (Cortes et al., 2015). Leveraging multiple policy tools will be critical to helping disadvantaged students translate skill gains into postsecondary and labor market success, thereby reducing inequality and promoting upward mobility.

References

Bailey, Martha J. and Susan M. Dynarski, "Inequality in Postsecondary Education," in Greg J. Duncan and Richard J. Murnane, eds., *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*, New York, NY: Russell Sage Foundation, 2011, pp. 117–132. Originally published as "Gains and Gaps: Changing Inequality in U.S. College Entry and Completion," NBER Working Paper No. 17633.

Bettinger, Eric P, Brent J Evans, and Devin G Pope, "Improving College Performance and Retention the Easy Way: Unpacking the ACT Exam," *American Economic Journal: Economic Policy*, 2013, *5* (2), 26–52.

BLS, "All Employees, Federal [CES9091000001]," https://fred.stlouisfed.org/series/CES9091000001/, 2025. Last accessed on July 7, 2025.

_ , "Civilian Labor Force Level [CLF16OV]," https://fred.stlouisfed.org/series/CLF16OV/, 2025. Last accessed on July 7, 2025.

_ , "Employment-Population Ratio - 25-54 Yrs. [LNS12300060]," https://fred.stlouisfed.org/series/LNS12300060, 2025. Last accessed on July 7, 2025.

Bound, John, Michael F. Lovenheim, and Sarah Turner, "Increasing Time to Baccalaureate Degree in the United States," *Education Finance and Policy*, 10 2012, *7* (4), 375–424.

Chetty, Raj, John N Friedman, and Jonah E Rockoff, "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review*, 2014, *104* (9), 2593–2632.

_ **, John N. Friedman, and Jonah E. Rockoff**, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review*, September 2014, *104* (9), 2633–79.

Cortes, Kalena E, Joshua S Goodman, and Takako Nomi, "Intensive Math Instruction and Educational Attainment: Long-Run Impacts of Double-Dose Algebra," *Journal of Human Resources*, 2015, *50* (1), 108–158.

Deming, David J, "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

DHS, "DHS STEM Designated Degree Program List," https://www.ice.gov/doclib/sevis/pdf/stemList2022.pdf, 2023. Last accessed on July 7, 2025.

Dougherty, Christopher, "Numeracy, Literacy and Earnings: Evidence from the National Longitudinal Survey of Youth," *Economics of Education Review*, 2003, *22* (5), 511–521.

Foote, Andrew and Kevin M Stange, "Attrition from Administrative Data: Problems and Solutions with an Application to Postsecondary Education," 2022. NBER Working Paper No. 30232.

Goodman, Joshua, "The Labor of Division: Returns to Compulsory High School Math Coursework," *Journal of Labor Economics*, 2019, *37* (4), 1141–1182.

Grogger, Jeff and Eric Eide, "Changes in College Skills and the Rise in the College Wage Premium," *Journal of Human Resources*, 1995, pp. 280–310.

Hanushek, Eric A, Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann, "Returns to Skills Around the World: Evidence from PIAAC," *European Economic Review*, 2015, *73*, 103–130.

Heckman, James J., Jora Stixrud, and Sergio Urzua, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 2006, *24* (3), 411–482.

Jackson, C Kirabo, "What Do Test Scores Miss? The Importance of Teacher Effects on Non-Test Score Outcomes," *Journal of Political Economy*, 2018, *126* (5), 2072–2107.

Lin, Dajun, Randall Lutter, and Christopher J. Ruhm, "Cognitive performance and Labour Market Outcomes," *Labour Economics*, 2018, *51*, 121–135.

Maryland State Archives, "Maryland Employment - Workforce," https://www.msa.maryland.gov/msa/mdmanual/01glance/economy/html/labor.html, 2025. Last accessed on July 7, 2025.

Minneapolis Fed, "Consumer Price Index, 1913-," https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-, 2025. Last accessed on July 7, 2025.

MSDE, "Technical Report 2003 for Maryland School Assessment," https://msa.maryland.gov/megafile/msa/speccol/sc5300/sc5339/000113/001000/001343/unrestricted/20054117e.pdf, 2003. Last accessed on July 7, 2025.

_ , "Maryland High School Assessment and Modified High School Assessment 2011 Technical Report," https://www.marylandpublicschools.org/about/Documents/DCAA/PRT/MD2011HSATechReport.pdf, 2012. Last accessed on July 7, 2025.

_ , "Report on Local, State, and Federally Mandated Assessments in Maryland," https://marylandpublicschools.org/Documents/commissiononassessments/LocalStateFederallyMandatedAssessmentsMD08312015Report.pdf, 2015. Last accessed on July 7, 2025.

_ , "Maryland School Assessment (MSA) Science Technical Report 2016," https://www.marylandpublicschools.org/about/Documents/DAAIT/Assessment/MISA/msa_sci_5_8_tech_report_2016.pdf, 2016. Last accessed on July 7, 2025.

_ , "Maryland Student Records System Manual," https://marylandpublicschools.org/about/Documents/OCP/Publications/2020-Maryland-Student-Records-System-Manual.pdf, 2020. Last accessed on July 7, 2025.

_ , "Maryland Integrated Science Assessments (MISA)," https://marylandpublicschools.org/about/Pages/DAAIT/Assessment/MISA/index.aspx, 2025. Last accessed on July 7, 2025.

Murnane, Richard J., John B. Willett, and Frank Levy, "The Growing Importance of Cognitive Skills in Wage Determination," *The Review of Economics and Statistics*, 1995, *77* (2), 251–266.

_ , _ , Yves Duhaldeborde, and John H. Tyler, "How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?," *Journal of Policy Analysis and Management*, 2000, *19* (4), 547–568.

NCES, "The Classification of Instructional Programs (CIP)," https://nces.ed.gov/ipeds/cipcode/browse.aspx?y=56, 2020. Last accessed on July 7, 2025.

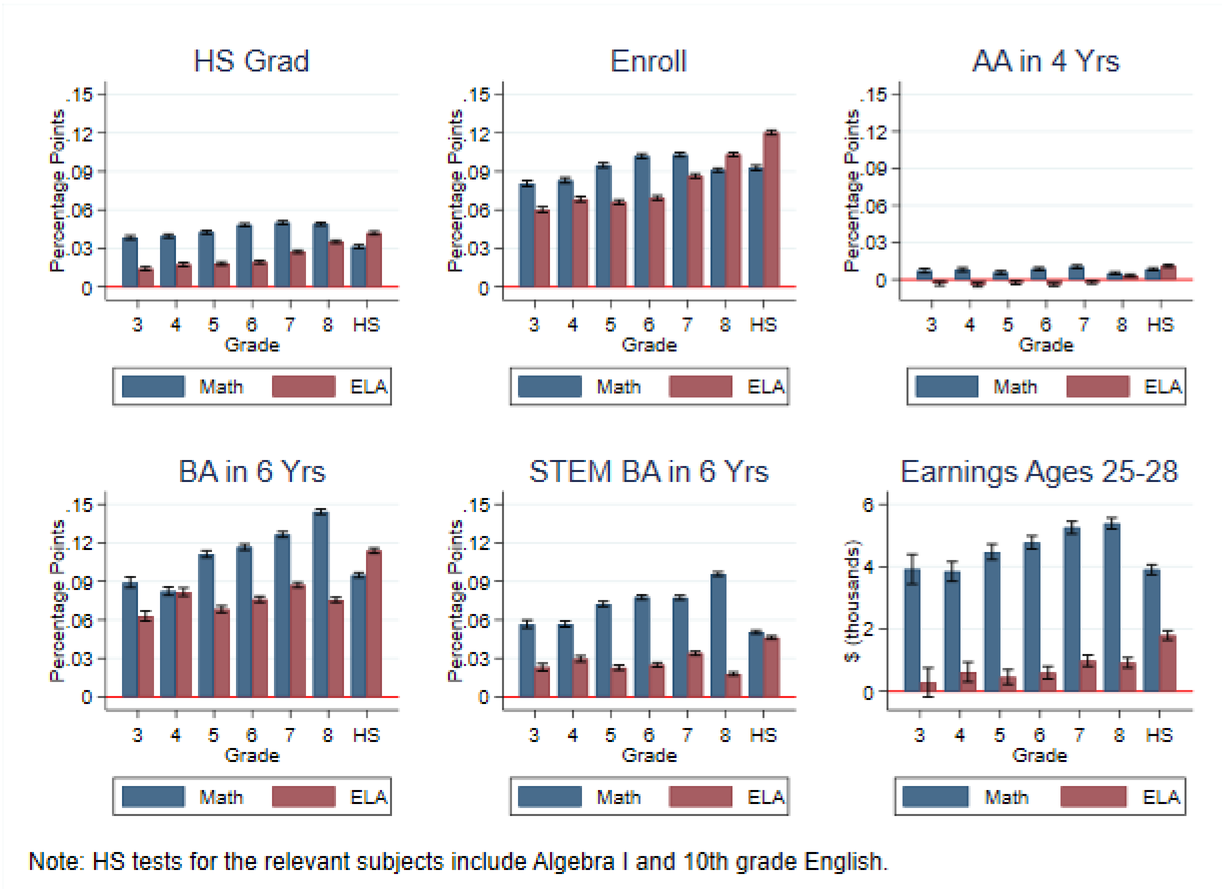
Neal, Derek A. and William R. Johnson, "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 1996, *104* (5), 869–895.

Petek, Nathan and Nolan G Pope, "The Multidimensional Impact of Teachers on Students," *Journal of Political Economy*, 2023, *131* (4), 1057–1107.

U.S. Congress, "H.R.1 - No Child Left Behind Act of 2001," https://www.congress.gov/bill/107th-congress/house-bill/1, 2001. Last accessed on July 7, 2025.

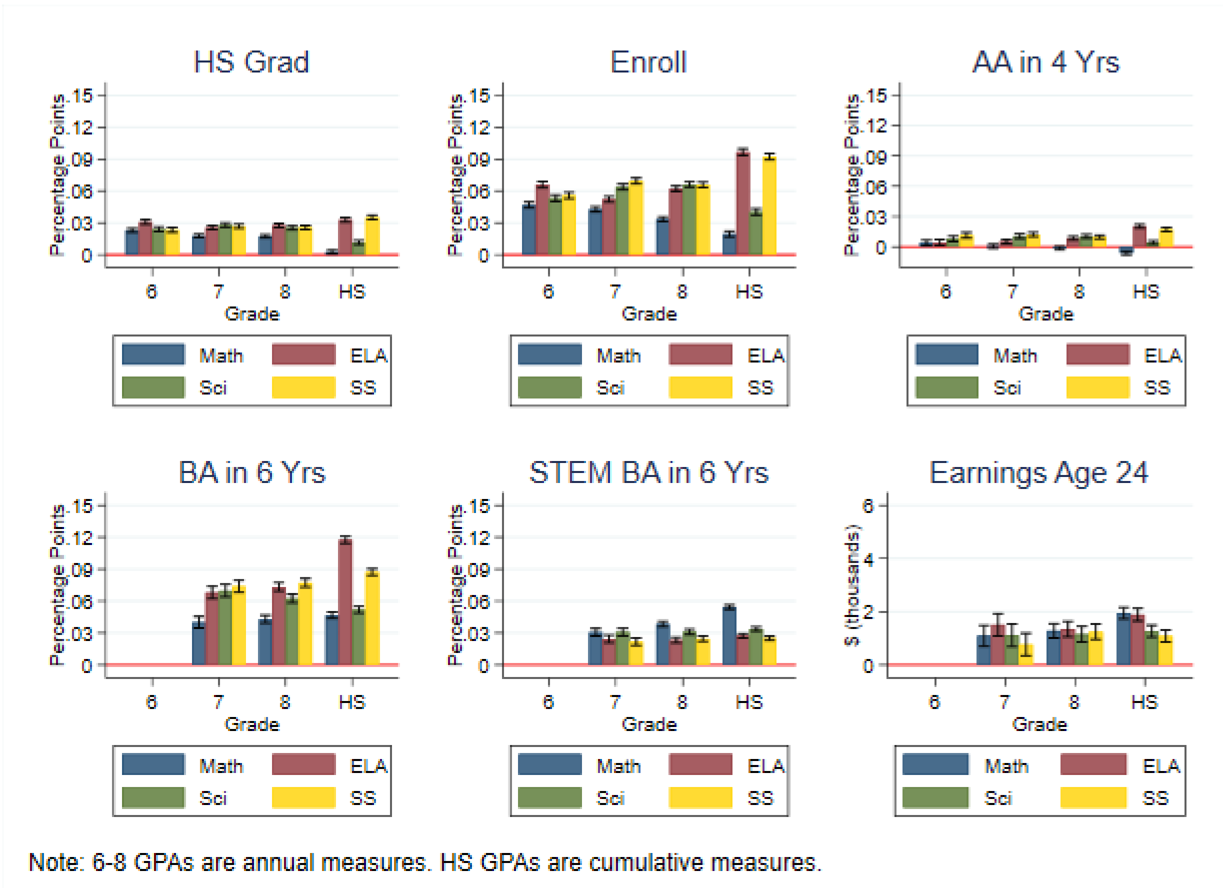
Figures and Tables

Figure 1: Relationship Between Test Scores and Outcomes by Grade



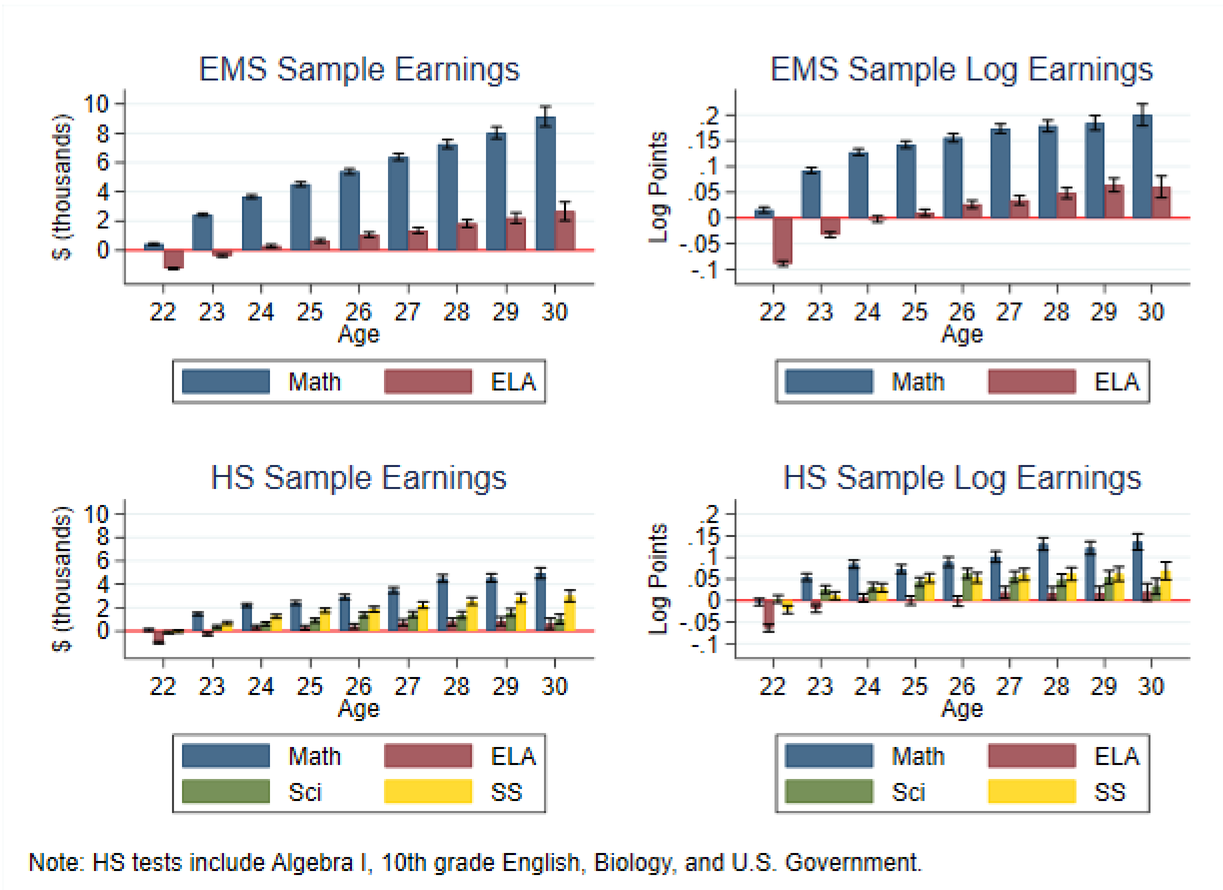
Notes: This figure shows estimates for the multivariate relationship between test scores and long-term outcomes by grade level. We use the EMS sample to construct estimates for grades 3-8 and the HS sample to construct estimates for HS. The samples are described in Section 2. Outcomes include educational attainment measures and earnings from ages 25-28. The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1, with only standardized math and ELA test scores as the main explanatory variables. The demographic controls include indicators for gender, race, gender-race interactions, FARMS, ELL, SPED, and imputed values for demographic variables. High school graduation is within four years and college enrollment is on-time relative to 9th grade enrollment. Average annual earnings from ages 25-28 are conditional on having positive observed earnings and measured in 2024 dollars. Robust 95 percent confidence intervals clustered at the student level are reported.

Figure 2: Relationship Between GPAs and Outcomes by Grade



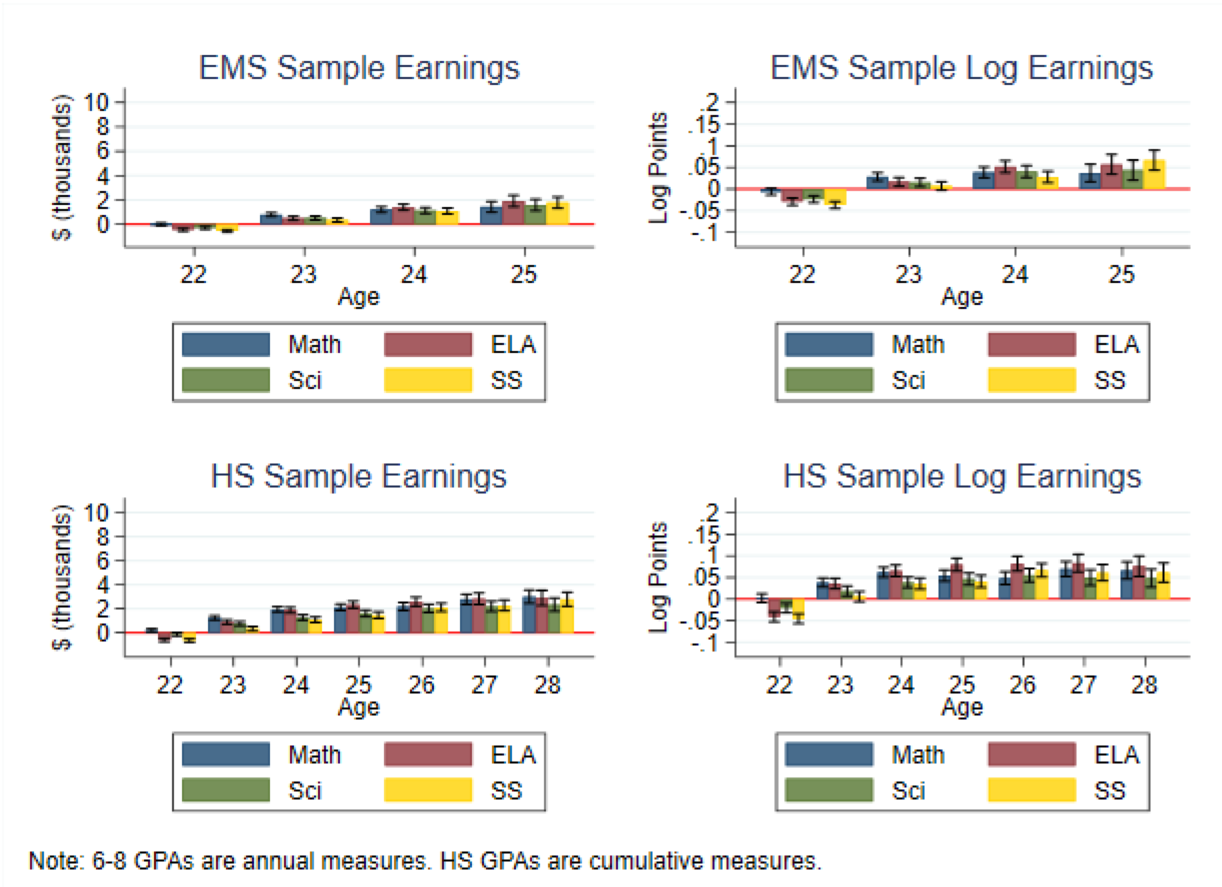
Notes: This figure shows estimates for the multivariate relationship between GPAs and long-term outcomes by grade level. We use the EMS sample to construct estimates for grades 6-8 and the HS sample to construct estimates for HS. The samples are described in Section 2. Outcomes include educational attainment measures and earnings at age 24. The specification is a multivariate GPA model with demographic controls and standardized GPAs in the four core subjects as the main explanatory variables. GPAs for grades 6-8 are annual measures and GPAs for HS are cumulative measures. High school graduation is within four years and college enrollment is on-time relative to 9th grade enrollment. Annual earnings at age 24 are conditional on having positive observed earnings and measured in 2024 dollars. Robust 95 percent confidence intervals clustered at the student level are reported.

Figure 3: Relationship Between Test Scores and Earnings by Age



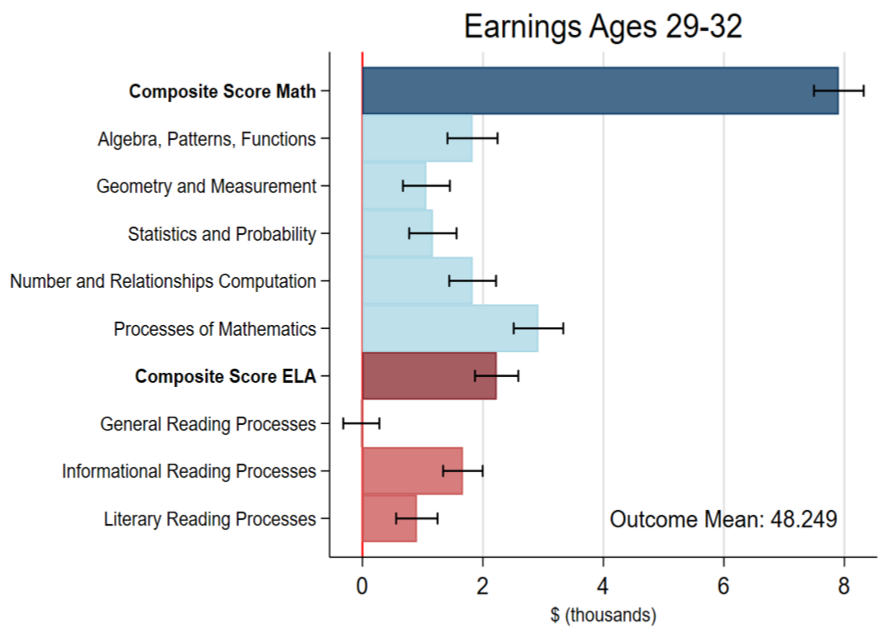
Notes: This figure shows estimates for the multivariate relationship between test scores and earnings by the age when earnings are measured. Estimates for the EMS sample are shown in the top two sub-figures and estimates for the HS sample are shown in the bottom two sub-figures. The samples are described in Section 2. Outcomes are annual earnings at ages 22-30, respectively, conditional on having positive observed earnings. Earnings are measured in 2024 dollars, with the two left sub-figures showing estimates in thousands of 2024 dollars and the two right sub-figures showing estimates for log earnings. The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1. Robust 95 percent confidence intervals clustered at the student level are reported.

Figure 4: Relationship Between GPAs and Earnings by Age



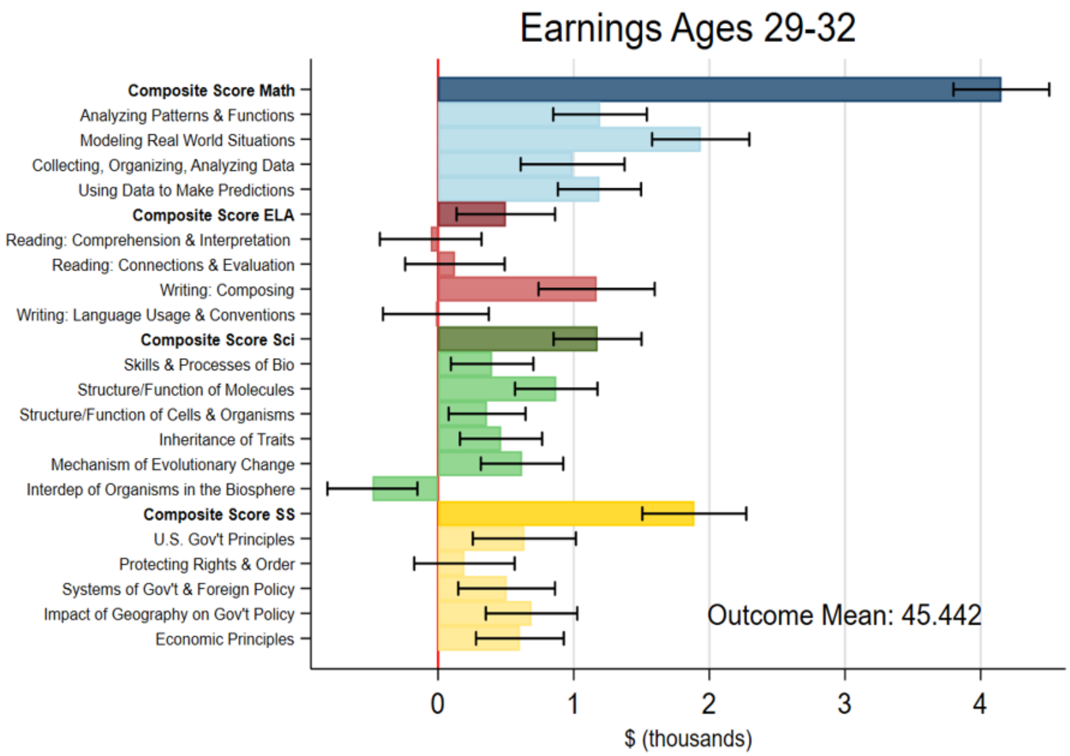
Notes: This figure shows estimates for the multivariate relationship between GPAs and earnings by the age when earnings are measured. Estimates for the EMS sample are shown in the top two sub-figures and estimates for the HS sample are shown in the bottom two sub-figures. The samples are described in Section 2. Outcomes are annual earnings at ages 22-28, respectively, conditional on having positive observed earnings. Earnings are measured in 2024 dollars, with the two left sub-figures showing estimates for thousands of dollars and the two right sub-figures showing estimates for log earnings. The specification is a multivariate GPA model with demographic controls and standardized GPAs in the four core subjects as the main explanatory variables. GPAs for grades 6-8 are annual measures and GPAs for HS are cumulative measures. Robust 95 percent confidence intervals clustered at the student level are reported.

Figure 5: Subscore decomposition for earnings at ages 29-32 (MS Sample)



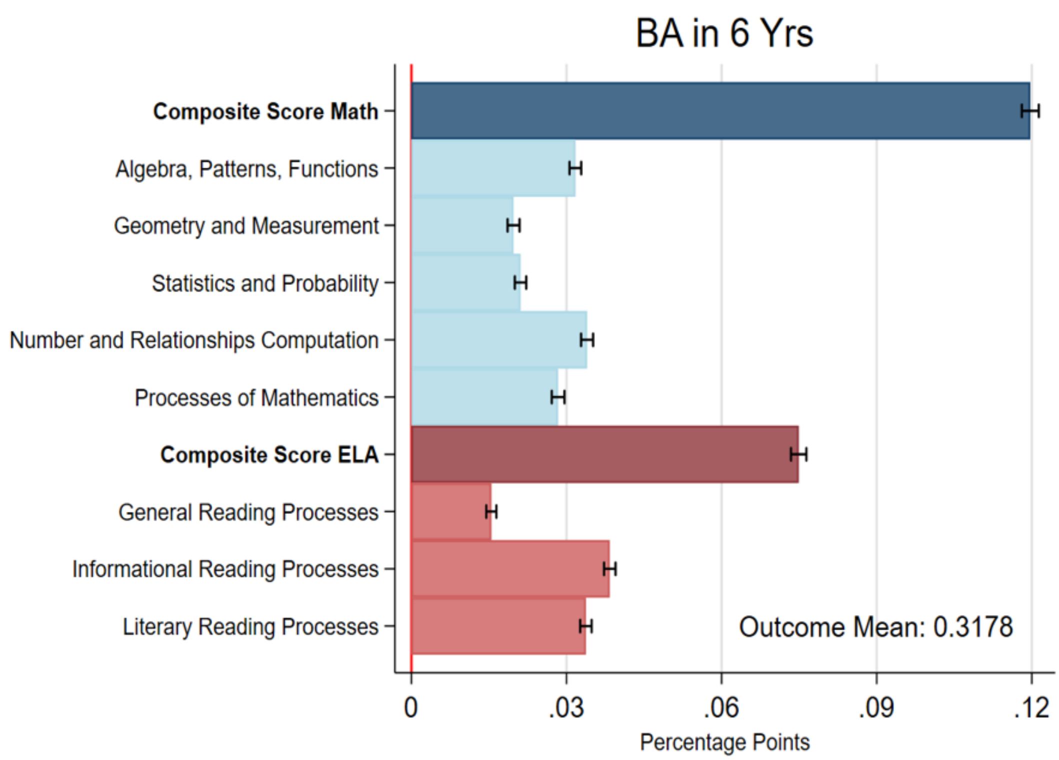
Notes: Notes: This figure reports coefficient estimates from multivariate regressions of average annual earnings at ages 29-32 on subject achievement measures from the Maryland elementary and middle school assessments. Earnings are measured in 2024 dollars (in thousands) and are conditional on having positive observed earnings; the outcome mean is shown in the figure. Dark bars report coefficients from the baseline multivariate specification that includes composite (subject-level) math and ELA test scores. Light bars report coefficients from specifications that replace one subject's composite score (math or ELA) with the full set of standardized subscores for that subject, while keeping the other subject in composite-score form. All test measures are standardized, and all regressions include the full set of demographic controls used in the main specification.

Figure 6: Subscore decomposition for earnings at ages 29-32 (H Sample)



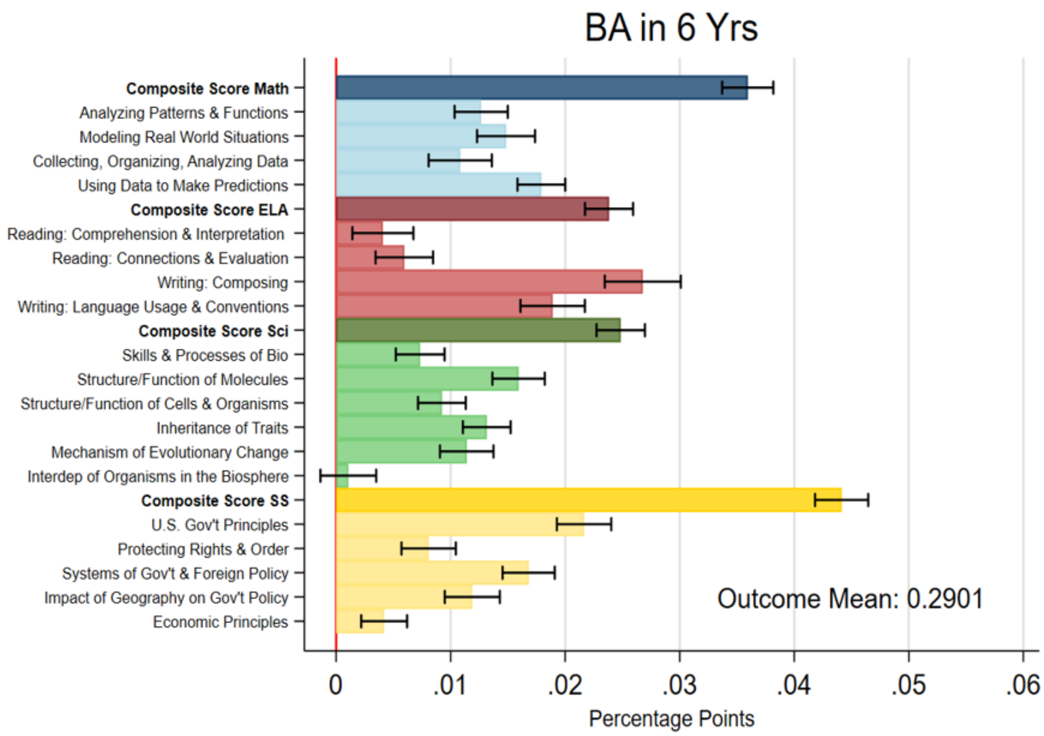
Notes: This figure reports coefficient estimates from multivariate regressions of average annual earnings at ages 29-32 on subject achievement measures from the Maryland high school end-of-course assessments. Earnings are measured in 2024 dollars (in thousands) and are conditional on having positive observed earnings; the outcome mean is shown in the figure. Dark bars report coefficients from the baseline multivariate specification that includes composite (subject-level) test scores in Algebra I, English 10, Biology, and U.S. Government. Light bars report coefficients from specifications that replace one subject's composite score with the full set of standardized subscores for that subject, while keeping the other subjects in composite-score form. All test measures are standardized, and all regressions include the full set of demographic controls used in the main specification.

Figure 7: Subscore decomposition for BA attainment in 6 years (MS Sample)



Notes: This figure reports coefficient estimates from multivariate regressions of bachelor's degree (BA) receipt within six years on subject achievement measures from the Maryland elementary and middle school assessments. The outcome is an indicator, and coefficients are reported in percentage points; the outcome mean is shown in the figure. Dark bars report coefficients from the baseline multivariate specification that includes composite (subject-level) math and ELA test scores. Light bars report coefficients from specifications that replace one subject's composite score (math or ELA) with the full set of standardized subscores for that subject, while keeping the other subject in composite-score form. All test measures are standardized, and all regressions include the full set of demographic controls used in the main specification.

Figure 8: Subscore decomposition for BA attainment in 6 years (HS Sample)



Notes: This figure reports coefficient estimates from multivariate regressions of bachelor's degree (BA) receipt within six years on subject achievement measures from the Maryland high school end-of-course assessments. The outcome is an indicator, and coefficients are reported in percentage points; the outcome mean is shown in the figure. Dark bars report coefficients from the baseline multivariate specification that includes composite (subject-level) test scores in Algebra I, English 10, Biology, and U.S. Government. Light bars report coefficients from specifications that replace one subject's composite score with the full set of standardized subscores for that subject, while keeping the other subjects in composite-score form. All test measures are standardized, and all regressions include the full set of demographic controls used in the main specification.

Table 1: Summary Statistics for EMS and HS Samples

	EMS Sample			HS Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	SD	N	Mean	SD	N
Panel A: Demographics						
Female	0.497	0.500	3,281,607	0.503	0.500	457,157
FARMS	0.419	0.493	3,281,607	0.364	0.481	457,157
Black	0.342	0.474	3,281,607	0.352	0.477	457,157
Hispanic	0.131	0.337	3,281,607	0.118	0.322	457,157
White	0.416	0.493	3,281,607	0.428	0.495	457,157
Asian	0.062	0.241	3,281,607	0.056	0.230	457,157
Other Race	0.049	0.217	3,281,607	0.047	0.211	457,157
ELL	0.043	0.202	3,281,607	0.036	0.186	457,157
SPED	0.133	0.340	3,281,607	0.127	0.333	457,157
Panel B: Explanatory Variables						
Comp Score Math	0.045	0.987	3,281,607	0.076	0.921	457,157
Comp Score ELA	0.009	0.996	3,281,607	0.024	0.955	457,157
Comp Score Sci	0.038	0.972	966,205	0.009	0.953	457,157
Comp Score SS				0.012	0.944	457,157
GPA Math	-0.013	0.969	1,025,365	-0.042	0.929	344,181
GPA ELA	-0.001	0.964	1,035,480	-0.003	0.916	355,160
GPA Sci	0.001	0.968	1,027,231	-0.026	0.919	333,653
GPA SS	0.005	0.965	1,020,668	0.001	0.910	339,639
Panel C: Outcomes						
HS Grad in 4 Yrs	0.874	0.332	3,281,607	0.917	0.275	457,157
Enroll in College	0.642	0.480	2,999,633	0.658	0.474	457,157
Persist in College	0.558	0.497	2,674,895	0.565	0.496	457,157
AA in 2 Yrs	0.025	0.157	2,674,895	0.023	0.151	457,157
AA in 4 Yrs	0.073	0.260	2,025,934	0.076	0.264	427,798
BA in 4 Yrs	0.208	0.406	2,025,934	0.188	0.390	427,798
BA in 6 Yrs	0.318	0.466	1,414,238	0.290	0.454	339,663
STEM BA in 4 Yrs	0.063	0.244	2,025,533	0.055	0.228	427,314
STEM BA in 6 Yrs	0.104	0.305	1,413,813	0.087	0.282	339,101
Employed Ages 22-24	0.829	0.377	1,800,494	0.840	0.367	382,751
Employed Ages 25-28	0.723	0.447	995,098	0.757	0.429	260,277
Employed Ages 29-32	0.602	0.489	152,752	0.646	0.478	124,378
Earnings Ages 22-24	23,138	17,831	1,492,104	23,263	17,617	321,399
Earnings Ages 25-28	36,697	26,399	719,675	35,528	25,478	197,068
Earnings Ages 29-32	48,249	34,439	91,999	45,442	32,611	80,362

Notes: Summary statistics are shown for the elementary and middle school (EMS) sample in columns (1)-(3) and the high school (HS) sample in columns (4)-(6). The samples are described in Section 2. Composite test score and GPA variables are standardized in the population to have mean zero and standard deviation one. College enrollment and persistence are "on-time" outcomes relative to the first observed year of enrollment in 9th grade in Maryland public schools. Employed is an indicator for having positive observed earnings. Average annual earnings are conditional on having positive observed earnings and measured in 2024 dollars.

Table 2: Univariate Relationship Between Test Scores and Educational Attainment and Earnings

	(1) HS Grad	(2) Enroll	(3) AA	(4) BA	(5) STEM BA	(6) Earn 22-24	(7) Earn 25-28	(8) Earn 29-32
Panel A: EMS Sample								
Comp Score Math	0.0601***	0.1436***	0.0064***	0.1690***	0.0937***	917***	5,376***	9,500***
	(0.0004)	(0.0005)	(0.0004)	(0.0007)	(0.0006)	(35)	(68)	(175)
Adj R-squared	0.0836	0.2159	0.0158	0.2509	0.1436	0.0389	0.1139	0.1514
Comp Score ELA	0.0523***	0.1377***	0.0032***	0.1502***	0.0729***	99***	3,726***	6,974***
	(0.0004)	(0.0005)	(0.0004)	(0.0007)	(0.0006)	(32)	(62)	(158)
Adj R-squared	0.0784	0.2122	0.0155	0.2363	0.1201	0.0372	0.1008	0.1325
Outcome Mean	[.8743]	[.6416]	[.0728]	[.3178]	[.1037]	[23,138]	[36,697]	[48,249]
N	3,281,607	2,999,633	2,025,934	1,414,238	1,413,813	1,492,104	719,675	91,999
Panel B: HS Sample								
Comp Score Math	0.0561***	0.1642***	0.0150***	0.1622***	0.0778***	882***	4,959***	7,806***
	(0.0006)	(0.0008)	(0.0004)	(0.0009)	(0.0006)	(40)	(70)	(141)
Adj R-squared	0.0611	0.1935	0.0181	0.2077	0.1059	0.0414	0.1064	0.1244
Comp Score ELA	0.0589***	0.1709***	0.0157***	0.1638***	0.0727***	187***	3,847***	6,236***
	(0.0006)	(0.0008)	(0.0004)	(0.0009)	(0.0006)	(38)	(67)	(135)
Adj R-squared	0.0661	0.2064	0.0184	0.2189	0.1051	0.0400	0.0992	0.1140
Comp Score Sci	0.0585***	0.1600***	0.0150***	0.1568***	0.0804***	568***	4,214***	6,239***
	(0.0006)	(0.0008)	(0.0004)	(0.0009)	(0.0006)	(37)	(65)	(129)
Adj R-squared	0.0662	0.1975	0.0183	0.2122	0.1155	0.0406	0.1027	0.1162
Comp Score SS	0.0624***	0.1762***	0.0155***	0.1681***	0.0756***	584***	4,401***	6,957***
	(0.0006)	(0.0008)	(0.0004)	(0.0008)	(0.0006)	(37)	(66)	(136)
Adj R-squared	0.0695	0.2113	0.0184	0.2246	0.1093	0.0407	0.1045	0.1203
Outcome Mean	[.9174]	[.658]	[.0756]	[.2901]	[.087]	[23,263]	[35,528]	[45,442]
N	457,157	457,157	427,798	339,663	339,101	321,399	197,068	80,362

Notes: This table shows estimates for the univariate relationship between test scores and long-term outcomes. Panel A shows results for the EMS sample and Panel B shows results for the HS sample. The samples are described in Section 2. Outcomes include educational attainment measures in columns (1)-(5) and earnings measures in columns (6)-(8). The specification is based on our main test score model with demographic controls in Section 3.1, Equation 1, but with only one test score variable included in the regression. Thus each cell in this table represents a separate regression. The demographic controls include indicators for gender, race, gender-race interactions, FARMS, ELL, SPED, and imputed values for demographic variables. High school graduation is within four years, college enrollment is on-time relative to 9th grade enrollment, AA receipt is within four years, and BA receipt outcomes are within six years. Average annual earnings are conditional on having positive observed earnings and measured in 2024 dollars. Robust standard errors are clustered at the student level.

*** p<0.01, ** p<0.05, * p<0.10

Table 3: Multivariate Relationship Between Test Scores and Educational Attainment and Earnings

	(1) HS Grad	(2) Enroll	(3) AA	(4) BA	(5) STEM BA	(6) Earn 22-24	(7) Earn 25-28	(8) Earn 29-32
Panel A: EMS Sample								
Comp Score Math	0.0446***	0.0922***	0.0073***	0.1183***	0.0771***	1,413***	4,874***	8,096***
	(0.0004)	(0.0006)	(0.0004)	(0.0008)	(0.0006)	(38)	(74)	(207)
Comp Score ELA	0.0237***	0.0791***	-0.0014***	0.0773***	0.0253***	-768***	775***	2,167***
	(0.0004)	(0.0006)	(0.0004)	(0.0008)	(0.0006)	(34)	(66)	(183)
Adj R-squared	0.0857	0.2273	0.0158	0.2630	0.1466	0.0397	0.1142	0.1530
Outcome Mean	[.8743]	[.6416]	[.0728]	[.3178]	[.1037]	[23,138]	[36,697]	[48,249]
N	3,281,607	2,999,633	2,025,934	1,414,238	1,413,813	1,492,104	719,675	91,999
Panel B: HS Sample								
Comp Score Math	0.0165***	0.0574***	0.0054***	0.0587***	0.0299***	910***	2,873***	4,676***
	(0.0008)	(0.0011)	(0.0006)	(0.0010)	(0.0007)	(51)	(88)	(174)
Comp Score ELA	0.0200***	0.0668***	0.0065***	0.0642***	0.0197***	-710***	369***	841***
	(0.0009)	(0.0011)	(0.0006)	(0.0011)	(0.0008)	(54)	(90)	(181)
Comp Score Sci	0.0184***	0.0353***	0.0043***	0.0361***	0.0370***	241***	1,159***	1,517***
	(0.0009)	(0.0012)	(0.0006)	(0.0011)	(0.0008)	(53)	(89)	(164)
Comp Score SS	0.0270***	0.0747***	0.0053***	0.0692***	0.0209***	397***	1,852***	2,787***
	(0.0010)	(0.0012)	(0.0006)	(0.0011)	(0.0007)	(55)	(93)	(188)
Adj R-squared	0.0776	0.2348	0.0192	0.2502	0.1289	0.0419	0.1120	0.1319
Outcome Mean	[.9174]	[.658]	[.0756]	[.2901]	[.087]	[23,263]	[35,528]	[45,442]
N	457,157	457,157	427,798	339,663	339,101	321,399	197,068	80,362

Notes: This table shows estimates for the multivariate relationship between test scores and long-term outcomes. Panel A shows results for the EMS sample and Panel B shows results for the HS sample. The samples are described in Section 2. Outcomes include educational attainment measures in columns (1)-(5) and earnings measures in columns (6)-(8). The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1, so each column in a panel represents a separate regression. High school graduation is within four years, college enrollment is on-time relative to 9th grade enrollment, AA receipt is within four years, and BA receipt outcomes are within six years. Average annual earnings are conditional on having positive observed earnings and measured in 2024 dollars. Robust standard errors are clustered at the student level.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 4: Multivariate Relationship Between Test Scores and GPAs and Outcomes

	(1) HS Grad	(2) Enroll	(3) AA	(4) BA	(5) STEM BA	(6) Earn 22-24	(7) Earn 25-28	(8) Earn 29-32
Panel A: EMS Sample								
Comp Score Math	0.0051***	0.0286***	-0.0097***	0.0773***	0.0765***	273***	3,471***	
	(0.0006)	(0.0009)	(0.0008)	(0.0020)	(0.0017)	(70)	(282)	
Comp Score ELA	0.0044***	0.0511***	-0.0058***	0.0393***	0.0135***	-1,187***	-902***	
	(0.0006)	(0.0009)	(0.0008)	(0.0018)	(0.0014)	(66)	(255)	
GPA Math	0.0173***	0.0268***	0.0032***	0.0225***	0.0185***	204***	823***	
	(0.0006)	(0.0008)	(0.0007)	(0.0017)	(0.0011)	(54)	(224)	
GPA ELA	0.0269***	0.0508***	0.0081***	0.0599***	0.0155***	16	1,779***	
	(0.0006)	(0.0009)	(0.0007)	(0.0017)	(0.0011)	(57)	(238)	
GPA Sci	0.0243***	0.0486***	0.0126***	0.0414***	0.0128***	155***	1,059***	
	(0.0006)	(0.0009)	(0.0007)	(0.0017)	(0.0011)	(56)	(241)	
GPA SS	0.0240***	0.0522***	0.0132***	0.0581***	0.0104***	-9	1,432***	
	(0.0006)	(0.0009)	(0.0007)	(0.0017)	(0.0011)	(56)	(237)	
Adj R-squared	0.0974	0.2707	0.0186	0.3253	0.1736	0.0317	0.1101	
Outcome Mean	[.8947]	[.6674]	[.0775]	[.3542]	[.1185]	[23,208]	[38,024]	
N	978,252	873,674	417,429	143,436	143,401	290,425	26,944	
Panel B: HS Sample								
Comp Score Math	0.0033***	0.0297***	-0.0013*	0.0325***	0.0205***	422***	2,051***	2,917***
	(0.0009)	(0.0012)	(0.0008)	(0.0013)	(0.0010)	(65)	(127)	(532)
Comp Score ELA	0.0006	0.0260***	-0.0014*	0.0304***	0.0101***	-1,182***	-548***	87
	(0.0009)	(0.0013)	(0.0008)	(0.0013)	(0.0010)	(68)	(128)	(596)
Comp Score Sci	0.0015	0.0050***	-0.0023***	-0.0064***	0.0262***	13	-108	1,125*
	(0.0010)	(0.0013)	(0.0008)	(0.0013)	(0.0011)	(69)	(139)	(581)
Comp Score SS	0.0140***	0.0479***	-0.0015**	0.0271***	0.0065***	312***	840***	2,405***
	(0.0011)	(0.0014)	(0.0008)	(0.0013)	(0.0010)	(70)	(132)	(603)
GPA Math	0.0004	0.0052***	-0.0052***	0.0363***	0.0453***	520***	1,805***	1,527***
	(0.0009)	(0.0014)	(0.0009)	(0.0015)	(0.0010)	(69)	(130)	(435)
GPA ELA	0.0312***	0.0872***	0.0209***	0.1091***	0.0222***	389***	2,339***	2,221***
	(0.0011)	(0.0016)	(0.0010)	(0.0016)	(0.0011)	(76)	(145)	(498)
GPA Sci	0.0087***	0.0248***	0.0053***	0.0409***	0.0241***	377***	1,494***	2,196***
	(0.0010)	(0.0015)	(0.0010)	(0.0016)	(0.0010)	(73)	(135)	(448)
GPA SS	0.0308***	0.0704***	0.0185***	0.0711***	0.0133***	79	1,399***	2,280***
	(0.0011)	(0.0016)	(0.0010)	(0.0016)	(0.0010)	(74)	(138)	(460)
Adj R-squared	0.0955	0.3028	0.0235	0.3718	0.1881	0.0381	0.1322	0.2013
Outcome Mean	[.9345]	[.6867]	[.0788]	[.3338]	[.1105]	[23,646]	[37,887]	[52,042]
N	319,470	319,470	291,985	206,941	206,915	215,793	101,746	7,734

Notes: Robust standard errors are clustered at the student level. *** p<0.01, ** p<0.05, * p<0.10

Table 5: Multivariate Relationship Between Test Scores and Degree Field

	(1) STEM	(2) Math/ Stats/CS	(3) Engi/ Arch	(4) Sci	(5) Soc Sci	(6) Hum	(7) Health	(8) Bus	(9) Edu
Panel A: EMS Sample									
Comp Score Math	0.0771***	0.0253***	0.0274***	0.0229***	0.0109***	0.0052***	0.0063***	0.0174***	0.0028***
	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Comp Score ELA	0.0253***	0.0040***	0.0050***	0.0139***	0.0276***	0.0192***	0.0047***	0.0032***	0.0007***
	(0.0006)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0002)
Adj R-squared	0.1466	0.0602	0.0497	0.0472	0.0425	0.0275	0.0257	0.0219	0.0175
Outcome Mean	[.1037]	[.0347]	[.0254]	[.0391]	[.074]	[.0362]	[.0227]	[.0413]	[.0176]
N	1,413,813	1,413,813	1,413,813	1,413,813	1,413,813	1,413,813	1,413,813	1,413,813	1,413,813
Panel B: HS Sample									
Comp Score Math	0.0299***	0.0105***	0.0123***	0.0068***	0.0061***	0.0004	0.0033***	0.0145***	0.0040***
	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0005)	(0.0003)
Comp Score ELA	0.0197***	0.0063***	0.0039***	0.0078***	0.0187***	0.0152***	0.0036***	0.0051***	0.0022***
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0003)
Comp Score Sci	0.0370***	0.0072***	0.0109***	0.0183***	-0.0022***	0.0050***	0.0041***	-0.0040***	-0.0008***
	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0003)
Comp Score SS	0.0209***	0.0073***	0.0045***	0.0082***	0.0247***	0.0107***	0.0027***	0.0080***	0.0011***
	(0.0007)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0003)	(0.0005)	(0.0003)
Adj R-squared	0.1289	0.0490	0.0411	0.0474	0.0439	0.0308	0.0247	0.0207	0.0187
Outcome Mean	[.087]	[.0287]	[.0207]	[.0341]	[.0692]	[.035]	[.0205]	[.0388]	[.0179]
N	339,101	339,101	339,101	339,101	339,101	339,101	339,101	339,101	339,101

Notes: This table shows estimates for the multivariate relationship between test scores and BA degree field outcomes within six years. Panel A shows results for the EMS sample and Panel B shows results for the HS sample. The samples and outcomes are described in Section 2. The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1, so each column in a panel represents a separate regression. Robust standard errors are clustered at the student level.
*** p<0.01, ** p<0.05, * p<0.10

Table 6: Test Scores and Earnings: Mediation Analysis Across Specifications

	(1) Main	(2) Ctrl Enroll	(3) Ctrl Enroll & BA	(4) Ctrl Enroll, BA, & Field
Panel A: EMS Sample				
Comp Score Math	8,114***	6,812***	4,763***	3,732***
	(208)	(210)	(206)	(202)
Comp Score ELA	2,152***	1,433***	339*	700***
	(183)	(183)	(180)	(177)
Adj R-squared	0.1531	0.1656	0.2060	0.2362
Outcome Mean	[48238]	[48238]	[48238]	[48238]
N	91,881	91,881	91,881	91,881
Panel B: HS Sample				
Comp Score Math	4,685***	4,129***	3,341***	2,988***
	(174)	(173)	(168)	(165)
Comp Score ELA	833***	371**	-159	-58
	(181)	(180)	(175)	(173)
Comp Score Sci	1,524***	1,143***	678***	553***
	(164)	(164)	(160)	(159)
Comp Score SS	2,778***	2,218***	1,246***	1,228***
	(188)	(187)	(182)	(180)
Adj R-squared	0.1321	0.1434	0.1851	0.2089
Outcome Mean	[45425]	[45425]	[45425]	[45425]
N	80,119	80,119	80,119	80,119

Notes: This table shows estimates for the multivariate relationship between test scores and earnings using different specifications. The earnings outcome is average annual earnings from ages 29-32 conditional on having positive observed earnings and measured in 2024 dollars. Column (1) shows our main multivariate test score model specification from Section 3.1, Equation 1. Column (2) adds a control for on-time college enrollment, column (3) adds a control for BA receipt within six years, and column (4) adds controls for the major fields in Table 5. Panel A shows results for the EMS sample and Panel B shows results for the HS sample. The samples are described in Section 2. Robust standard errors are clustered at the student level.
*** p<0.01, ** p<0.05, * p<0.10

Table 7: Heterogeneity Estimates of the Relationship Between Test Scores and Outcomes for EMS Sample

	(1) FARMS	(2) Non-FARMS	(3) Black	(4) Hispanic	(5) White	(6) Asian	(7) Q1	(8) Q2	(9) Q3
Panel A: Enroll in College									
Comp Score Math	0.1018***	0.0854***	0.0994***	0.0875***	0.0958***	0.0393***	0.1043***	0.1141***	0.0347***
	(0.0010)	(0.0007)	(0.0011)	(0.0019)	(0.0009)	(0.0016)	(0.0012)	(0.0015)	(0.0008)
Comp Score ELA	0.0993***	0.0657***	0.0929***	0.0919***	0.0720***	0.0210***	0.0938***	0.0995***	0.0248***
	(0.0010)	(0.0007)	(0.0011)	(0.0018)	(0.0008)	(0.0015)	(0.0012)	(0.0015)	(0.0007)
Adj R-squared	0.1573	0.1368	0.1879	0.1799	0.2384	0.0647	0.1048	0.0930	0.0561
Outcome Mean	[.4599]	[.7701]	[.5549]	[.5429]	[.6993]	[.9019]	[.3915]	[.6682]	[.8641]
N	1,243,120	1,756,513	1,026,135	380,014	1,262,634	183,495	995,705	1,005,580	998,348
Panel B: BA in 6 Yrs									
Comp Score Math	0.0743***	0.1393***	0.0938***	0.1018***	0.1341***	0.1234***	0.0491***	0.1494***	0.1024***
	(0.0011)	(0.0011)	(0.0013)	(0.0024)	(0.0013)	(0.0033)	(0.0010)	(0.0020)	(0.0016)
Comp Score ELA	0.0530***	0.0869***	0.0625***	0.0708***	0.0885***	0.0635***	0.0269***	0.1001***	0.0603***
	(0.0010)	(0.0010)	(0.0012)	(0.0022)	(0.0012)	(0.0030)	(0.0009)	(0.0020)	(0.0014)
Adj R-squared	0.1319	0.2093	0.1677	0.2015	0.2431	0.1740	0.0543	0.0917	0.1094
Outcome Mean	[.1294]	[.4352]	[.1908]	[.2114]	[.4]	[.6388]	[.0828]	[.2822]	[.5988]
N	542,826	871,412	487,347	155,015	621,338	78,417	472,646	484,618	456,974
Panel C: Earnings Ages 29-32									
Comp Score Math	6,649***	8,680***	7,597***	6,743***	8,397***	8,499***	5,956***	9,185***	8,503***
	(301)	(270)	(310)	(641)	(324)	(1,167)	(332)	(472)	(530)
Comp Score ELA	2,557***	1,902***	2,912***	1,034*	1,559***	3,183***	2,367***	2,679***	1,018**
	(262)	(243)	(266)	(577)	(289)	(1,108)	(273)	(468)	(463)
Adj R-squared	0.1095	0.1158	0.0942	0.0613	0.1077	0.0678	0.0997	0.0717	0.0481
Outcome Mean	[38,384]	[53,857]	[37,449]	[48,731]	[55,696]	[63,157]	[36,008]	[49,028]	[62,490]
N	33,340	58,659	34,685	8,704	40,812	3,671	32,412	33,558	26,029

Notes: This table shows estimates for the multivariate relationship between test scores and outcomes across subgroups for the EMS sample. The subgroups in columns (7)-(9) are achievement terciles from the lowest achievement tercile (Q1) to the highest achievement tercile (Q3). Terciles are defined based on the average of the math and ELA test scores. Educational attainment and earnings outcomes are shown in Panels A-C. The earnings outcome is average annual earnings from ages 29-32 conditional on having positive observed earnings and measured in 2024 dollars. The sample and attainment outcomes are described in Section 2. The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1, so each column in a panel represents a separate regression. Robust standard errors are clustered at the student level.
*** p<0.01, ** p<0.05, * p<0.10

Table 8: Heterogeneity Estimates of the Relationship Between Test Scores and Outcomes for HS Sample

	(1) FARMS	(2) Non-FARMS	(3) Black	(4) Hispanic	(5) White	(6) Asian	(7) Q1	(8) Q2	(9) Q3
Panel A: Enroll in College									
Comp Score Math	0.0530***	0.0594***	0.0492***	0.0569***	0.0706***	0.0238***	0.0440***	0.0861***	0.0294***
	(0.0017)	(0.0014)	(0.0018)	(0.0031)	(0.0017)	(0.0034)	(0.0016)	(0.0027)	(0.0016)
Comp Score ELA	0.0719***	0.0629***	0.0669***	0.0699***	0.0737***	0.0189***	0.0622***	0.0809***	0.0291***
	(0.0018)	(0.0014)	(0.0019)	(0.0033)	(0.0017)	(0.0039)	(0.0017)	(0.0028)	(0.0017)
Comp Score Sci	0.0383***	0.0337***	0.0406***	0.0416***	0.0316***	0.0203***	0.0331***	0.0510***	0.0035*
	(0.0017)	(0.0015)	(0.0018)	(0.0032)	(0.0019)	(0.0043)	(0.0016)	(0.0032)	(0.0018)
Comp Score SS	0.0772***	0.0713***	0.0778***	0.0727***	0.0672***	0.0497***	0.0626***	0.0976***	0.0273***
	(0.0017)	(0.0016)	(0.0019)	(0.0030)	(0.0019)	(0.0050)	(0.0016)	(0.0032)	(0.0021)
Adj R-squared	0.1882	0.1859	0.1955	0.2506	0.2450	0.1122	0.1084	0.0764	0.0421
Outcome Mean	[.4993]	[.7487]	[.5954]	[.5456]	[.7041]	[.8752]	[.3948]	[.6988]	[.8803]
N	166,298	290,859	160,773	53,897	195,445	25,723	152,386	152,386	152,385
Panel B: BA in 6 Yrs									
Comp Score Math	0.0280***	0.0789***	0.0360***	0.0476***	0.0857***	0.0667***	0.0107***	0.1053***	0.0834***
	(0.0011)	(0.0016)	(0.0013)	(0.0025)	(0.0020)	(0.0053)	(0.0007)	(0.0030)	(0.0030)
Comp Score ELA	0.0412***	0.0732***	0.0488***	0.0564***	0.0709***	0.0612***	0.0126***	0.0754***	0.0752***
	(0.0012)	(0.0016)	(0.0014)	(0.0030)	(0.0020)	(0.0056)	(0.0008)	(0.0031)	(0.0029)
Comp Score Sci	0.0265***	0.0425***	0.0325***	0.0386***	0.0420***	0.0646***	0.0088***	0.0597***	0.0366***
	(0.0011)	(0.0017)	(0.0012)	(0.0026)	(0.0022)	(0.0063)	(0.0007)	(0.0036)	(0.0032)
Comp Score SS	0.0439***	0.0880***	0.0560***	0.0468***	0.0834***	0.0936***	0.0173***	0.1216***	0.0876***
	(0.0011)	(0.0018)	(0.0014)	(0.0027)	(0.0022)	(0.0068)	(0.0007)	(0.0034)	(0.0037)
Adj R-squared	0.1382	0.2328	0.1670	0.1997	0.2466	0.2527	0.0342	0.0779	0.1103
Outcome Mean	[.1291]	[.3817]	[.1871]	[.1839]	[.3652]	[.5630]	[.0552]	[.2577]	[.5857]
N	123,087	216,576	122,170	37,298	146,380	17,816	117,225	116,450	105,988
Panel C: Earnings Ages 29-32									
Comp Score Math	3,365***	5,771***	3,328***	3,870***	6,960***	4,872***	2,777***	7,349***	7,236***
	(222)	(257)	(213)	(516)	(355)	(1,216)	(182)	(466)	(662)
Comp Score ELA	850***	722***	1,124***	999*	546	758	890***	1,138**	-1,049
	(232)	(268)	(224)	(584)	(342)	(1,457)	(189)	(522)	(677)
Comp Score Sci	1,357***	1,633***	1,860***	914*	852**	1,416	798***	1,666***	2,058***
	(211)	(248)	(192)	(536)	(358)	(1,284)	(168)	(523)	(782)
Comp Score SS	2,602***	2,725***	2,835***	2,235***	2,128***	6,528***	1,165***	4,420***	3,362***
	(244)	(278)	(234)	(600)	(369)	(1,397)	(204)	(510)	(730)
Adj R-squared	0.0973	0.1154	0.0739	0.0628	0.1005	0.0825	0.0801	0.0579	0.0372
Outcome Mean	[38,155]	[49,613]	[36,824]	[46,960]	[52,543]	[57,792]	[35,159]	[47,784]	[60,107]
N	29,251	51,111	33,670	7,575	33,029	2,881	32,715	29,402	18,245

Notes: Heterogeneity estimates for the HS sample; robust standard errors are reported. *** p<0.01, ** p<0.05, * p<0.10

Table 9: Effect of Teacher Test Score Value-Added on Educational Attainment and Earnings

	(1) HS Grad	(2) Enroll	(3) AA 2 Yrs	(4) AA 4 Yrs	(5) BA 4 Yrs	(6) BA 6 Yrs	(7) STEM	(8) Earn 22-24
Panel A: Univariate Models								
Math TVA	-0.0010*	0.0012	-0.0007	-0.0005	0.0063***	0.0019	0.0134***	164*
	(0.0006)	(0.0013)	(0.0005)	(0.0012)	(0.0017)	(0.0039)	(0.0032)	(95)
Adj R-squared	0.0942	0.2516	0.0223	0.0321	0.2567	0.3080	0.1820	0.0601
ELA TVA	0.0001	0.0025	-0.0000	0.0001	0.0055**	0.0054	0.0002	-110
	(0.0010)	(0.0017)	(0.0007)	(0.0017)	(0.0025)	(0.0066)	(0.0043)	(172)
Adj R-squared	0.0937	0.2500	0.0219	0.0316	0.2522	0.3022	0.1733	0.0599
Outcome Mean	[.8988]	[.6853]	[.0316]	[.0826]	[.2589]	[.395]	[.1345]	[23,289]
N	1,080,311	919,422	723,722	341,840	341,840	103,850	103,817	236,408
Panel B: Multivariate Models								
Math TVA	-0.0011*	0.0007	-0.0007	-0.0005	0.0056***	0.0011	0.0133***	184*
	(0.0006)	(0.0013)	(0.0005)	(0.0012)	(0.0017)	(0.0039)	(0.0032)	(95)
ELA TVA	0.0004	0.0022	0.0001	0.0002	0.0043*	0.0052	-0.0028	-155
	(0.0010)	(0.0017)	(0.0007)	(0.0017)	(0.0026)	(0.0064)	(0.0044)	(175)
Adj R-squared	0.0943	0.2526	0.0225	0.0326	0.2580	0.3100	0.1821	0.0604
Outcome Mean	[.8988]	[.6853]	[.0316]	[.0826]	[.2589]	[.395]	[.1345]	[23,289]
N	1,080,311	919,422	723,722	341,840	341,840	103,850	103,817	236,408

Notes: This table shows estimates for the effect of teacher valued-added (TVA) for students' test scores on educational attainment and earnings. The sample is our student-year level TVA sample described in Section 2, restricted to observations with a non-missing leave-out TVA measure. This table reports the effect of a one standard deviation increase in test score TVA on outcomes. The specification is our main TVA model with TVA controls in Section 3.2, Equation 6. The TVA controls include: i) lags of a cubic polynomial in students' math and ELA test scores; ii) lags of a cubic polynomial in class- and grade-level means of those test scores; iii) the same current demographic controls used in our descriptive test score model (Equation 1): indicators for gender, race, gender-race interactions, FARMS, ELL, SPED, and imputed values for missing demographics; and iv) class- and grade-level means of those demographic variables. All these covariates are interacted with grade fixed effects, and we include a control for class size. When lagged scores in the other subject are missing, we set the other subject lagged score to zero and include an indicator for missing data in the other subject interacted with controls for lagged own-subject test scores. Panel A shows results using a univariate model, so each cell in Panel A represents a separate regression. Panel B shows results using a multivariate model, so each column in Panel B represents a separate regression. Average annual earnings from ages 22-24 are conditional on having positive observed earnings and measured in 2024 dollars. Robust standard errors are clustered at the school level.
*** p<0.01, ** p<0.05, * p<0.10

Appendix A: Tables and Figures

Table A1: HSA Subscore Descriptions

HSA Test	HSA Subscore
Algebra I	Analyzing Patterns and Functions
Algebra I	Modeling Real World Situations
Algebra I	Collecting, Organizing, and Analyzing Data
Algebra I	Using Data to Make Predictions
English 10	Reading/Literature: Comprehension and Interpretation
English 10	Reading/Literature: Making Connections and Evaluation
English 10	Writing: Composing
English 10	Writing: Language Usage and Conventions
Biology	Skills and Processes of Biology
Biology	Structure and Function of Biological Molecules
Biology	Structure and Function of Cells and Organisms
Biology	Inheritance of Traits
Biology	Mechanism of Evolutionary Change
Biology	Interdependence of Organisms in the Biosphere
U.S. Government	U.S. Government Structure, Functions, and Principles
U.S. Government	Protecting Rights and Maintaining Order
U.S. Government	Systems of Government and U.S. Foreign Policy
U.S. Government	Impact of Geography on Governmental Policy
U.S. Government	Economic Principles, Institutions, and Processes

Notes: This table shows the subscores for the Maryland High School Assessments (HSA) (MSDE, 2012).

Table A2: MSA Subscore Descriptions

MSA Test	MSA Subscore
Math	Algebra, Patterns, or Functions
Math	Geometry and Measurement
Math	Statistics and Probability
Math	Number and Relationships Computation
Math	Processes of Mathematics
ELA	General Reading Processes
ELA	Informational Reading Processes
ELA	Literary Reading Processes
Science	Skills and Processes
Science	Earth/Space Science
Science	Life Science
Science	Chemistry
Science	Physics
Science	Environmental Science

Notes: This table shows the subscores for the Maryland School Assessments (MSA) (MSDE, 2003, 2016).

Table A3: Teacher Value-Added Estimates of Forecast Bias

	(1) Math	(2) ELA
TVA	1.1153***	1.0992***
	(0.0281)	(0.0448)
Adj R-squared	0.7517	0.7204
N	1,712,724	1,671,687

Notes: This table reports the effect of teacher value-added (TVA) on current-year student test scores, serving as a validity check of the TVA identification strategy. The sample includes student-year observations from the TVA sample (Section 2) with non-missing leave-out TVA measures, where TVA is scaled in student-level test score standard deviations and estimated using data from other years taught by the same teacher (Section 3.2). Each column shows the effect of subject-specific TVA on the corresponding standardized test score. The specification follows our main TVA model (Equation 6), including: i) lags of a cubic polynomial in students' math and ELA scores; ii) lags of a cubic polynomial in class- and grade-level means of those scores; iii) demographic controls (indicators for gender, race, gender-race interactions, FARMS, ELL, SPED, and missing demographics); and iv) class- and grade-level means of these demographic variables. All controls are interacted with grade fixed effects, and class size is included. For missing lagged scores in the non-matching subject, we set the value to zero and include a missing indicator interacted with the own-subject lag. Robust standard errors are clustered at the school level.

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A4: Multivariate Relationship Between Test Scores and Labor Market Outcomes

	(1) Emp 22-24	(2) Emp 25-28	(3) Emp 29-32	(4) Earn 22-24 Uncond	(5) Earn 25-28 Uncond	(6) Earn 29-32 Uncond	(7) Earn 22-24 Cond	(8) Earn 25-28 Cond	(9) Earn 29-32 Cond
Panel A: EMS Sample									
Comp Score Math	-0.0198***	-0.0303***	-0.0314***	513***	1,863***	2,772***	1,413***	4,874***	8,096***
	(0.0007)	(0.0011)	(0.0023)	(34)	(68)	(172)	(38)	(74)	(207)
Comp Score ELA	-0.0201***	-0.0350***	-0.0358***	-1,224***	-1,033***	-675***	-768***	775***	2,167***
	(0.0007)	(0.0010)	(0.0022)	(31)	(60)	(155)	(34)	(66)	(183)
Adj R-squared	0.0139	0.0232	0.0190	0.0201	0.0250	0.0252	0.0397	0.1142	0.1530
Outcome Mean	[.8287]	[.7232]	[.6023]	[17,806]	[24,930]	[28,697]	[23,138]	[36,697]	[48,249]
N	1,800,494	995,098	152,752	1,800,494	995,098	152,752	1,492,104	719,675	91,999
Panel B: HS Sample									
Comp Score Math	-0.0098***	-0.0102***	-0.0046**	395***	1,519***	2,607***	910***	2,873***	4,676***
	(0.0010)	(0.0014)	(0.0023)	(48)	(82)	(150)	(51)	(88)	(174)
Comp Score ELA	-0.0124***	-0.0165***	-0.0316***	-891***	-460***	-921***	-710***	369***	841***
	(0.0011)	(0.0015)	(0.0025)	(51)	(85)	(158)	(54)	(90)	(181)
Comp Score Sci	-0.0078***	-0.0143***	-0.0114***	-65	306***	498***	241***	1,159***	1,517***
	(0.0011)	(0.0015)	(0.0023)	(51)	(84)	(145)	(53)	(89)	(164)
Comp Score SS	-0.0146***	-0.0246***	-0.0212***	-134**	298***	597***	397***	1,852***	2,787***
	(0.0011)	(0.0015)	(0.0026)	(53)	(87)	(163)	(55)	(93)	(188)
Adj R-squared	0.0129	0.0206	0.0184	0.0215	0.0289	0.0269	0.0419	0.1120	0.1319
Outcome Mean	[.8397]	[.7571]	[.6461]	[18,109]	[24,917]	[28,455]	[23,263]	[35,528]	[45,442]
N	382,751	260,277	124,378	382,751	260,277	124,378	321,399	197,068	80,362

Notes: This table shows estimates for the multivariate relationship between test scores and employment and earnings. Panel A shows results for the EMS sample and Panel B shows results for the HS sample. The samples are described in Section 2. Columns (1)-(3) show estimates for employment at ages 22-24, 25-28, and 29-32, respectively. Employment is defined using a binary indicator for having positive earnings observed in Maryland UI data in each respective age range. Columns (4)-(6) show estimates for unconditional average annual earnings for the same respective age ranges with zeros imputed for those who are missing earnings. Columns (7)-(9) show estimates for conditional average annual earnings for the same respective age ranges, which are identical to our estimates in Table 3, columns (6)-(8). The specification is our main multivariate test score model with demographic controls in Section 3.1, Equation 1, so each column in a panel represents a separate regression. Average annual earnings are measured in 2024 dollars. Robust standard errors are clustered at the student level.

*** p<0.01, ** p<0.05, * p<0.10

Appendix B: Maryland Assessment Background

Policy Overview. The publication of *A Nation at Risk* in 1983 ushered in an era of education reform that emphasized rigorous curricula and increased use of standardized testing for accountability. This increased focus on conceptual reasoning and application of knowledge over rote memorization led to three critical waves of policy change affecting state standardized testing in Maryland. First, Maryland introduced the Maryland School Performance Assessment Program (MSPAP) for elementary and middle school students in 1990 and first administered end-of-course high school assessments (HSA) in 2000. Second, the passage of the federal No Child Left Behind (NCLB) Act in 2001 required Maryland to develop the Maryland School Assessments (MSA) so that achievement data could be disaggregated by student subgroups. Third, the Maryland State Board of Education adopted the Common Core State Standards (CCSS) in 2010, leading to the implementation of the CCSS-aligned tests from the Partnership for Assessment of Readiness for College and Careers (PARCC) (MSDE, 2015). Similarly, the state adopted the Next Generation Science Standards (NGSS) in 2013, leading to the implementation of the NGSS-aligned Maryland Integrated Science Assessment (MISA) in 2018 (MSDE, 2025).

MSPAP and HSA. Maryland's focus on rigorous learning standards and corresponding assessment dates to at least 1990 with the introduction of the Maryland School Performance Assessment Program (MSPAP). This test was given to 3rd, 5th, and 8th grade students to assess competency in reading, language, writing, math, science, and social studies. To complement the MSPAP, the state also established the high school assessments (HSA) in the 1990s with the first tests administered in 2000. Students were assessed via high-stakes exams upon completion of their Algebra I, 10th grade English, Biology, and U.S. Government courses.[21] The HSA tests continued to be administered through the mid- to late-2010s depending on the subject, while the MSPAP was phased out with the introduction of the MSA to satisfy the requirements of NCLB (MSDE, 2015).

NCLB and MSA. The passage of the landmark federal No Child Left Behind (NCLB) legislation in 2001 placed greater importance on assessment, data, and accountability in schools nationwide. This legislation required states to adopt state-level academic standards and develop aligned tests. Schools had to assess students annually in reading and math in grades 3-8 and once in high school. The law also required states to disaggregate test data by student subgroups to provide greater transparency about educational inequities. This emphasis on assessment and data was paired with accountability mechanisms. Schools were required to demonstrate Adequate Yearly Progress (AYP) towards all students achieving proficient levels on their tests, and schools failing to to hit AYP goals faced accountability measures such as school improvement plans or restructuring (U.S. Congress, 2001).

[21] Data collection from HSA exams includes the overall composite scores and proficiency levels as well as subscores focused on particular skill areas. Appendix Table A1 shows subscores for each of these exams. The Algebra I exam has 4 subscores (e.g. Analyzing Patterns and Functions), the English 10 exam has 4 subscores (e.g. Reading and Literature: Comprehension and Interpretation), the Biology exam has 6 subscores (e.g. Skills and Processes of Biology), and the U.S. Government exam has 5 subscores (e.g. U.S. Government Structure, Functions, and Principles) (MSDE, 2012).

In response to the requirements of NCLB, Maryland developed the Maryland School Assessments (MSA) in reading and math. These tests allowed the state to report testing results by student subgroups. Students in grades 3, 5, and 8 were first assessed in 2003, while those in grades 4, 6, and 7 were first assessed in 2004. The MSA science tests was first administered to students in grades 5 and 8 in 2007.[22] The HSA assessments first administered in 2000 were also part of the NCLB-era testing regime given the law's requirement to test all high school students at least once (MSDE, 2015).

CCSS, PARCC, and NGSS. In 2010, a multi-state effort the Common Core State Standards (CCSS) Initiative began with the aim of strengthening the rigor and consistency of state academic standard nationwide. These standards focused on the knowledge and skills that students should possess in math and ELA by the end of each grade. Maryland's State Board of Education adopted CCSS in 2010 and the state joined the Partnership for Assessment of Readiness for College and Careers (PARCC) consortium to develop and administer the standards-aligned tests. PARCC assessments in math and ELA were first given to students in grades 3-8 and high school in 2015 and continued through 2019 (MSDE, 2015).[23]

Continuing the trend of implementing more rigorous standards and tests, the Maryland State Board of Education also adopted the Next Genereation Science Standards (NGSS) in 2013. Similar to CCSS, these standard focus more on depth over breadth, conceptual reasoning, and knowledge application. NGSS focuses on three broad areas that students are expected to master: i) Science and Engineering Practices, ii) Crosscutting Concepts, and iii) Disciplinary Core Ideas. Following the adoption of NGSS, Maryland established the NGSS standards-aligned Maryland Integrated Science Assessments (MISA). MISA was first administered to 5th and 8th grade students in 2018 and replaced the MSA science test while the HS MISA test was first administered to HS students in 2019 as an end-of-course Biology exam that replaced the HSA Biology test MSDE (2025).

Together, these waves of policy reform reshaped Maryland's K-12 assessment system over nearly three decades, expanding both the scope and stakes of standardized testing. The resulting data, spanning multiple subjects, grade levels, and assessment regimes, form the foundation for our analysis. We discuss Maryland's assessment data in more detail in the next Section (2).

[22]Data collection from MSA tests includes the overall composite scores and proficiency levels as well as subscores focused on particular skill areas. Appendix Table A2 shows subscores for each of these tests. The math test has 5 subscores (e.g. Algebra, Patterns, or Functions), the ELA test has 3 subscores (e.g. General Reading Processes), and the science test has 6 subscores (e.g. Skills and Processes) (MSDE, 2003, 2016).

[23]The PARCC tests for high school students were for Algebra I and English 10.