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The Effect of Passing a CTE Technical Assessment on College Enrollment

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Highlights

- We study the relationship between passing a CTE technical assessment and college attendance using a regression discontinuity design from more than 50 assessments.
- There is wide variation in correlations between CTE assessment scores and standardized test scores (English Language Arts and math) across different assessments.
- Among CTE students, assessment takers are less likely to be White and have lower standardized test scores on average.
- We find no effect of passing a technical assessment on college enrollment for students just above the passing threshold compared to students just below the threshold.

Introduction

In recent years, high schools across the United States have expanded and diversified the range of course offerings in Career and Technical Education (CTE). This change follows a broader shift in the high school curriculum from a focus on a "college for all" model to one that prepares students for "college and career." The purpose is to provide students with course options that can be used as preparation for career-focused post-secondary degrees or as direct workforce preparation for potentially non-college-bound high school graduates.

The implementation of the Carl D. Perkins Career and Technical Education Act of 2006, commonly referred to as *Perkins IV*, codified many of these changes in legislation providing federal funds for CTE. It accounts for the majority of state funding for CTE education.[1] *Perkins IV* included core performance indicators that held states accountable for the effectiveness of their programs. In addition to performance in core academic subject exams, such as math, reading, and English Language Arts (ELA) among CTE concentrators (those taking an aligned sequence of CTE courses), and graduation and post-secondary enrollment rates for those students, the legislation also required measures of "technical skill attainment." While *Perkins IV* gave no explicit definition of technical skill attainment, the core performance indicator included "[s]tudent attainment of an industry-recognized credential, a certificate, or a degree"[2] that states measured as the share of CTE concentrators who passed a technical skill assessment aligned with industry-recognized standards.

Given the difficulty of generating an aligned technical skill assessment for each of the hundreds of CTE pathways (which are aligned three-course sequences such as Architectural Drawing and Design) within 16 recognized career clusters (e.g., Architecture and Construction), the majority of these assessments came from existing industry credentialing exams (e.g., Autodesk Revit Architecture Certified User Exam). In other words, using existing third-party exams for industry purposes was seen as a good strategy. One potential advantage of this arrangement was that by earning a credential or passing an exam already recognized by employers, students could then use that as a signal of skill attainment in the labor market.

To date, little evidence exists as to whether employers value technical assessments taken by CTE students. In fact, there is little evidence as to how well the assessments measure student learning or skill attainment. Both of these challenges are in large part due to a lack of data. While *Perkins IV* mandated states to use technical skill attainment as a performance indicator, the law only required states to report the share of CTE concentrators who passed the exam, not scores. An implication is that districts and states frequently did not collect individual-level scores for students, and even a student's pass/fail indicator seldom made its way into state longitudinal databases.

In this study, we find that students who took a technical assessment enrolled in more CTE courses on average than students who took CTE coursework but no assessment—likely reflecting that assessments are normally given at the end of a sequence. Technical assessment-takers were less likely to be White and had lower math and ELA scores on standardized tests. We also find wide variation in correlations between technical assessments and standardized math and ELA scores, and that technical assessments are more strongly correlated on average with ELA than math.

When we compare college-going for students just on either side of the passing threshold for an assessment, pooling together all assessments, we find that passing a technical assessment has no impact on the likelihood of attending college. We similarly find no impact on college-going when we restrict the analysis sample to a subset of the most popular tests (with some exceptions). For those on the margin of passing a technical assessment, the signal afforded to students from passing the assessment does not appear to affect students' propensity to attend college.

Research Questions

The paucity of existing evidence on CTE technical assessments raises related issues of how well the assessments gauge student learning and whether they are valued by employers in the labor market. Although we cannot directly answer either of these questions, in this study, we investigate three broad related research questions in the hope of building a foundation for future work:

RQ1. Who takes technical assessments, and which assessments do they take?

RQ2. Are technical assessment scores correlated with other exams?

RQ3. Does passing a technical assessment affect students' propensity to attend college?

Answering RQ3 is our main goal and is intended to provide insight as to whether the technical assessments add "value" for students. If assessments are valuable in terms of finding a job, passing might lead students to be less likely to enroll in college because their prospects for immediate employment are higher. On the other hand, assessments may be a stepping-stone for students on their way to a two- or four-year degree, making college enrollment more likely.

Sample Description and Summary Statistics

We use data from four large metro-Atlanta school districts. The data cover over 13,000 students who took at least one of 52 unique NOCTI technical assessment in Grade 12 between 2011 and 2018 and other students' data that allows us to compare them to non-test takers.[3] Our first analysis sample includes students who took a NOCTI technical assessment for whom we observe at least one valid score. Many students, regardless of whether they took a NOCTI exam, may have taken exams issued by other test providers. We cannot observe test taking by other providers, but we expect that few students took exams from other providers as only a small share took more than one NOCTI test. We refer to the first analysis sample as the *main sample*.

Our second analysis sample limits the first analysis sample to students in district-cohorts for whom we can observe college enrollment using National Student Clearinghouse (NSC) data. In practice, this restriction involves limiting the sample to students observed in Grade 12 in a school year in which their district requested NSC records. College enrollment includes enrollment in two-

Table 1. Summary Statistics Across Analysis Samples

	College sample			All Students
	No CTE	CTE, no NOCTI	Took NOCTI	Took NOCTI
Female	0.60	0.48	0.51	0.49
White	0.50	0.36	0.22	0.22
Black	0.33	0.50	0.68	0.67
Hispanic	0.14	0.15	0.12	0.12
Asian	0.15	0.10	0.07	0.08
Any CTE		1.00	0.99	0.95
CTE credit hours		2.77	4.67	3.67
Number of tests taken			1.08	1.09
Number of distinct tests			1.04	1.04
Graduated high school	0.90	0.91	0.96	0.63
Enrolled in college	0.84	0.78	0.76	0.51
ELA score (std.)	0.74	0.19	-0.01	0.07
ELA score missing	0.30	0.23	0.15	0.14
Math score (std.)	0.83	0.31	0.07	0.06
Math score missing	0.30	0.23	0.15	0.19
Observed in Grade 9	0.57	0.67	0.84	0.84
In college sample	1.00	1.00	1.00	0.60
Observations	41,092	117,351	13,603	22,788

Notes. Columns 1-3 include students who are in the college sample (i.e., those who were in Grade 12 in a district-year where National Student Clearinghouse records were requested and available to us). “No CTE” are students who have no record of a CTE course. “No NOCTI” are CTE students who never took a NOCTI exam in our records. “Took NOCTI” are students who ever took a NOCTI exam in our data. Column 4 shows all students who ever took a NOCTI assessment in our records, regardless of whether they are in the college sample. Race categories are not mutually exclusive.

year or four-year degrees. We refer to the second analysis sample, which is a subset of the main sample, as the *college sample*.

Table 1 shows summary statistics. The table comprises our main sample, with the college sample limited to columns 1–3. The first three columns compare NOCTI technical assessment takers (column 3) with students taking CTE but no NOCTI test (column 2) and students who did not enroll in any CTE course (column 1). Students who never took CTE (column 1) were more likely to be female, White, and to enroll in college.[4] They also had higher average math and ELA standardized test scores than students who took CTE coursework. Students who took a NOCTI test (column 3), as compared with CTE students who did not take one (column 2), were similar in gender, more likely to be Black, and have lower average math and ELA scores. We are more likely to observe technical assessment takers in Grade 9, indicating that assessment-taking might be more prominent among students with lower out-of-district mobility.[5]

The rightmost column of Table 1 presents statistics for the sample of students who ever took a NOCTI test, regardless of whether we observe them in a Grade 12 cohort for which we have NSC records. These students have similar demographic characteristics with test-takers who are in the college sample, but they have fewer CTE credits and are less likely to graduate high school. The sample of all students includes many whom we do not observe in Grade 12, due to either transfer or dropout, suggesting they are similar to the college sample but not enrolled in one of the four metro-Atlanta districts in Grade 12.

Appendix Table A1 presents the complete list of the 52 NOCTI technical assessments, the number of assessment-takers (for the main sample and college sample), pass-rates, the share of takers who were female, and the share of takers who enrolled in college. Some students take an assessment more than once or take more than one test; we count each assessment instance separately. In some cases, the assessment name or other factors (such as passing thresholds) changed over time. We create a harmonized list of assessments that accounts for changes in the assessment name and passing threshold by using an assessment-year-specific cut score. A large number of assessments were well-populated, while about 20 have fewer than 50 takers. For much of the analysis, we focus on the top 25 (and in some cases the top 10) most popular assessments.[6]

Empirical Methods

We use descriptive methods to address RQ1 and RQ2 and a regression discontinuity design (RDD) to estimate the causal effect of passing a NOCTI technical assessment in RQ3. The RDD compares college-going between students who barely passed a CTE technical assessment and students who barely failed. This empirical method rests on the assumption that students who were separated by only a few points in their technical assessment score were otherwise similar, including in their likelihood of attending college. Hence, by comparing students within a few points of passing or not passing an assessment, any differences in outcomes across students who were around the passing threshold were due to the effect of passing alone and not due to differences in skills measured by the assessment. In this sense, we are estimating the effect of the signal that passing an assessment sends to students rather than skill differences between those who do and do not pass.

For RQ3, we estimate the following regression model:

$$y_i = \beta_0 + \beta_1 Passed_i + \beta_2 ScoreBelow_i + \beta_3 ScoreAbove_i + X_i'\Pi + \epsilon_i,$$

where y_i is college attendance for student i and $Passed_i$ is an indicator set to 1 if i student passed the technical assessment. The running variable (the student's assessment score) is estimated separately above ($ScoreAbove_i$) and below ($ScoreBelow_i$) the threshold. X_i is a set of student demographic characteristics including gender, race, and scores on academic standardized tests such as math and ELA. The model is estimated only for students within a small range of technical assessment scores around the passing threshold; the size of this bandwidth is determined using a data-driven computational procedure.[7]

We take two approaches to address the fact that not all assessments have the same cutoff and that each cutoff, even if a similar score, may represent a different level of difficulty—affecting students at different skill margins. In the first approach, we estimate the regression model below pooled over all assessments and include indicators for the specific assessment (fixed effects), the year the student took the assessment, the year the student was in Grade 12, and the student's district. The assessment scores are centered at that test's passing threshold. Estimating this model (shown below) compares across students taking the same assessment in the same year who were in Grade 12 in the same year and the same district.

$$y_{ij} = \beta_0 + \beta_1 Passed_{ij} + \beta_2 ScoreBelow_{ij} + \beta_3 ScoreAbove_{ij} + X_i'\Pi + \Psi_j + \tau_t + \delta_d + \gamma_c + \epsilon_{ij},$$

where j indicates assessment, t indicates assessment year, d indicates the student's district, and c is the student's Grade 12 cohort. The variable of interest is β_1, the effect of passing a technical assessment on enrolling in college. The two score variables allow the relationship between the score and outcomes to vary differentially across the passing threshold.

As a supplement to this approach, we re-estimate the model separately by technical assessment for assessments with a sufficient number of test-takers. The aim is to examine whether there are differences in effect sizes across assessments. This comes at the cost of statistical power, as we have much smaller samples to work with. Hence, in this section, we restrict this analysis to the top 10 most frequently taken tests among students in the college sample.

Finally, we note that some students took more than one test. For example, they may have taken the same test twice if they failed the first time, or they may have taken two or more different tests. To account for multiple-takers, we estimate a model using a fuzzy RDD in which we limit the sample to students who only took one test and use the student's first test as an instrument for ever passing any test.

To assess the internal validity of the RDD, we test for manipulation of technical assessment scores by students close to the passing threshold. The test verifies that there is not a significantly larger number of students who barely pass compared to the number of students who barely fail, which might be evidence that students close to the threshold manipulated their scores to barely pass or exerted additional effort if they knew they were close to the threshold.[8] We show a density test pooled for all technical assessments in Appendix Figure A1 and examine the density test for each of the top 25 most popular assessments separately (not shown). We do not find evidence of manipulation of technical assessment scores around the passing threshold.

We also verify that students' demographic covariates are smooth across the passing threshold; if observed characteristics were not smooth, it might suggest differences in unobserved characteristics as well. Appendix Table A2 presents the estimated effects for covariates, which are all insignificantly different from zero and therefore smooth across the passing threshold.

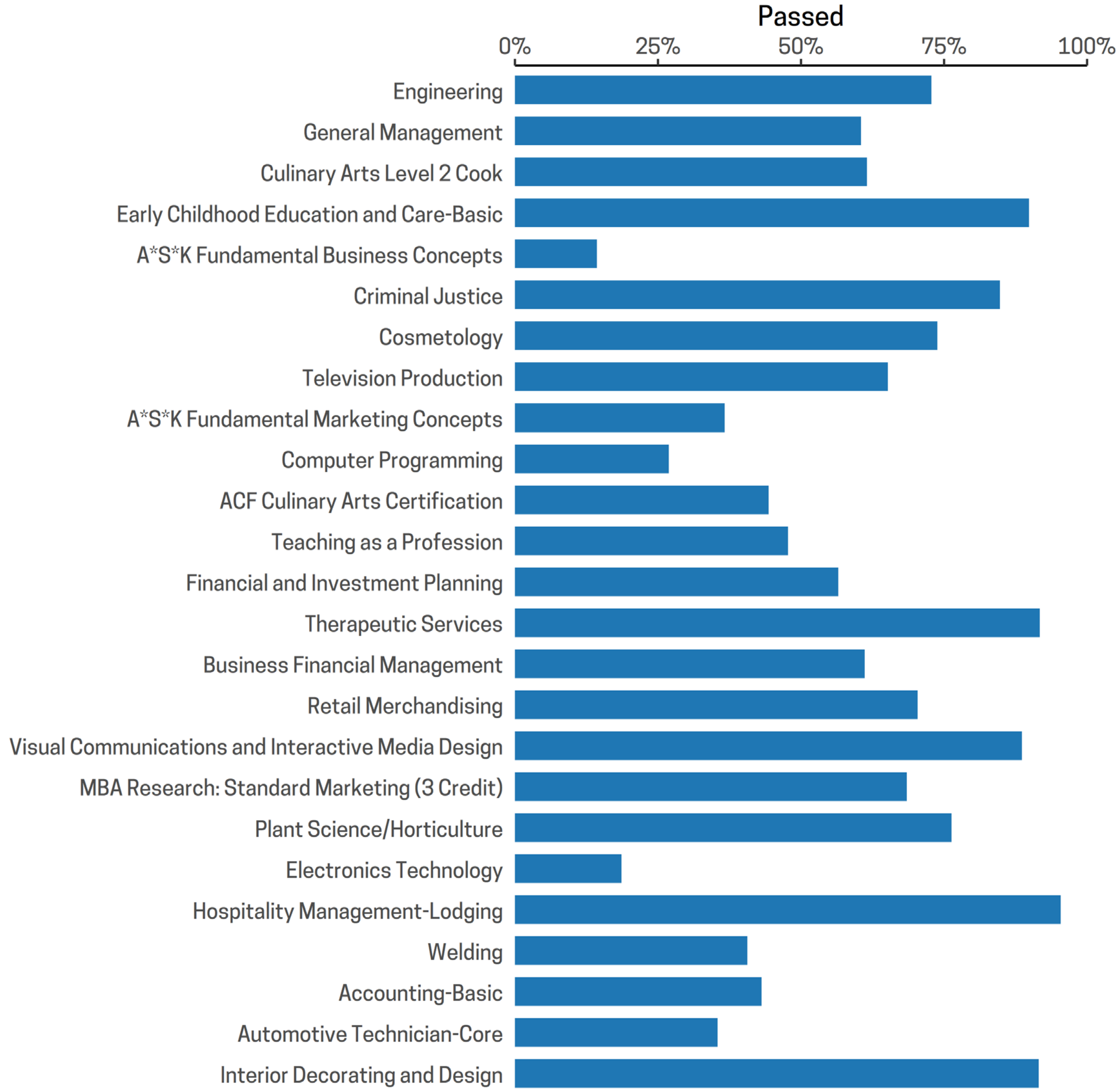
Findings

RQ1: Who takes technical assessments, and which assessments do they take?

Table 1 shows differences in the population of students who took a technical assessment compared with CTE students who did not. Among those whom we observe in Grade 12, we show that assessment-takers were less likely to be White and had lower scores on math and ELA exams. We also find that exam takers were more likely to graduate high school but slightly less likely to enroll in college. We next consider the assessments themselves.

Figure 1 shows pass rates for the 25 most popular technical assessments sorted by the number of test takers. Pass rates varied meaningfully across assessments, ranging from almost 90 percent (Early Childhood, Therapeutic Services, Hospitality, and Interior Design) to below 30 percent (ASK Business Concepts, Electronics Technology, Computer Programming). Across all tests, the average

Figure 1. Share of Students who Passed a Technical Assessment for the 25 Most Common Assessments

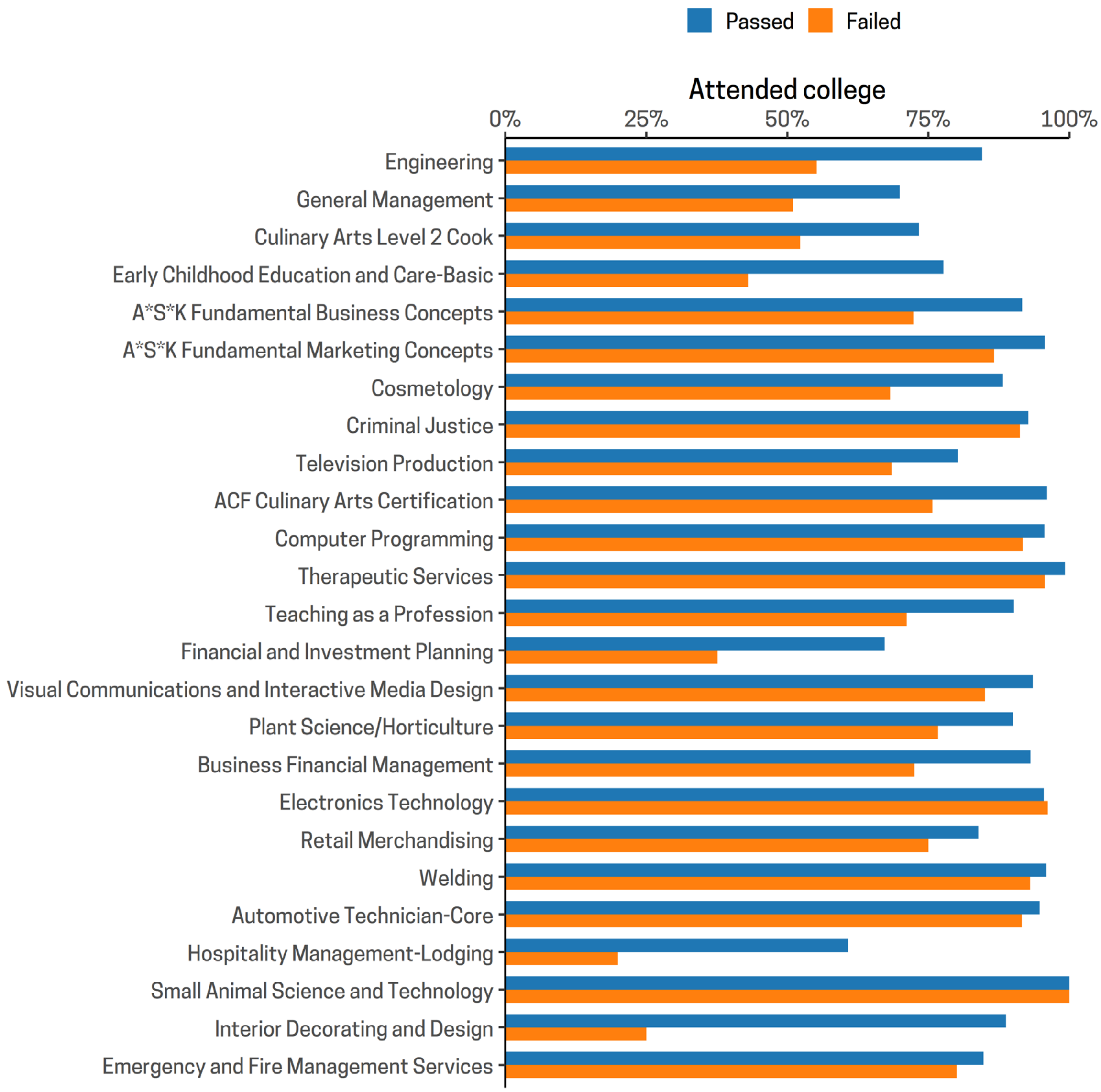


Notes. The figure shows passing rates for the 25 most common technical assessments among all takers regardless of whether we observe their college enrollment status. Technical assessments are sorted by the number of takers; Engineering has the highest number of takers. Passing shares are similar if the sample is restricted to students with college enrollment data.

pass rate was approximately 63%. This statistic is important, as our empirical strategy relies on having enough students near the passing threshold.

Figure 2 provides intuition for the RDD by displaying the share of students in the college sample who enrolled in college by assessment and passing status. While Figure 2 does not show causal evidence, as we compare all students who

Figure 2. College Attendance by Assessment Outcome, 25 Most Common Assessments

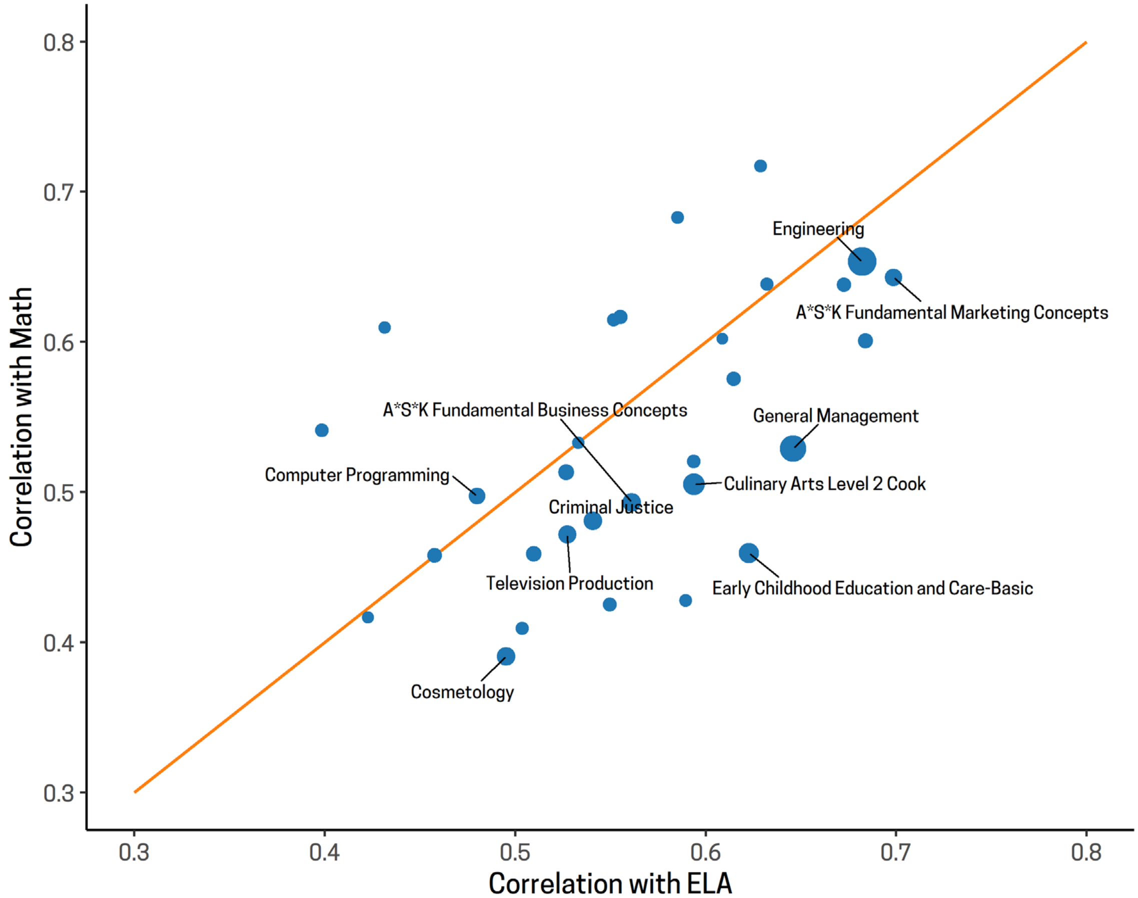


Notes. The figure shows college enrollment rates by technical assessment passing status for the 25 most common technical assessments among students with college enrollment data. Technical assessments are sorted by the number of takers; Engineering has the highest number of takers.

passed with all who failed, the RDD estimate will be based solely on students who just passed and just failed.

Figure 2 shows that, for almost all tests, those who passed a technical assessment were more likely to attend college than those who did not pass. In some cases, the difference was large (e.g., Interior Design, Hospitality, and Early Childhood Education). We also find wide variation in college-going across tests regardless of passing status. For example, all students who took Animal Science

Figure 3. Correlation Between NOCTI Technical Assessment Scores and Math and ELA Standardized Test Scores



Notes. Points represent the correlation between technical assessment scores and ELA standardized test scores (horizontal axis) and the correlation between technical assessment scores and math standardized test scores (vertical axis). The sample includes students with technical assessment scores and math and ELA standardized test scores regardless of whether we observe their college enrollment status. Point size increases with the number of test takers. The 10 technical assessments with the most takers are labeled.

went to college (regardless of passing status), while few students who took Hospitality enrolled in college. We do not find a strong correlation between the share of students who passed a test (possibly a measure of difficulty) and the share who attended college.

RQ2: Are technical assessment scores correlated with other exams?

We examine correlations between technical assessment scores (normalized by test to have mean score 0 and standard deviation 1) and standardized math and ELA test scores taken in Grade 9 (for students who have these scores, also normalized to mean 0 and standard deviation 1). We limit this analysis to the 25 tests with the highest number of takers. Figure 3 shows the correlation between technical assessment scores and ELA test scores on the horizontal axis and the correlation between technical assessment scores and math test scores on the vertical axis. Point size increases with the number of technical assessment takers; the 10 tests with the highest number of takers are labeled.

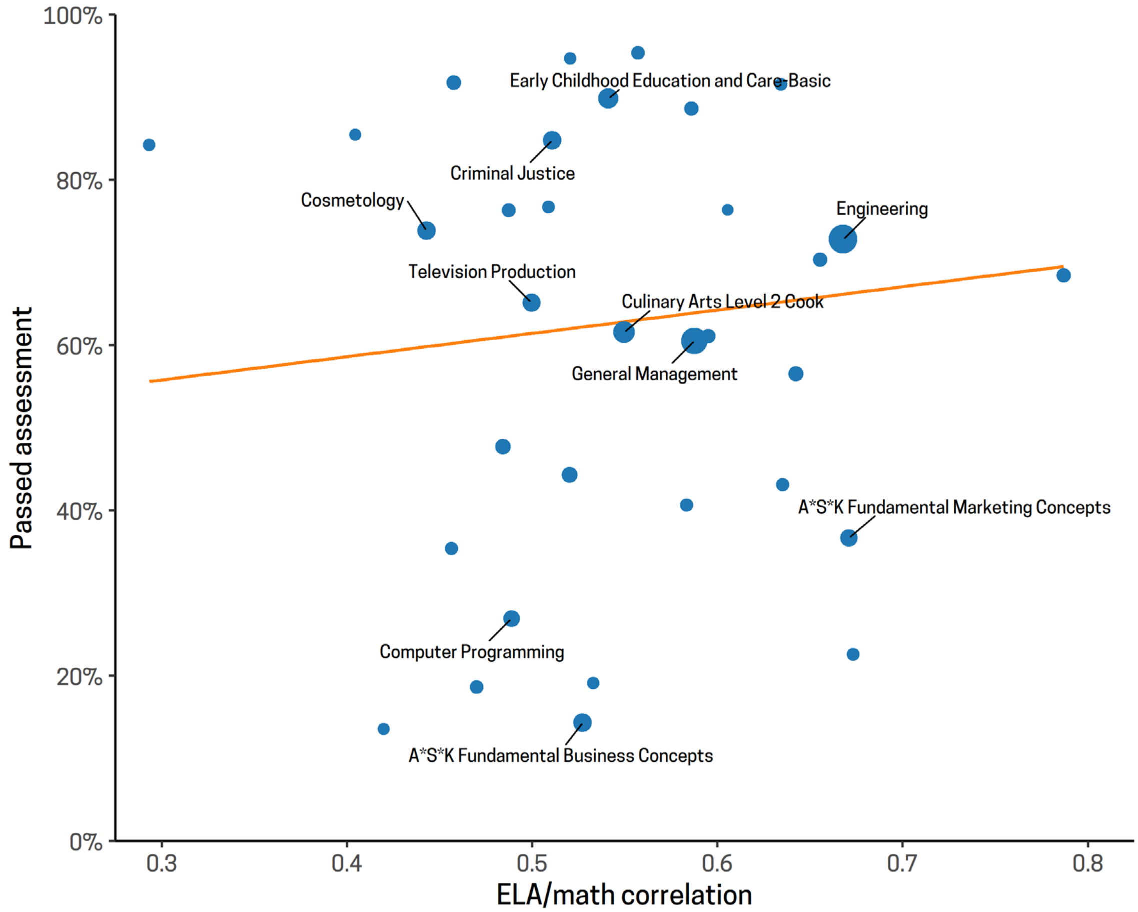
Data points farther to the northeast corner of Figure 3 represent technical assessments that were highly correlated with both math and ELA test scores (i.e., students who scored highly on that technical assessment and scored highly on both math and ELA tests). For example, Engineering technical assessment scores had a 0.68 correlation with ELA scores and 0.65 correlation with math. Technical assessments closer to the origin of the graph were weakly correlated with both math and ELA test scores. Assessments falling below the 45-degree (diagonal) line were more highly correlated with ELA than math, and those above the 45-degree line were more highly correlated with math than ELA. For example, while performance on the Cosmetology technical assessment was weakly correlated with both ELA and math test scores, it was more closely correlated with ELA (a correlation of 0.50) than with math (a correlation of 0.38). Similarly, Early Childhood and General Management technical assessments were more strongly correlated with ELA than math. On average, technical assessment scores were more strongly correlated with ELA scores than math scores.

We also consider whether technical assessments that were more highly correlated with standardized tests have differential pass rates. Figure 4 displays the correlation of technical assessments with both standardized tests (the average of ELA and math correlations) and the share of students who passed the test. We find a weak, positive correlation, suggesting that technical assessments more closely aligned with academic test scores had higher pass rates. One interpretation is that there is a general knowledge component to some of the technical assessments, while assessments that were weakly correlated with math and ELA scores are more topic-specific.

RQ3: Does passing a technical assessment affect students' propensity to attend college?

Table 2 shows results from the RDD model described above using data pooled across all technical assessments, including several alternative specifications. The first column shows the effect of passing any test with no additional controls (including no assessment fixed effects). The point estimate of 0.02 represents a small two-percentage-point increase in the likelihood of attending college, but the estimate is not statistically significantly different from zero.

Figure 4. ELA and Math Standardized Test Correlations and Technical Assessment Pass Rates



Notes. Points represent the average correlation between standardized test scores for math and ELA, the technical assessment score, and the technical assessment pass rate for all test takers in the main sample.

In column 2 of Table 2, we add assessment fixed effects, and the point estimate is approximately zero with the standard errors ruling out effect sizes beyond about four percentage points in either direction. We add cohort, assessment year, and district fixed effects in column 3 and individual covariates, including race, gender, and math and ELA scores, in column 4; the estimates remain relatively unaffected by the additional control variables. In column 5, we drop the individual covariates (as they have no impact) and limit the sample to those taking only one test (again, with no change to the estimated effect). Finally, in column 7, we use each test as an instrument for passing any test (effective only for those with more than one test) and again find no effect on college attendance. In other specifications not shown, we limit to students who took only one exam or only to the largest 25 assessments with little change to results.

Table 2. Effect of Passing a NOCTI Technical Assessment on College Attendance

	No controls	+ Assess. F.E.	+ Year and district F.E.	+ Indiv. controls	Only took one assess.	Fuzzy RDD
	(1)	(2)	(3)	(4)	(5)	(6)
Passed	0.023	-0.001	-0.009	0.002	-0.003	-0.004
	(0.051)	(0.020)	(0.020)	(0.021)	(0.021)	(0.025)
Obs. below threshold	4,086	3,262	3,099	2,649	2,652	2,231
Obs. above threshold	6,415	4,748	4,495	3,697	4,306	2,981
Bandwidth	18.2	12.9	11.8	9.7	13.1	8.2

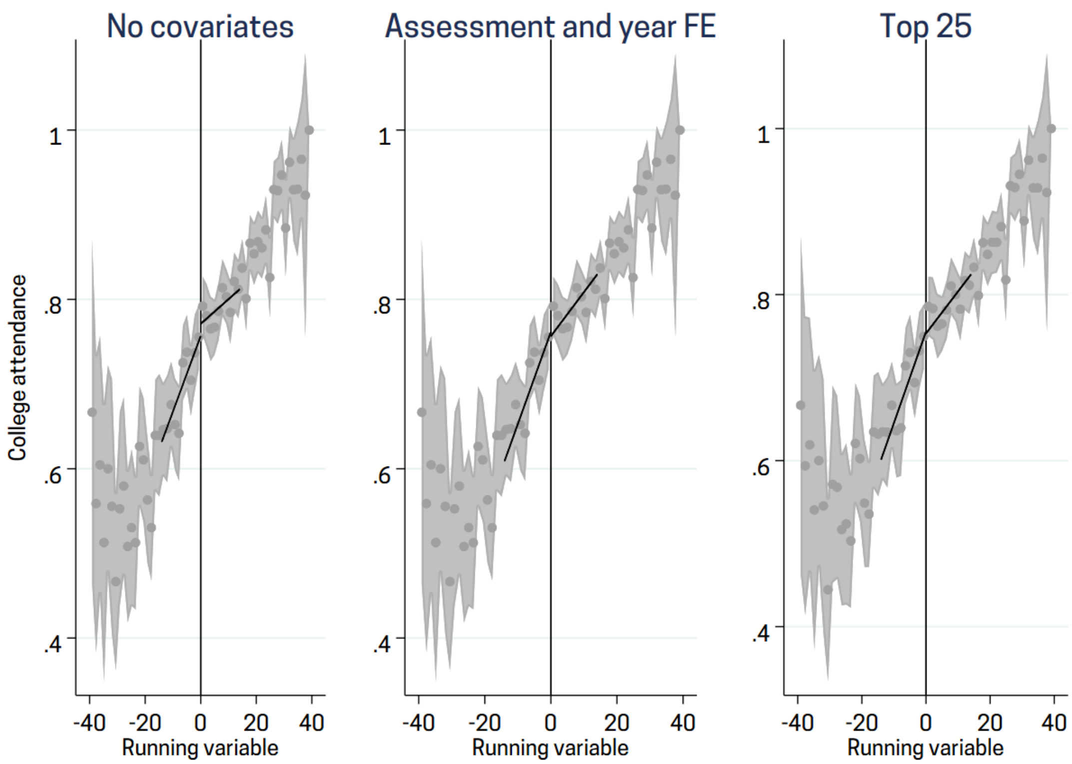
Notes. Optimal bandwidths and estimation procedures are taken from Calonico, Cattaneo, & Titiunik (2014). Dependent variable is ever enrolled in college. Running variable (technical assessment score) is interacted with passing in all models. Assessment fixed effects (F.E.) include an indicator for each test. Year and District FE are indicators for test-year, Grade 12 cohort, and for each district. Individual controls include race/ethnicity, gender, and math and ELA academic standardized test scores. "Only took one assessment" includes only students who took one NOCTI assessment. Fuzzy RDD uses each technical assessment as an instrument for passing any assessment. The sample includes students for whom we observe college enrollment status.

Figure 5 depicts some of the specifications in Table 2 graphically. The black line indicates the effective bandwidth used, while the shaded area represents the 95 percent confidence interval. Panel A shows the estimate in the first column of Table 2 with no fixed effects. Panel B shows the result with assessment and assessment-year fixed effects, and Panel C limits the sample to the top 25 most popular assessments. All estimated effects suggest no discontinuous change across the passing threshold in college attendance.

The estimated effects shown in Table 2 are based on a pooled sample of all tests. While we do not have sufficient sample size to estimate the model for each individual test, we can estimate the model for some of the most popular tests. In Figure 6, we show estimated effects for a model that includes only cohort fixed effects (which largely aligns with assessment-year fixed effects). We plot the effect of passing an assessment on college attendance for each of the 10 most popular tests in our sample. Point size represents the share of students passing each exam.

Figure 6 reinforces the pooled estimate effects, although this result is somewhat mechanical as the most popular tests are given the most weight in the pooled regression model with all assessments. Eight of the 10 estimates are close to zero, and the confidence interval for all estimates includes zero, indicating that none of the 10 tests individually show meaningful effects. Two outliers are worth mentioning. On the low end of the range of estimated effects, students just passing Television Production show some evidence of lower

Figure 5. Estimated Effects on College Attendance from Regression Discontinuity Design Models

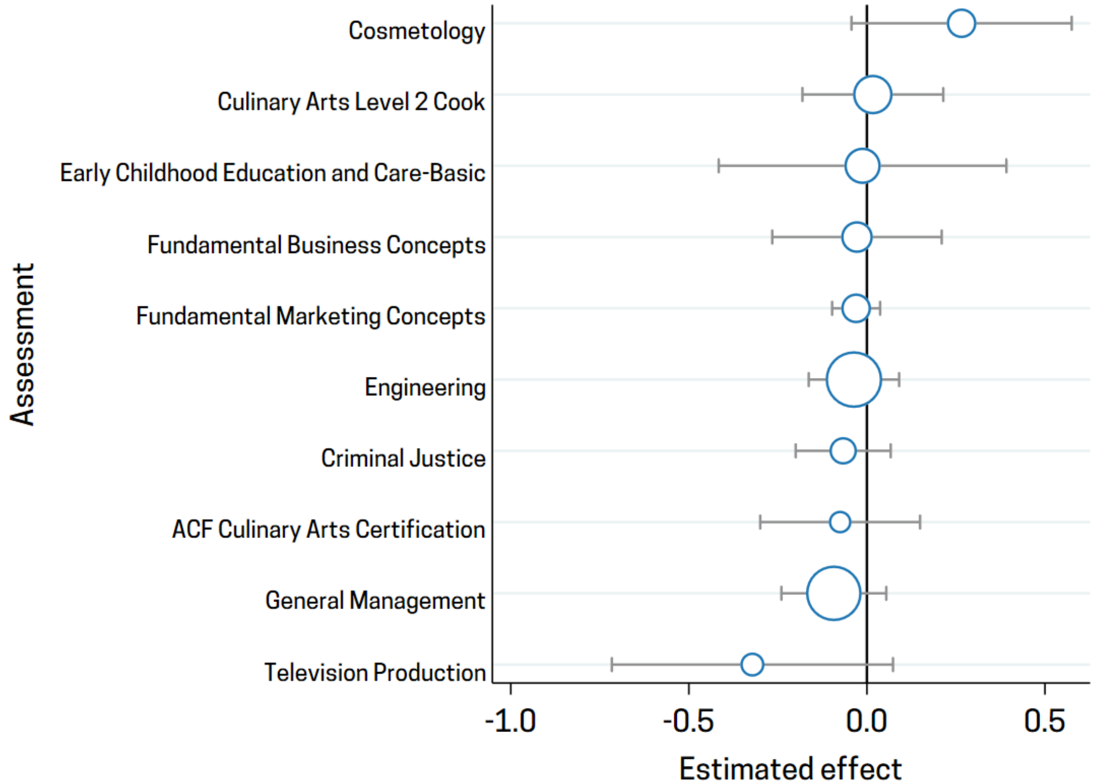


Notes. The figure shows the estimated effect of passing a technical assessment on college attendance from a regression discontinuity design model. FE are fixed effects for technical assessments and years. Top 25 are the 25 most popular assessments by the number of takers.

college enrollment, but the estimate is not statistically different from zero. On the high end, we find the opposite for Cosmetology. Again, the coefficient is not significantly different from zero, but the estimate suggests that passing Cosmetology might lead to higher college enrollment.

None of the eleventh to twenty-fifth most popular tests have effects on college enrollment that are statistically different from zero, though some are larger than Cosmetology and smaller than Television Production. That said, the less popular tests naturally have larger confidence intervals due to smaller sample sizes and do not change our conclusion that passing a technical assessment does not have an effect on college enrollment.

Figure 6. Estimated Effects on College Attendance for the 10 Most Popular Technical Assessments by Number of Takers



Notes. Points represent the estimated effect of passing a technical assessment on college attendance from a regression discontinuity design model with assessment-year fixed effects. Point size represents the average pass rate for the assessment, where assessments with larger points had more students who passed. The bars show 95% confidence intervals for the estimated effect. If a confidence interval bar crosses zero estimated effect, we do not have confidence in the direction of the effect.

Conclusion

We examine whether passing a CTE technical assessment has an effect on college enrollment. For NOCTI technical assessments, we find no evidence that it does. In fact, we find relatively strong evidence that passing a technical assessment does not have an effect on college enrollment. What implications follow?

First, we might expect small impacts on employment and earnings if we could observe them. This is conjecture, to be sure. Nonetheless, if it were the case that passing a technical assessment increased employability or potential earnings, we might see corresponding differences in college enrollment as well.

Still, that analysis is certainly worthwhile, and we believe it is a logical next step in this line of inquiry.

In our analysis, we also undertake a descriptive study of who takes the assessments available to us and, further, other correlations of the test scores. We find that among CTE students, test-takers are less likely to be White, have lower standardized test scores, and take more CTE courses on average. We also note that test passers, on average, are more likely to enroll in college. We also show wide heterogeneity across assessments in correlations with math and ELA scores. Other correlates not available to us might also be valuable, such as teacher characteristics.

It is important to note that we estimate the impact of the signal of passing the test as our regression models compare students with similar scores on either side of the passing threshold. That passing among this slice of students has no impact on college attendance suggests that, while the tests may be indicative of learning (a hypothesis we are not in position to confirm), they do not seem to alter students' future academic plans. Why this is the case is beyond the scope of our work and suggests that future qualitative analyses of student, teacher, and employer perceptions would be of value. We also note that we cannot observe all assessments available to students but rather only those offered by NOCTI for which we can obtain scores. Hence, we recommend that districts or state administrators keep scores on all tests when possible, which could be linked not only to college outcomes but also to workforce outcomes.

Endnotes

1. Estimated state allocations under the Perkins Act are available at cte.ed.gov/grants/state-allocations.

2. Carl D. Perkins Career and Technical Education Act of 2006, Sec. 113. Accountability (S. 250-15). See congress.gov/109/plaws/publ270/PLAW-109publ270.pdf

3. NOCTI is one of the leading providers of career and technical assessments in the U.S. See nocti.org/credentials/.

4. Race and ethnicity are not mutually exclusive categories.

5. Student mobility is defined by a student moving out of their district.

6. For some older technical assessments, students were less likely to be in the college sample; hence, the top 25 tests are not necessarily the top 25 most common tests among students with potential NSC records.

7. We use procedures laid out in Calonico, Cattaneo, & Titiunik (2014). See Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, *82(6)*, 2295-2326.

8. See Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, *48(2)*, 281-355.

9. Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, *82(6)*, 2295-2326.

10. Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. The Stata Journal, 18(1), 234-261. (See notes with Appendix Figure A1.)

About the Authors

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Daniel Kreisman is an associate professor of economics at Georgia State University. His research addresses topics at the intersection of labor economics, education finance, and education policy. He is also the faculty director of the Career & Technical Education Policy Exchange (CTEx)—a consortium of researchers and state partners working to inform the future of CTE policy with cutting-edge research. Along with publications in top journals, his work has been funded by the Smith Richardson Foundation, Arnold Ventures, the Annie E. Casey Foundation, the Pew Foundation, the Russell Sage Foundation, and the Institute for Research on Poverty. Prior to joining Georgia State University, he earned his Ph.D. and M.P.P. in public policy from the University of Chicago, his B.A. in philosophy and history from Tulane University, and was a high school teacher in New Orleans.

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About the Georgia Policy Labs

The Georgia Policy Labs is an interdisciplinary research center that drives policy and programmatic decisions that lift children, students, and families—especially those experiencing vulnerabilities. We produce evidence and actionable insights to realize the safety, capability, and economic security of *every* child, young adult, and family in Georgia by leveraging the power of data. We work alongside our school district and state agency partners to magnify their research capabilities and focus on their greatest areas of need. Our work reveals how policies and programs can be modified so that every child, student, and family can thrive.

Housed in the Andrew Young School of Policy Studies at Georgia State University, we have three components: the Metro Atlanta Policy Lab for Education (metro-Atlanta K-12 public education), the Child & Family Policy Lab (supporting children, families, and students through a cross-agency approach), and the Career & Technical Education Policy Exchange (a multi-state consortium exploring high-school based career and technical education).

Learn more at gpl.gsu.edu.