High School Teachers and College-Relevant Skill Production: Evidence from ACT Score Value Added*

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Abstract

The transition from high school to college is crucial for children's later life outcomes, yet little is known about the impacts of teachers on children's skill development during the final years of high school. I provide the first estimates of teacher value added on college admissions test scores, using administrative data from North Carolina to estimate the impacts of high school teachers on students' ACT performance. I then estimate the impacts of ACT score value added on college enrollment, college choice, and college performance. Assignment to a math teacher with high ACT score value added increases on-time 4-year college enrollment and decreases 2-year college enrollment. Assignment to an English teacher with high ACT score value added increases enrollment in selective colleges, conditional on 4-year college enrollment. Both math and English teachers with high ACT score value added increase freshman college GPA and credits and decrease freshman dropout, conditional on college enrollment. My results suggest that high school teachers have significant scope to influence the accumulation of college-relevant cognitive skills.

JEL Classification: I23, J24

Keywords: teacher value added, higher education, college admissions testing

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1 Introduction

The final years of high school form a crucial transition period during which children make the pivotal decisions of whether and where to attend college. Prior work makes it clear that college attendance significantly impacts later life success on a number of dimensions (Chetty et al., 2017; Heckman et al., 2018). Despite the importance of the college transition years for children's later life outcomes, models of child skill development suggest that educational inputs may be more effective during early childhood due to dynamic complementarities in the production of cognitive skills (Cunha et al., 2006). Thus, it remains an open question whether educational inputs can significantly influence the production of college-relevant cognitive skills by the time students reach the end of high school.

In this paper, I study what are arguably the most influential educational inputs at the high school level: high school teachers. Teachers are foundational for children's development both inside and outside of the classroom. Indeed, a large body of literature documents the multifaceted effects of teachers during elementary and middle school (Bacher-Hicks and Koedel, 2023). Yet, little is known about the impacts of teachers during pivotal college application and college decision making years.

I begin by estimating the impacts of 11^{th} grade teachers on students' 11^{th} grade ACT scores, providing the first estimates of "ACT score value added." I utilize detailed administrative data on the universe of public high school students in North Carolina linked with enrollment records from public 4-year colleges and universities in the University of North Carolina System. In North Carolina, the ACT test is administered in public high schools during the school day, free of charge, to all 11^{th} grade students, allowing me to estimate the impacts of teachers on students' ACT scores without needing to account for non-random selection into ACT-taking. To obtain subject-specific estimates of ACT score value added, I estimate the impacts of English teachers on English and reading ACT scores and the impacts of math teachers on math ACT scores. My identification strategy leverages quasi-random assignment of teachers within high schools, conditional on course choice, and I employ standard empirical Bayes estimation methods from the teacher value added literature (Chetty et al., 2014a). I find that assignment to an English teacher with value added one standard

deviation above the mean increases English and reading ACT scores by 0.06 standard deviations. Assignment to a comparably skilled math teacher increases math ACT scores by 0.08 standard deviations, approximately 0.5 points on the 36-point ACT test scale.

I next estimate the long-run impacts of ACT score value added on college enrollment using a nested logit model in which students first choose whether to attend a 4-year college and then choose which 4-year college to attend. While math ACT score value added impacts 4-year college enrollment, English ACT score value added impacts enrollment in selective colleges, conditional on 4-year enrollment. Assignment to a math teacher with ACT score value added one standard deviation above the mean increases on-time enrollment in 4-year colleges by approximately 1.47 percentage points, 5% relative to the full sample on-time enrollment rate. The increase in 4-year college enrollment is offset by a decline in 2-year college enrollment. Assignment to an English teacher with high ACT score value added, on the other hand, increases enrollment in the two stage flagship universities, University of North Carolina at Chapel Hill and North Carolina State University, conditional on 4-year college enrollment.

The 1.47 percentage point impact of a one standard deviation increase in math ACT score value added on 4-year college enrollment is similar in magnitude to previously studied large-scale policies designed to increase college admissions testing access. Estimates of the impact of testing center proximity, identified by Bulman (2015), suggest that opening an SAT testing center in every U.S. high school would increase 4-year college enrollment by 1.6 percentage points. Hyman (2017) finds that mandating the ACT test in Michigan increased 4-year college enrollment by 1.9 percentage points. Moreover, I find that math ACT score value added has a larger impact than a purely random increase in ACT score induced by rounding, which increases 4-year college enrollment by 0.67 percentage points (Haggag et al., 2024). This comparison suggests that ACT score value added captures not just "teaching to the test", but improved academic achievement which could translate to improvements in college performance as well as increases in college enrollment and selectivity.

To understand whether the impacts of ACT score value added on college enrollment translate to improved college performance, I estimate the impacts of ACT score value added on persistence (measured by dropout during or after freshman year), freshman year GPA

and accumulated credits, and graduation within 4 or 5 years of initial enrollment. I employ a selection correction procedure from Lee (1983) to disentangle the direct effects of ACT score value added on academic performance from indirect effects through selection into different college enrollment choices. I find that students exposed to English or math teachers with high ACT score value added earn higher freshman college GPAs and credits, are less likely to drop out during or after freshman year, and are more likely to graduate within four years of initial college enrollment. Effects of a one standard deviation increase in math teacher value added are similar in magnitude to effects of a similarly large increase in English teacher value added. In particular, both math and English teacher value added reduce freshman dropout rates by roughly 0.7 percentage points or 8% of the full sample mean.

This paper contributes to a long literature estimating K-12 teacher value added on cognitive achievement and subsequent long-run effects on later life outcomes. Prior work has shown large and multifaceted effects of teachers during elementary school (Bacher-Hicks and Koedel, 2023). Less is known about the impacts of teachers during middle school years, and even fewer studies evaluate high school teachers (Aaronson et al., 2007; Koedel, 2009; Jackson, 2014, 2018; Mansfield, 2015; Cook and Mansfield, 2016; Liu and Loeb, 2021; Backes et al., 2024). Moreover, a growing body of recent work documents significant effects of K-12 teacher value added on long-run outcomes including college enrollment, college selectivity, and adult earnings (Chetty et al., 2014b; Jackson, 2018; Gilraine and Pope, 2021; Petek and Pope, 2023; Backes et al., 2024).[1] I contribute to this literature in two ways. First, I provide novel estimates of teacher value added on college admissions test scores. Cognitive outcomes in all prior studies of teacher value added are limited to state standardized test scores, which are largely unobservable to colleges. ACT scores, on the other hand, are a large component of students' college application portfolios and have direct effects on college enrollment and selectivity. Second, I provide novel estimates of the effects of teacher value added on students' postsecondary academic performance, as prior work on the long-run effects of teacher value added has been limited to college enrollment and completion outcomes. It remains an open question the extent to which skills accumulated in high school are relevant to college-level

[1]This paper is also related to literature on the relationship between other high school educational inputs and college outcomes, including school quality (Deming et al., 2014; Totty, 2020), charter status (Angrist et al., 2016), school spending (Jackson and Mackevicius, 2024), and peer quality (Bifulco et al., 2014).

course grades, preparing students for success within the college classroom.[2]

This paper also contributes to the empirical literature and ongoing policy debate regarding the use of college admissions tests in the United States college admissions process. During the Covid-19 pandemic, test-optional policies increased rapidly in prevalence due to disruptions in testing availability (Lovell and Mallinson, 2024). In recent years post-pandemic, colleges and universities have reverted to a spectrum of admissions testing policies (Knox, 2024). Prior research has demonstrated that complexity in the college application process creates unnecessary barriers to college enrollment for low income students (Page and Scott-Clayton, 2016; Dynarski et al., 2023). Thus, it is crucial to understand the extent to which college admissions test scores are a useful screening tool and, consequently, whether the direct and indirect costs of admissions testing requirements are justified. Indeed, a long "validity" literature attempts to estimate the predictive power of admissions test scores for postsecondary academic performance, finding mixed results (Rothstein, 2004; Westrick et al., 2019; Friedman et al., 2025; Sacerdote et al., 2025). I contribute to this debate by evaluating whether marginal increases in students' subject-specific ACT scores, induced by quasi-random shocks to teacher quality, are predictive of postsecondary academic performance.[3] I am the first to move beyond correlational analysis and evaluate the predictive power of ACT scores for college performance using quasi-random shocks to the skills measured by the ACT test.

Finally, this work is situated in a broad multidisciplinary literature which seeks to understand the technology of child skill production. Prior work demonstrates the importance of the early childhood years for children's development (Cunha et al., 2006; Knudsen et al., 2006). As children age and the posterior part of the brain becomes less plastic, so too does

[2]This paper is also related to a growing body of evidence on the college persistence of marginal students. While it is common in the college access literature to estimate the impacts of policy changes and other factors on college enrollment, less is known about whether marginal students induced into college enrollment ultimately persist and graduate or whether they find themselves unprepared academically, socially, or financially. Estimates of persistence will likely differ based on the margin of enrollment or selectivity that is being studied. For example, the marginal student induced into college attendance by a high quality teacher and subsequently high ACT score may differ from the marginal student induced into college attendance by a scholarship incentive program; therefore, these students may have differing levels of college success. These divergent outcomes once enrolled are a policy-relevant concern. Previous literature on college persistence and graduation among marginal students includes Turner (2004), Zimmerman (2014), Castleman and Long (2016), and Hyman (2020).

[3]By comparing the predictive power of value added across subjects, my work relates to prior evidence finding that English and Math ACT scores are more predictive of college performance than Reading and Science ACT scoresBettinger et al. (2013).

the income gap in educational outcomes to some extent (Loeb and Bassok, 2012). Yet, recent evidence has pointed to adolescence as a second crucial period for child development, particularly the development of advanced cognitive skills associated with the frontal lobe of the brain (Steinberg, 2014; Hoxby, 2021). This evidence calls into question researchers' traditional focus on early childhood inputs and underscores the need for additional evidence on skill production during adolescence, a period termed the "missing middle" between early childhood and realized adult outcomes (Almond et al., 2018). I contribute to this literature by evaluating whether advanced cognitive skills, as measured by the ACT test,[4] are responsive to educational inputs by the time children reach middle to late adolescence.[5]

[4]More so than K-12 state standardized achievement tests, the ACT purports to measure "cross-cutting cognitive competencies ... such as critical thinking, problem solving, and metacognition." Source: https://www.act.org/content/act/en/research/reports/act-publications/beyond-academics/act-holistic-framework-of-education-and-work-readiness/act-assessments-across-broad-domains.html

[5]The American Academy of Pediatrics defines the three stages of adolescence as follows: early adolescence is ages 10-13, middle adolescence from ages 14-17, and late adolescence from ages 18-21. Source: https://www.healthychildren.org/English/ages-stages/teen/Pages/Stages-of-Adolescence.aspx

2 Data

My study leverages detailed administrative data on the universe of K-12 public school students in North Carolina, provided by the North Carolina Department of Public Instruction (NC DPI), linked with enrollment records from all sixteen public 4-year colleges and universities in North Carolina, provided by the University of North Carolina (UNC) System. Beginning in 2013, North Carolina mandated the ACT test as part of the state's school accountability program. The test is now administered in public high schools during the school day, free of charge, to all 11th grade students, allowing me to estimate the impacts of 11th grade teachers on students' ACT scores without needing to account for non-random selection into ACT-taking. The test is administered during the spring semester, on or near March 1st. This universal college admissions testing regime, along with the linkage between detailed K-12 and postsecondary education records, makes North Carolina an ideal setting for the first study of teacher value added on college admissions test scores.

During my sample period, college admissions test scores were widely used in selective college admissions. Among U.S. colleges and universities that are not open enrollment, over 75% of schools either required, recommended, or considered SAT or ACT scores (Bloem et al., 2021). Every 4-year college and university in the United States accepts the SAT and ACT interchangeably (Goodman, 2016), although the tests differ slightly in content and format. My study focuses solely on the ACT test, which has four sections: math, English, reading, and science. Each section is scored on a scale of 1-36, and a composite score is formed as the rounded average of each section score.

I leverage NC DPI data on student demographics, ACT scores, lagged standardized test scores, and course enrollments linked with teacher identifiers, demographics, experience, and credentials to estimate teacher value added on ACT scores. I then utilize UNC system data to evaluate college outcomes of interest, including college enrollment, college choice, and college performance (measured by dropout during or after freshman year, intended and completed STEM major, freshman year GPA, and college completion). I match NC DPI and UNC System data with publicly available institution-level data on the characteristics of colleges and universities attended by students and teachers in my sample. This data is

provided by the Integrated Postsecondary Education Data System (IPEDS) and the U.S. Department of Education College Scorecard.

My sample includes 493,894 North Carolina public high school students who took the 11th grade ACT test between 2014 and 2018, corresponding to the high school graduating classes of 2015-2019.[6] I match students with their 11th grade teachers in math and English. For students who took different courses within the same subject in the fall and spring semesters, I match them with their fall semester teacher to maximize the amount of exposure prior to taking the ACT test. For students who took different courses within the same subject concurrently, I match them with their teacher in the least advanced course.[7] The students in my sample are matched with 6,804 math teachers and 6,318 English teachers.

I match the 399,701 students from the high school graduating classes of 2016-2019 with UNC system enrollment records from Fall 2016-Spring 2024 and graduation records from Fall 2016-Fall 2023.[8] Approximately 70% of on-time college enrollments among North Carolina public high school are in colleges within the UNC system (Tippett and Kahn, 2018), suggesting that administrative data from the UNC system covers a large fraction of college enrollments among students in my sample. To capture enrollment in colleges outside of the UNC system, I leverage high school graduation survey data from the Graduate Data Verification System (also called the Graduate Survey). This survey is administered to all students during the spring of 12th grade, and school counselors are responsible for verifying and submitting the graduate survey data. Students' post-graduation plans are classified into the following categories: 2-year college, 4-year college, trade, business, or nursing school, military, employment, and other/unknown plans. Students intending to complete postsecondary education are asked whether they plan to attend a public or private institution and whether they plan to enroll in-state or out-of-state. The high school graduation survey overreports

[6]Students in my sample graduated from high school prior to the onset of the Covid-19 pandemic; therefore, all students took the ACT test in-person and would have been required or recommended to submit a college admissions test score to roughly 75% of U.S. colleges and universities (Bloem et al., 2021). Students in my sample who enrolled in college were impacted by the Covid-19 pandemic at different points during their undergraduate careers; therefore, I include cohort fixed effects in all of my analyses of college outcomes.

[7]I define the less advanced course as the course with the lower numeric course code. Lower numeric course codes typically correspond to core courses rather than electives.

[8]I match a subset of the full sample with college enrollment records because my college enrollment data begins in 2016.

UNC system enrollment relative to administrative data: Only 79% of students who intend to enroll in a 4-year public in-state institution are present in UNC system enrollment records.

Table 1 presents summary characteristics for the students in my sample. The sample is racially, ethnically, and socioeconomically diverse, reflecting the composition of the youth population of North Carolina. Over 90% of students in the sample are matched with an 11^{th} grade teacher in both English and math. 13.2% of students intend to enroll in a 4-year private or out-of-state college and 35.1% intend to enroll in a 2-year college. 25.3% of students enroll in a 4-year public college in the UNC system on-time during the summer or fall semester following high school graduation and 33.8% eventually enroll by Spring 2021. Among students who enroll in the UNC system, 9.5% drop out during or after freshman year and 61.1% graduate with a bachelor's degree within 4 years.

Table 2 presents summary characteristics for the teachers in my sample. On average, teachers in the sample have approximately 12 years of experience and are present during two to three years of the five year sample period. Teachers are matched with approximately 70 11^{th} grade students in the sample, on average. Students are spread out across fewer sections in English than in math. This is because, while English classrooms typically contain students from the same grade level, math classrooms often contain students from multiple grade levels. Since only 11^{th} grade students take the ACT test, my sample is restricted to a subset of some math classrooms.

Table 3 presents summary characteristics for the 16 colleges in the UNC system. Within the UNC system, there is a wide range of college selectivity, as measured by mean ACT scores among students in my sample who enroll in the institution.[9] There is also a wide range of quality, as measured by 4-year completion rate among students in my sample to enroll in the institution on-time as well as median earnings of employed graduates 10 years after enrollment from the College Scorecard. Colleges also vary on other characteristics, such as the proportion of students with an intended or completed STEM major.[10]

[9]My data includes only one ACT score per student and therefore does not capture repeated test-taking, which typically increases students' scores (Shah, 2022). Therefore, mean ACT scores among my sample will be lower than publicly reported mean ACT scores among matriculated students at each college.

[10]I classify majors as STEM (Science, Technology, Engineering, and Math) using a method similar to Altonji et al. (2016) and Ransom (2021) to aggregate 2-digit Classification of Instruction Programs (CIP) codes established by the National Center for Education Statistics (NCES).

Table 1: Student Summary Statistics

	Mean	Min	Max	Count
Economically Disadvantaged	0.386	0	1	490616
Female	0.507	0	1	490616
Black	0.247	0	1	490616
Hispanic	0.125	0	1	490616
ACT Composite	18.61	1	36	492141
	(5.161)			
ACT Math	19.03	1	36	493191
	(4.820)			
ACT English+Reading Average	18.07	1	36	492737
	(5.997)			
Math Teacher Match	0.937	0	1	493582
English Teacher Match	0.946	0	1	493582
Math and English Teacher Match	0.919	0	1	493582
Intend to Enroll in 2-Year College	0.351	0	1	470594
Intend to Enroll in 4-Year Private/Out-of-State College	0.132	0	1	470594
Enrolled in UNC On-Time (After High School)	0.255	0	1	399389
Freshman UNC GPA	2.968	0	4.333	124733
Freshman UNC Dropout	0.0937	0	1	135258
Graduated from UNC within 4 Years	0.611	0	1	101743
Graduated from UNC within 5 Years	0.708	0	1	76562
Observations	493582			

Table 2: Teacher Summary Statistics

	English			Math		
	Mean (SD)	Min	Max	Mean (SD)	Min	Max
Holds Graduate Degree	0.446	0	1	0.385	0	1
Nonwhite	0.190	0	1	0.211	0	1
Experience (Years)	11.74	0	52	12.34	0	50
	(9.087)			(9.947)		
Years in Sample	2.352	1	5	2.823	1	5
	(1.445)			(1.419)		
Switched Schools	0.142	0	1	0.188	0	1
Number of 11^{th} Grade Students	73.47	1	961	67.15	1	724
	(113.5)			(82.26)		
Number of Sections w/ 11^{th} Grade Students	6.375	1	74	9.616	1	66
	(6.573)			(8.315)		
Observations	6318			6804		

Table 3: College Summary Statistics

	(1) Student Count	(2) Mean ACT	(3) Acceptance Rate	(4) STEM Intent	(5) STEM Completion	(6) Freshman GPA	(7) Freshman Dropout	(8) Completion	(9) Earnings
R1 Universities									
UNC Chapel Hill	10545	27.42	0.305	0.458	0.369	3.311	0.0281	0.885	55,600
NC State	13294	26.14	0.504	0.484	0.493	3.313	0.0438	0.750	52,500
UNC School of the Arts	227	23.52	0.344	0	0.0110	3.286	0.0664	0.771	35,500
UNC Asheville	1970	23.39	0.785	0	0.332	2.932	0.126	0.542	34,500
UNC Wilmington	6241	23.25	0.610	0	0.333	3.193	0.0716	0.714	41,600
Appalachian State	10528	23.04	0.664	0.307	0.230	3.166	0.0620	0.699	38,800
UNC Charlotte	11458	22.74	0.633	0.382	0.464	3.131	0.0786	0.640	44,000
Western Carolina	6661	20.88	0.403	0.343	0.350	2.912	0.104	0.531	37,700
East Carolina	13033	20.85	0.690	0.539	0.404	2.753	0.0819	0.559	40,500
UNC Greensboro	9109	20.53	0.586	0.337	0.218	2.807	0.135	0.497	37,500
UNC Pembroke	3623	18.51	0.744	0.311	0.284	2.487	0.160	0.370	34,400
HBCU's									
NC A&T	5442	18.02	0.605	0.270	0.285	2.584	0.153	0.398	34,700
NC Central	3088	16.83	0.659	0.247	0.170	2.367	0.134	0.354	32,900
Fayetteville State	1898	16.81	0.604	0.109	0.232	2.555	0.158	0.289	31,200
Winston-Salem State	3043	16.77	0.585	0.483	0.402	2.612	0.149	0.404	33,200
Elizabeth City State	924	16.78	0.700	0.261	0.202	2.558	0.163	0.386	30,400
4-Year Private/Out of State	48923	21.25							
2-Year College	132397	16.51							
No College	117297	16.76							
Observations	399701	398570	135204	135204	88622	121781	132562	399065	

Columns (1)-(8) calculated using estimation sample of North Carolina public high school (in-state) students

Column (9) calculated using the U.S. Department of Education College Scorecard, including both in-state and out-of-state graduates

Intended major measured during first semester of college enrollment. Intended major unavailable at UNC Asheville and UNC Wilmington

3 Estimating ACT Score Value Added

3.1 Model and Estimation Strategy

I estimate the impacts of math teachers on math ACT scores and the impacts of English teachers on the average of English and Reading ACT scores to obtain subject-specific estimates of ACT score value added. I employ a variant of the standard linear value added model, which can recover causal effects of teachers on ACT scores under conditional independence of teacher assignment. Specifically, I assume that teacher assignment is independent from students' expected 11^{th} grade ACT performance after controlling for lagged student achievement and observable characteristics. I account for non-random selection into high school courses and spillovers across subjects by controlling for the 11^{th} grade English and math courses each student is enrolled in, along with the course level (standard, honors, or college-level).

Most schools in the United States do not explicitly label courses of study; yet, students are often placed into different courses based on academic achievement (Betts, 2011). My approach controls for implicit tracking practices by comparing students taking the same 11^{th} grade courses at the same level. Additionally, I account for tracking into advanced math courses based on the timing of Algebra 1 course-taking, a well-documented gateway to advanced math coursework (Dougherty et al., 2015). I restrict my math value added estimation sample to students who took Algebra 1 in 8^{th} grade (the "advanced" track) or 9^{th} grade (the "standard" track). This excludes very advanced students and remedial students, who may be taking a wide range of different math courses during 11^{th} grade.

In North Carolina, high school students take standardized "end-of-course" tests after completing specific math, English, and science courses. The timing of end-of-course tests therefore varies across subjects and differs for students who take math courses above their assigned grade level. In my sample, all students take an end-of-course English test in 10^{th} grade, providing a 1-year lagged test score. Students take an end-of-course Algebra 1 test in either 8^{th} or 9^{th} grade. Students take an end-of-course Biology test in either 9^{th} grade or 10^{th} grade. I control for all available lagged end-of-course test scores in both English and

math value added specifications, shown in equations (1) and (2).

$$\text{ACT_English}_{ijst} = \beta_0 + \beta_1 \text{EOC}_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \theta_{\text{English},j} T_{j,\text{English},t} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (1)$$

$$\text{ACT_Math}_{ijst} = \beta_0 + \beta_1 \text{EOC}_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \theta_{\text{Math},j} T_{j,\text{Math},t} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (2)$$

Here, $\text{ACT_English}_{ijst}$ is the average English and reading ACT score of student i assigned to teacher j in school s and year t. ACT_Math_{ijst} is the student's math ACT score. EOC_{it-1} is a vector of lagged end-of-course test scores.[11] X_{it} is a vector of student-level and classroom-level controls,[12] Z_{it} is a vector of controls for 11^{th} grade course enrollments in all core subjects. T_{jkt-1} and T_{jkt} are vectors of subject k 10^{th} and 11^{th} grade teacher indicator variables, respectively. $\theta_{\text{English},j}$ and $\theta_{\text{Math},j}$ are the parameters of interest, representing the causal effects of English teacher j on English and Reading ACT scores and math teacher j on math ACT scores, respectively. α_s and γ_t are school and cohort fixed effects, respectively. After conditioning on school fixed effects, teacher value added is identified using teacher "switchers" who move schools during the sample period (Mansfield, 2015).

I estimate teacher value added using a standard estimation method adapted from Chetty et al. (2014a), which predicts each teacher's year t value added based on student ACT scores from student assigned to the teacher in other academic years. This estimation procedure embeds three features which are desirable in my setting. First, the procedure generates leave-year-out estimates of teacher quality. Because I will use teacher value added estimates as treatment variables in subsequent analysis, it is necessary to use leave-year-out value added estimates to prevent mechanical endogeneity from using the same students to form both the treatment variable and the outcomes. Second, estimates are shrunk towards an empirical prior of zero, the mean teacher effect. This shrinkage accounts for the fact that

[11] All test score covariates are standardized to have mean 0 and standard deviation 1 within each cohort. End-of-course test scores include English 2, Algebra 1, and Biology. Students with missing English 2 or Algebra 1 end-of-course test scores are excluded from the sample. Missing Biology end-of-course test scores are imputed using the standardized mean of 0 and missing test score indicators are included as covariates. Algebra 1 end-of-course test scores are interacted with an indicator for math track.

[12] X_{it} includes 8^{th} grade end-of-grade (EOG) math, English, and science test scores, math track, economically disadvantaged status, ethnicity, and gender, as well as the following classroom-level variables to account for peer effects on student achievement: classroom size, racial/ethnic composition, percent female, percent economically disadvantaged, and mean lagged test score. Missing 8^{th} grade EOG test scores are imputed using the standardized mean of 0 and missing test score indicators are included as covariates.

student test scores are a noisy signal of teacher quality, particularly for teachers assigned to a small number of students. Third, this estimation procedure allows for teacher effects to vary or "drift" over time by allowing student ACT scores from years close to year t to receive more weight in the prediction than years further away.

My estimation procedure produces consistent estimates of teacher value added under the following assumptions. First, I assume that the distributions of teacher quality and student ACT scores are stationary; that is, the means of the teacher quality distribution and the (normalized) student ACT score distribution are the same throughout the sample period and the correlations between teacher-level and classroom-level shocks across any two years depends only on the time between them. Second, as discussed previously, I assume that teacher assignment is independent from students' expected 11^{th} grade ACT performance after accounting for the covariates included in the model. I test this assumption empirically by regressing 10^{th} grade school absences, residualized on value added model covariates, on 11^{th} grade teacher fixed effects. An F-test for joint significance of the teacher fixed effects suggests that the relationship is not economically significant; that is, 11^{th} grade teacher assignment is not meaningfully predictive of 10^{th} grade student achievement after accounting for value added model covariates. 11^{th} grade math teacher assignment is less correlated with residualized 10^{th} grade student achievement than 11^{th} grade English teacher assignment, despite the fact that a 1-year lagged math test score covariate is unavailable in my setting. This suggests that the multi-year lagged Algebra 1 end-of-course test score covariate, coupled with more recent test scores in English and Biology, sufficiently account for student-teacher sorting in math based on student achievement. Results from this conditional balance test are shown in Table 4. Appendix D describes the process used by North Carolina public high schools to create students' course schedules, which provides further support for the quasi-random nature of teacher assignment in this setting.

Table 4: Conditional Balance Test: Joint Significance of Teacher Assignment

	(1) English	(2) Math
Observations	409053	408686
R^2	0.0272	0.0267
F-Statistic	2.310	1.895

F-Statistics from OLS regressions of residualized absences on teacher fixed effects

The estimation procedures for English and math ACT score value added proceed analogously; for purposes of illustration, I use English value added as an example. First, I residualize ACT scores on the set of covariates included in the value added model:

$$\hat{\epsilon}_{ijst} = \text{ACT_English}_{ijst} - \hat{\beta}_0 - \hat{\beta}_1 \text{EOC}_{it-1} - \hat{\beta}_2 X_{it} - \hat{\beta}_3 Z_{it} - \hat{\alpha}_s - \hat{\gamma}_t \tag{3}$$

where the coefficients $\hat{\beta}$ are estimated using an OLS regression. I construct the mean residualized ACT score $\bar{\epsilon}_{jt}$ within each teacher-year cell, denoting $\bar{\epsilon}_{j,-t}$ as the vector of mean residualized ACT scores in all other periods. The estimator for teacher j's value added in period t is

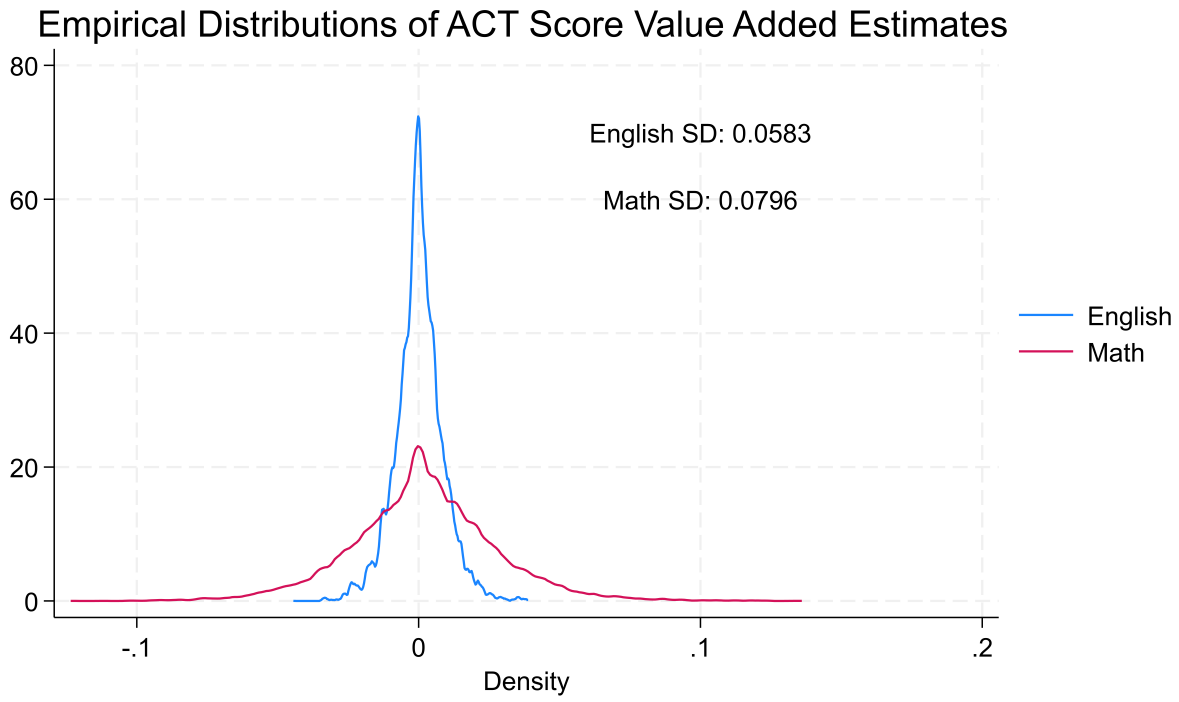
$$\hat{\theta}_{jt} = \psi_t' \bar{\epsilon}_{j,-t} \tag{4}$$

where ψ_t are the coefficients from an OLS regression of $\bar{\epsilon}_{jt}$ on $\bar{\epsilon}_{j,-t}$. These coefficients are chosen to minimize the mean square error of the value added forecasts, making $\hat{\theta}_{jt}$ the best linear predictor of $\bar{\epsilon}_{jt}$ based on ACT scores from other years. The standard deviation of teacher value added is estimated by computing classroom-level residualized ACT scores $\bar{e}_{cjt}$, then randomly pairing each classroom with another classroom assigned to the same teacher. The standard deviation of teacher value added is estimated as the square root of the covariance of residualized ACT scores across all classroom pairs in the sample (Chetty et al., 2014a; Jackson, 2014).

3.2 Value Added Estimates

Figure 1 plots the empirical distributions of shrunken leave-year-out value added estimates across all teacher-year observations in the sample. The estimated standard deviation of English teacher ACT score value added is 0.0583. The estimated standard deviation of math teacher ACT score value added is roughly half as large, 0.0796. That is, assignment to an English teacher with value added one standard deviation above the mean increases a student's predicted English and Reading ACT score by 0.0583 standard deviations. Assignment to a comparably skilled math teacher increases a student's predicted math ACT score by just 0.0796 standard deviations, approximately 0.5 points on the 36-point ACT test scale. These findings align with prior literature, which typically finds that the variance of teacher value added on math achievement is larger than the variance of teacher value added on reading achievement (Hanushek and Rivkin, 2010; Bacher-Hicks and Koedel, 2023).

Figure 1: Empirical Distribution of ACT Score Value Added



3.3 Interpretation of ACT Score Value Added Measures

ACT score value added is distinct from observable teacher qualifications. Observable teacher characteristics predict approximately 1% of the variation in value added estimates across teachers, as demonstrated in Table 5. Appendix A provides additional detail on the relationships between ACT score value added and observable teacher characteristics, including experience and education.

Table 5: ACT Score Value Added and Observable Teacher Characteristics

	(1) English	(2) Math
Attended HBCU	0.0000107	0.000586
	(0.000281)	(0.000964)
Acceptance Rate of Bachelor's Degree Institution	0.000399	-0.00152
	(0.000453)	(0.00167)
Years of Experience	0.00000482	0.000158***
	(0.00000759)	(0.0000251)
Female	0.000253	0.00278***
	(0.000165)	(0.000502)
Completed Bachelor's Degree in NC	-0.0000407	-0.00103*
	(0.000152)	(0.000571)
N	10076	9922
R^2	0.00555	0.0170

Robust standard errors in parentheses

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

Coefficients from OLS regressions of value added on teacher characteristics, including controls for race/ethnicity.

ACT score value added is also distinct from teacher value added on traditional standardized test score measures. To test this, I estimate math teacher value added on 9th grade Algebra 1 end-of-course (EOC) test scores.[13] The estimation sample includes 9th grade Algebra 1 test-takers from 2013-2018 who are matched with math teachers.[14] I construct a

[13] I conduct a similar exercise for English teachers by estimating English teacher value added on 10th grade English 2 end-of-course (EOC) test scores. I find similar results, shown in Appendix E.

[14] By restricting to 9th grade Algebra 1 students, I effectively restrict my estimation sample to students on the "standard track" in math. This is a similar restriction to Jackson (2014), which estimates a similar measure of teacher value added on 9th grade Algebra 1 end-of-course test scores.

sample of 438,680 math students using similar procedures to those used in the estimation of ACT score value added.[15] I estimate the following value added model using the Chetty et al. (2014a) estimation procedure, to maintain close comparability with ACT score value added estimates.

$$\text{EOC_Math}_{ijst} = \beta_0 + \beta_1 \text{EOG}_{it-1} + \beta_2 \text{EOG}_{it-2} + \beta_3 X_{it} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (5)$$

Here, EOC_Math_{ijst} is the Algebra 1 end-of-course test score of student i assigned to teacher j in school s and year t. EOG_{it-1} includes the student's 8^{th} grade lagged end-of-grade (EOG) math, reading, and science test scores and EOG_{it-2} includes the student's 7^{th} grade EOG math and reading test scores.[16] X_{it} is the same vector of student-level controls included in ACT score value added specifications. T_{jt} is a vector of 9^{th} grade Algebra 1 teacher indicator variables, and θ_j are the parameters of interest.

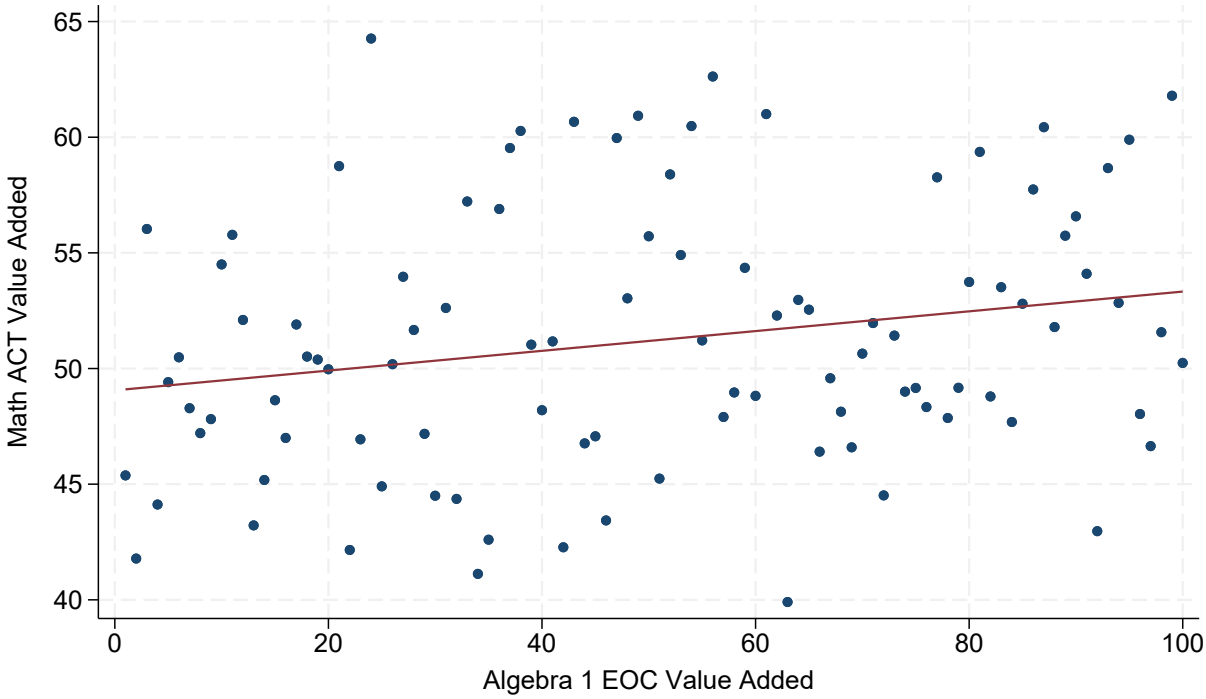
The estimated standard deviation of teacher value added on Algebra 1 EOC test scores is 0.1854, similar to prior estimates found by Jackson (2014, 2018) using an earlier sample period and a similar specification with high school fixed effects.[17] Among the 32.21% of math teachers in my sample who taught both 11^{th} grade students and 9^{th} grade Algebra 1 students during the sample period, I find a positive but relatively low correlation of 0.0715 between ACT score value added and Algebra 1 EOC score value added. Figure 2 plots the percentiles of Algebra 1 EOC score value added distribution against the mean percentiles of the corresponding teachers' ACT score value added estimates.

[15] On average, each Algebra 1 teacher is observed in 8 sections with 93 students over 2.76 years. I use students' fall 9^{th} grade Algebra 1 course enrollments if they are enrolled in different fall and spring Algebra 1 courses and spring enrollments otherwise.

[16] Students with missing 8^{th} grade math or reading end-of-grade test scores are excluded from the sample. Missing 8^{th} grade science end-of-grade test scores and missing 7^{th} grade math and reading end-of-grade test scores are imputed using the standardized mean of 0 and missing test score indicators are included as covariates.

[17] Jackson's preferred estimates include school-track fixed effects, leveraging a narrower source of identifying variation by comparing students enrolled in the same set of core academic courses. Thus, Jackson's main estimates report a smaller standard deviation of math teacher value added. The identification of school-track fixed effects in the ACT score value added setting is infeasible due to divergence in student course-taking patterns later in high school. Thus, I estimate teacher value added on Algebra 1 EOC test scores without school-track fixed effects for comparability across ACT and EOC value added estimates.

Figure 2: Algebra 1 EOC Score Value Added vs ACT Score Value Added



The low within-teacher correlation between Algebra 1 EOC score value added and ACT score value added is consistent with prior literature on multidimensional teacher quality, which typically finds weak relationships between teacher effects across skill measures (Loeb and Candelaria, 2012; Papay, 2011; Jackson, 2018; Petek and Pope, 2023; Backes et al., 2024) and subjects (Cook and Mansfield, 2016). One potential explanation is that the ACT math test measures different latent constructs than the Algebra 1 EOC test; in particular, the ACT test is designed to measure college readiness, while end-of-course tests evaluate mastery of course-specific content. Teachers may reasonably differ in their effectiveness across these domains (Papay, 2011).[18]

To understand the relative predictive power of ACT score value added versus EOC score value added for long-run outcomes, I regress both ACT score value added and EOC score value added measures on an indicator for on-time enrollment in the UNC system during

[18]Other potential explanations include test timing, score standardization, and teacher test preparation incentives (Papay, 2011; Riehl and Welch, 2023). EOC tests are offered at the end of each semester, while the in-school ACT test is offered once a year in March. EOC tests are designed and scaled within the state of North Carolina, while the ACT test is nationally normed. Unlike the ACT test, EOC test scores factor in to teacher, school, and student accountability measures.

the summer or fall semester immediately following high school graduation, conditioning on student-level covariates and school and cohort fixed effects.[19] I find that ACT score value added explains more variation in college attendance than EOC score value added. Moreover, after conditioning on ACT sore value added, EOC score value added does not explain additional variation in college attendance. This suggests that teacher value added on ACT scores is not only distinct from traditional value added measures, but potentially a more empirically relevant predictor of long-run postsecondary outcomes. Given that ACT scores are a direct input to the college application process, this result is perhaps unsurprising but justifies the study of ACT score value added as a novel measure of teacher quality.

Table 6: Impacts of ACT vs EOC Value Added on College Enrollment

	(1)	(2)	(3)
Math ACT Score Value Added	0.0125		0.0118
	(0.0121)		(0.0120)
Math EOC Score Value Added		0.0305	0.0397
		(0.0267)	(0.0249)
N	66794	66794	66794
R^2	0.230	0.227	0.230

Standard errors in parentheses

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

Coefficients from OLS regression of college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

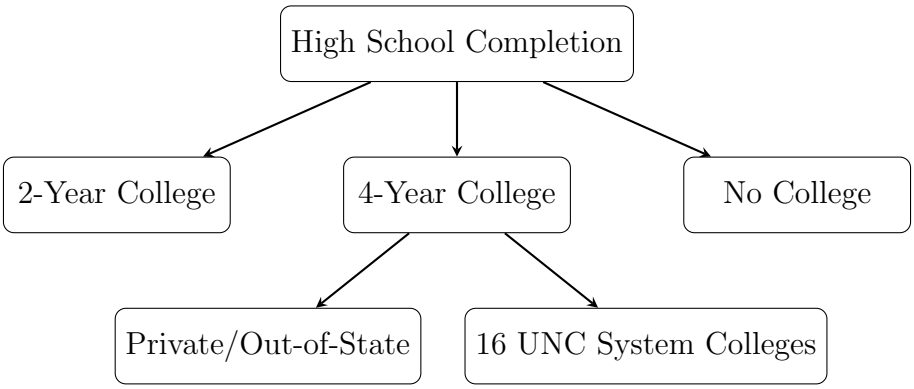
[19] The student-level covariate vector X_{it} is defined in the value added estimation model shown in equations (1) and (2).

4 ACT Score Value Added and College Outcomes

4.1 ACT Score Value Added and College Choice

I model college choice using a two-stage nested logit model, with the student's decision problem depicted in Figure 3.

Figure 3: College Decision Problem



I estimate the nested logit model in two stages. The second stage utility of attending college c, conditional on attending a 4-year college, can be expressed as:

$$U_{icst} = \delta_{0c} + \delta_{1,English,c}\hat{\theta}_{English-t} + \delta_{1,Math,c}\hat{\theta}_{Math-t} + \delta_{2c}X_{it} + \delta_{3c}S_{st} + \alpha_{ct} + \eta_{icst} \quad (6)$$

Here, c indexes college choices, which include the 16 colleges in the UNC system as well as one choice capturing enrollment in all private or out-of-state 4-year colleges which are not individually observed in the data. $\hat{\theta}_{k-t}$ is a "leave-year out" estimate of subject k ACT score value added.[20][21] X_{it} is a vector of student-level covariates defined in the value

[20]Throughout the analysis, I include both English and math teacher value added in the same model. Results are robust to estimating separate models by subject, as the within-student correlation between English and math teacher value added is low (0.1038).

[21]The shrinkage procedure described in Section 3 corrects for measurement error in teacher value added estimates; therefore, including shrunken value added estimates on the right hand side of an OLS regression will yield coefficient estimates which do not suffer from attenuation bias (Walters, 2024). In logit models, attenuation bias due to measurement error is larger than in a linear regression framework (Kao and Schnell, 1987), and there is no closed form expression for the asymptotic attenuation bias which could be used to adjust the shrinkage procedure for logit models. Thus, logit coefficients on teacher value added may be

added estimation model shown in equations (1) and (2), and α_{ct} are cohort fixed effects. S_{st} is a vector of school-level controls.[22] η_{icst} follows a type 1 extreme value (Gumbel) distribution. I allow all coefficients to vary across colleges c; that is, all model covariates are allowed to impact the utility of enrollment differently across colleges. The utility of attending Winston-Salem State University is normalized to 0; that is, all coefficient estimates are relative to the excluded choice of Winston-Salem State University. Winston-Salem State is among the least selective schools in the UNC system and has the lowest mean ACT score among enrolled students in my sample. Thus, coefficient estimates can be interpreted as relationships between covariates and the utility of attending a more selective college.

The first stage utility of choosing college type l immediately following high school graduation can be expressed as:

$$U_{ilst} = \kappa_{0l} + \kappa_{1,English,l}\hat{\theta}_{English-t} + \kappa_{1,Math,l}\hat{\theta}_{Math-t} + \kappa_{2l}X_{it} + \kappa_{3l}IV_{ist} + \gamma_{ls} + \alpha_{lt} + \eta_{ilst} \quad (7)$$

Here, l indexes college types, which include 2-year college, 4-year college, and no college. All covariates are defined as in the second stage model. X_{it} is a vector of student-level covariates defined in the value added estimation model shown in equations (1) and (2). γ_{ls} are high school fixed effects, accounting for cross-high school differences in the propensity to enroll in college, and α_{lt} are cohort fixed effects to account for time trends in college enrollment. IV_{ist} is the inclusive value term representing the expected utility associated with choosing student i's preferred choice in the 4-year college nest, representing the link between the first and second stage decisions:

$$IV_{ist} = \log\left(\sum_{c} \delta_{0c} + \delta_{1,English,c}\hat{\theta}_{English-t} + \delta_{1,Math,c}\hat{\theta}_{Math-t} + \delta_{2c}X_{it} + \delta_{3c}S_{st} + \alpha_{ct}\right) \quad (8)$$

diminished by attenuation bias. Wooldridge (2010) and Cramer (2005) show that, despite attenuation bias in the coefficient estimates, average marginal effect estimates will be consistent in logit models.

[22] S_{st} includes indicators for locale type (city, suburb, town, rural), average daily membership, average daily membership squared, percentage of grade level proficient students, percentage of fully licensed teachers, percentage of teachers with three years of experience or less, percentage of teachers with advanced degrees, percentage of students on free or reduced-price lunch, short-term suspension rate, number of crimes or acts of violence per 1,000 students, racial composition of student body, total per-pupil funding, distance (in kilometers) to the nearest college in the UNC system and its square, and the shares of students in the prior graduating class attending each college in the UNC system.

If $\kappa_{3l} = 0$, the model reduces to a multinomial logit model; that is, there is no nesting of the college enrollment and college choice decisions. η_{icst} follows a type 1 extreme value (Gumbel) distribution. I allow all coefficients to vary across colleges c; that is, all model covariates are allowed to impact the utility of enrollment differently across colleges. The utility of attending Winston-Salem State University is normalized to 0; that is, all coefficient estimates are relative to the excluded choice of Winston-Salem State University. Winston-Salem State is among the least selective schools in the UNC system and has the lowest mean ACT score among enrolled students in my sample. Thus, coefficient estimates can be interpreted as relationships between covariates and the utility of attending a more selective college.

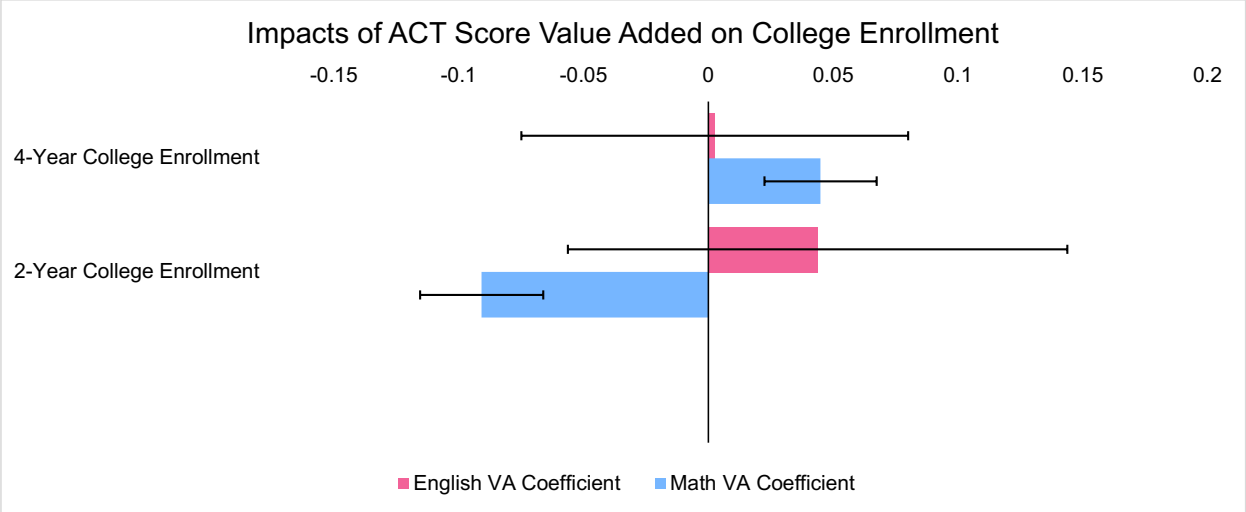
The parameters of interest are $\delta_{1,k,c}$ and $\kappa_{1,k,l}$, the causal effects of subject k ACT score value added on the probabilities of choosing college c and college type l, respectively. The coefficient estimates will reflect the true causal effect of teacher ACT score value added on students' college choices if assignment to high and low value added teachers within schools is driven solely by observable characteristics X_{it}, or by unobservable characteristics which are orthogonal to college outcomes. This selection on observables assumption is a weaker assumption than the random teacher assignment assumption made in the value added estimation model; if teacher assignment is orthogonal to observable characteristics in the model, then so is teacher value added. This assumption may fail if students planning to attend college make strategic course choices to target teachers with high ACT score value added.

The interpretation of $\hat{\delta}_{1,k,c}$ and $\hat{\kappa}_{1,k,l}$ will change if ACT score value added is correlated with other aspects of teacher quality that impact college choice; for example, teacher value added on high school GPA. In this case, I will attribute the effects of teachers on college enrollment to the mechanism of increased ACT scores, when in fact the effects may be coming from other channels. Prior literature typically finds low within-teacher correlations across dimensions of teacher quality (Jackson, 2018; Petek and Pope, 2023; Backes et al., 2024).

Figure 4 presents the estimated effects of ACT score value added on enrollment in 4-year and 2-year colleges. Coefficients from a multinomial logit regression demonstrate that math ACT score value added increases enrollment in 4-year colleges and decreases enrollment in 2-year colleges. The positive coefficient of math ACT score value added on 4-year college

enrollment translates to an average marginal effect of approximately 1.47 percentage points, and the negative coefficient on 2-year college enrollment translates to an average marginal effect of approximately 2.07 percentage points in response to a one standard deviation increase in value added.

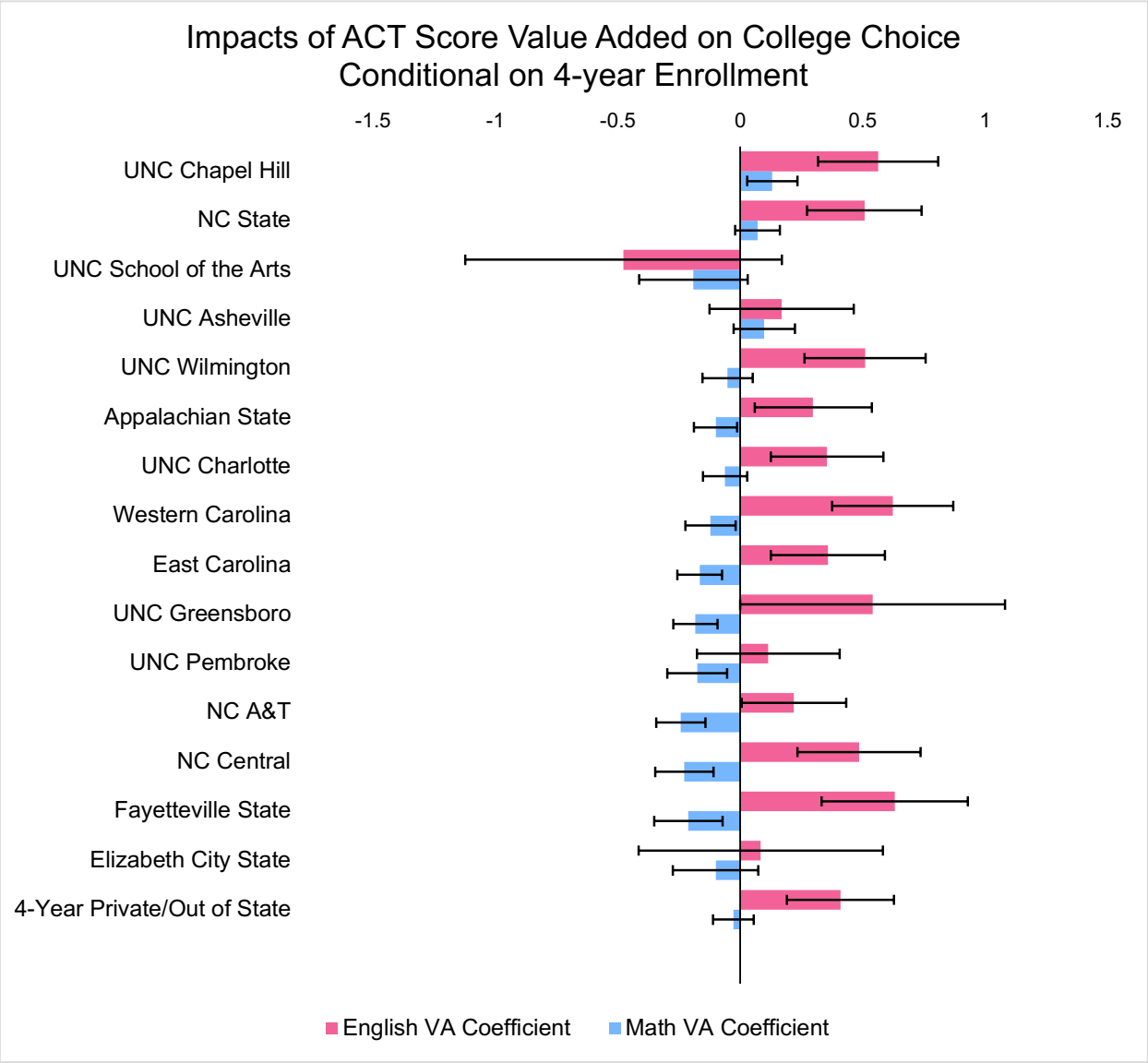
Figure 4: Impacts of ACT Score Value Added on College Choice



Multinomial logit coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Coefficient estimates with standard errors reported in Appendix E.
Coefficients normalized relative to no college enrollment.

Figure 5 presents the estimated effects of ACT score value added on enrollment in specific colleges within the UNC system and on enrollment in colleges outside of the UNC system, conditional on 4-year college enrollment. Coefficients from a multinomial logit regression demonstrate that English ACT score value added increases enrollment in the two R1 universities within the UNC system, UNC Chapel Hill and North Carolina State University (NC State).

Figure 5: Impacts of ACT Score Value Added on College Choice



Multinomial logit coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Coefficient estimates with standard errors reported in Appendix E.
Coefficients normalized relative to less-selective Winston-Salem State University.

4.2 ACT Score Value Added and College Performance

Next, I evaluate the effects of ACT score value added on college performance measures, including freshman year GPA and accumulated credits, persistence (measured by dropout during or after freshman year), and graduation within 4 or 5 years of initial enrollment. To understand the effects of ACT score value added on postsecondary academic performance,

it is necessary to disentangle three potential channels. First, as shown in Section 4.1, ACT score value added impacts selection into UNC system enrollment. Since I only observe college performance measures for students who enroll in the UNC system, changing selection into UNC system enrollment will impact the observed relationship between ACT score value added and college performance measures. Second, as shown in Section 4.1, ACT score value added impacts selection into specific colleges within the UNC system. Since different colleges have different grading curves and dropout rates, changing selection into specific colleges will impact observed college performance measures. Third, ACT score value added could measure persistent human capital accumulation that directly improves student performance in college, conditional on whether and where a student enrolls within the UNC system.

To disentangle these three channels, I generalize the Heckman selection correction procedure to a nested logit college selection model, using methods from Lee (1983).[23] This model allows for the relationship between college performance and selection into college enrollment to vary across colleges within the UNC system. Given the wide range of quality and selectivity within the UNC system, shown in Table 3, it is plausible that selection into the most selective schools is positively correlated with latent student achievement driving college performance outcomes, while the correlation is negative among less selective institutions. I model college performance as follows:

$$\begin{aligned} College_Performance_{icst} = \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ + \pi_3 S_{st} + \alpha_t + \tau_c + u_{icst} \end{aligned} \tag{9}$$

Here, $\hat{\theta}$, X_{it}, α_t, and τ_c are defined as in equations (13) and (14). S_{st} is defined as in equations (13) and (14), excluding lagged within-high school enrollment at each college in the UNC system. This exclusion restriction implies that the previous cohort's enrollment at each college in the UNC system within a student's high school impacts that student's college choice, but does not impact their college performance conditional on other high school characteristics.[24] The second stage outcome $College_Performance_{icst}$ is observed only when

[23]The Lee (1983) selection correction allows for any parametric distribution of errors in the first stage selection equation and nests the canonical Heckman selection correction when the first stage is binary with normally distributed errors (Bourguignon et al., 2007).

[24]This exclusion restriction provides exogenous variation in students' propensities to attend college, so

a student chooses some college choice c in the UNC system. I make the standard conditional independence assumption: $\hat{\theta} \perp u \mid X, S, \alpha_t$. I assume that u follows a normal distribution with mean zero and that the first stage nested logit error terms η_j follow a generalized extreme value (GEV) distribution. The main distributional assumption is that the joint distribution of $(u, J_{\epsilon_c}(\epsilon_c \mid \Gamma))$ does not depend on Γ for any c corresponding to a college in the UNC system, where Γ is the information set of covariates and coefficient estimates from the nested logit selection equation. ϵ_c is defined based on the first stage selection equation, such that choice c is chosen when $\epsilon_c < 0$. J is a function of the CDF of ϵ_c.[25] The distributional assumption implies that the correlation between unobservables and the choice of alternative c against any other alternative is equal to the correlation between unobservables and college performance. For example, if unobservable student ability is positively correlated with the choice of UNC Chapel Hill, it should also be positively correlated with college performance at UNC Chapel Hill. This assumption seems plausible and allows for the wide range of selectivity and quality within the UNC system (for example, unobservable student ability could be negatively correlated with both selection into the lower-quality schools and college performance).

Under these assumptions, consistent estimates of $\pi_{1English}$ and π_{1Math} can be obtained using the following procedure. First, I use the nested logit model estimates from Section 4.1 to obtain selection terms s_c corresponding to a college in the UNC system, as a function of the first stage nested logit choice probabilities $P_c = P_{c|\text{4-year college}} P(\text{4-year college})$.

$$s_c = log(P_c) + \sum_{i \neq c} log(P_i) \frac{P_i}{P_i - 1} \tag{10}$$

I then estimate the second stage equation using an OLS regression for continuous college performance outcomes or a probit regression for binary college performance outcomes, con-

that identification in the Lee selection correction model is not based solely on nonlinearities in the nested logit selection equation.

[25] Let F_{ϵ_c} be the CDF of ϵ_c. Then, $F_{\epsilon_c}(0 \mid \Gamma) = P_c$ and $J_{\epsilon_c}(\epsilon \mid \Gamma) = \Phi^{-1}(F_{\epsilon_j}(\epsilon \mid \Gamma))$.

trolling for selection terms s_c to account for cross-college differences in selection.

$$College_Performance_{icst} = \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} + \pi_3 S_{st} + \alpha_t + \tau_c + \sum_c \pi_c \mathbb{1}(enroll_in_c) s_c + u_{icst} \quad (11)$$

Table 7 presents χ^2 statistics from tests of joint instrument significance in equation (8), demonstrating that the lagged enrollment instruments are highly predictive of enrollment at each college in the UNC system and enrollment in 4-year private or out of state colleges. In particular, coefficient estimates reveal that a student is significantly more likely to attend a particular college if more students in the prior cohort of their high school attended that college. Recent work classifies shift-share style instruments as leveraging either exogenous shifts or exogenous shares of a particular variable (Borusyak et al., 2025). This instrument leverages exogenous shifts in college enrollment; while high schools with high enrollment at specific colleges are not randomly assigned, within-high school college enrollment patterns are subject to plausibly exogenous changes over time.

Table 7: First Stage: Testing Relevance of Lagged Enrollment Instruments

X^2 Appalachian State University	32.64
X^2 East Carolina University	18.51
X^2 Elizabeth City State University	47.52
X^2 Fayetteville State University	15.93
X^2 NC A&T University	19.76
X^2 NC Central University	13.43
X^2 UNC Asheville	22.72
X^2 UNC Chapel Hill	36.23
X^2 UNC Charlotte	22.47
X^2 UNC Greensboro	23.02
X^2 UNC Pembroke	26.92
X^2 UNC Wilmington	18.79
X^2 Western Carolina University	36.27
X^2 Winston-Salem State University	19.09
X^2 NC State University	26.09
X^2 UNC School of the Arts	35.96
X^2 Private/Out of State	12.57

X^2 statistic from joint test of instrument significance using binary probit regressions of college choice on instruments and covariates from equation (8)

Due to the underlying selection problem, it is not possible to directly test the exclusion restrictions in this model, which require that lagged within-high school enrollment at each college in the UNC system has no effect on college performance. Regressing the lagged enrollment instruments directly on college performance measures could yield significant coefficients even if there is no direct relationship, because the instruments shift selection into the observed college performance data. Instead, it is typical to test the relationship between the instruments and a student achievement measure that is observed regardless of whether students enroll in college (Garlick and Hyman, 2022). Tables 8 and 9 demonstrate that lagged within-high school enrollment at each college in the UNC system is not significantly predictive of 12^{th} grade GPA or composite ACT score, respectively, providing evidence in support of the exclusion restriction.

Table 8: Exclusion Restriction: Impacts of Lagged College Enrollment on 12$^{\text{th}}$ Grade GPA

	(1)
Lagged Appalachian State Enrollment	-0.144
	(0.157)
Lagged East Carolina Enrollment	-0.215
	(0.163)
Lagged Elizabeth City State Enrollment	0.528
	(0.435)
Lagged Fayetteville State Enrollment	-0.219
	(0.155)
Lagged NC A&T Enrollment	0.0344
	(0.0716)
Lagged NC Central Enrollment	0.0602
	(0.0836)
Lagged NC State Enrollment	0.0345
	(0.163)
Lagged UNC School of the Arts Enrollment	-0.665
	(0.978)
Lagged UNC Wilmington Enrollment	0.0131
	(0.0756)
Lagged UNC Asheville Enrollment	-0.127
	(0.243)
Lagged UNC Chapel Hill Enrollment	0.191
	(0.178)
Lagged UNC Charlotte Enrollment	0.000269
	(0.138)
Lagged UNC Greensboro Enrollment	-0.273**
	(0.118)
Lagged UNC Pembroke Enrollment	0.146
	(0.272)
Lagged Western Carolina Enrollment	-0.0254
	(0.201)
Lagged Winston-Salem State Enrollment	-0.190
	(0.308)
Observations	169982
Mean	3.048
R^2	0.398
χ^2	2.691

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of GPA on instruments with covariates from equation (9)

Table 9: Exclusion Restriction: Impacts of Lagged College Enrollment on Composite ACT

	(1)
Lagged Appalachian State Enrollment	-0.976*
	(0.533)
Lagged East Carolina Enrollment	0.340
	(0.586)
Lagged Elizabeth City State Enrollment	1.911
	(1.202)
Lagged Fayetteville State Enrollment	-0.0528
	(0.546)
Lagged NC A&T Enrollment	-0.134
	(0.247)
Lagged NC Central Enrollment	0.508
	(0.367)
Lagged NC State Enrollment	0.550
	(0.565)
Lagged UNC School of the Arts Enrollment	-1.625
	(5.029)
Lagged UNC Wilmington Enrollment	0.123
	(0.290)
Lagged UNC Asheville Enrollment	0.618
	(0.899)
Lagged UNC Chapel Hill Enrollment	0.790
	(0.562)
Lagged UNC Charlotte Enrollment	0.0762
	(0.531)
Lagged UNC Greensboro Enrollment	0.807*
	(0.422)
Lagged UNC Pembroke Enrollment	-0.444
	(0.593)
Lagged Western Carolina Enrollment	-0.376
	(0.683)
Lagged Winston-Salem State Enrollment	1.146
	(0.829)
Observations	254488
Mean	18.78
R^2	0.797
χ^2	3.277

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of ACT on instruments with covariates from equation (9)

Table 11 presents estimates from the second stage college performance equation (11) with the selection correction. Compared to reduced form estimates shown in Table 10, second-stage coefficients on freshman year GPA, freshman year earned credits, and freshman year dropout are larger in magnitude. This suggests that ACT score value added shifts "marginal" students at higher risk of poor college performance into enrollment at colleges for which they may be academically underprepared. Therefore, the reduced-form relationship between ACT score value added and college performance is biased downward. After correcting for selection, coefficient estimates indicate that a one standard deviation increase in English ACT score value added increases freshman GPA by 0.04 GPA points, while a similar increase in math ACT score value added increases freshman GPA by 0.03 GPA points. These increases translate to 5% and 3% of a standard deviation on the freshman GPA distribution, respectively. While the effects of English ACT score value added on freshman earned credits and freshman dropout are statistically insignificant, they are similar in magnitude to coefficients on math ACT score value added. A one standard deviation increase in math ACT score value added increases freshman earned credits by 0.11 and reduces dropout by 0.07 percentage points. The effect on dropout translates to an 8% decline, relative to the full sample freshman dropout rate. Effects of math and English ACT score value added on 4-year and 5-year college completion rates are positive but statistically insignificant.

Table 10: Second Stage: Impacts on College Performance without Selection Correction

	(1) GPA	(2) Credits	(3) Dropout	(4) 4-Year Completion	(5) 5-Year Completion
English ACT VA	0.0248	0.126	-0.00952	0.0214*	0.0108
	(0.0182)	(0.0892)	(0.00614)	(0.0118)	(0.0131)
Math ACT VA	0.0197***	0.0511*	-0.00655***	0.00720	0.00822
	(0.00705)	(0.0292)	(0.00254)	(0.00492)	(0.00516)
Observations	86620	93688	93688	70940	54785
Mean	2.976	28.653	0.0866	0.6088	0.7050
R^2/Pseudo-R^2	0.209	0.0586	0.0570	0.1152	0.1176

Standard errors in parentheses, clustered at the high school level

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

Columns (1)-(2): Coefficients from OLS regressions

Columns (3)-(5): Average marginal effects from probit regressions

Coefficients standardized to reflect 1σ increase in value added

Table 11: Second Stage: Impacts on College Performance with Lee Selection Correction

	(1) GPA	(2) Credits	(3) Dropout	(4) 4-Year Completion	(5) 5-Year Completion
English ACT VA	0.0410**	0.124	-0.00718	0.0191	0.00973
	(0.0197)	(0.117)	(0.00741)	(0.0122)	(0.0133)
Math ACT VA	0.0273***	0.106***	-0.00742**	0.00680	0.00667
	(0.00807)	(0.0403)	(0.00296)	(0.00513)	(0.00533)
Observations	62270	62270	65814	66290	50729
Mean	2.972	28.629	0.0876	0.6061	0.7015
R^2/Pseudo-R^2	0.245	0.0902	0.0575	0.1147	0.1174

Standard errors in parentheses, clustered at the high school level

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

Columns (1)-(2): Coefficients from OLS regressions

Columns (3)-(5): Average marginal effects from probit regressions

Coefficients standardized to reflect 1σ increase in value added

5 Conclusion

Appreciating the multifaceted contributions of teachers is a timely and policy-relevant concern, as declines in teacher satisfaction have been accelerating in recent years and were exacerbated by the Covid-19 pandemic (Kraft and Lyon, 2022). My results provide new evidence on the importance of high school teachers for students' later life success. I find that 11$^{\text{th}}$ grade math and English teachers have significant influence on the production of college-relevant cognitive skills, as measured by ACT scores. Skill accumulation at the end of high school has persistent positive impacts on students' postsecondary academic performance, suggesting that there is scope for educational inputs to matter during middle to late adolescence.

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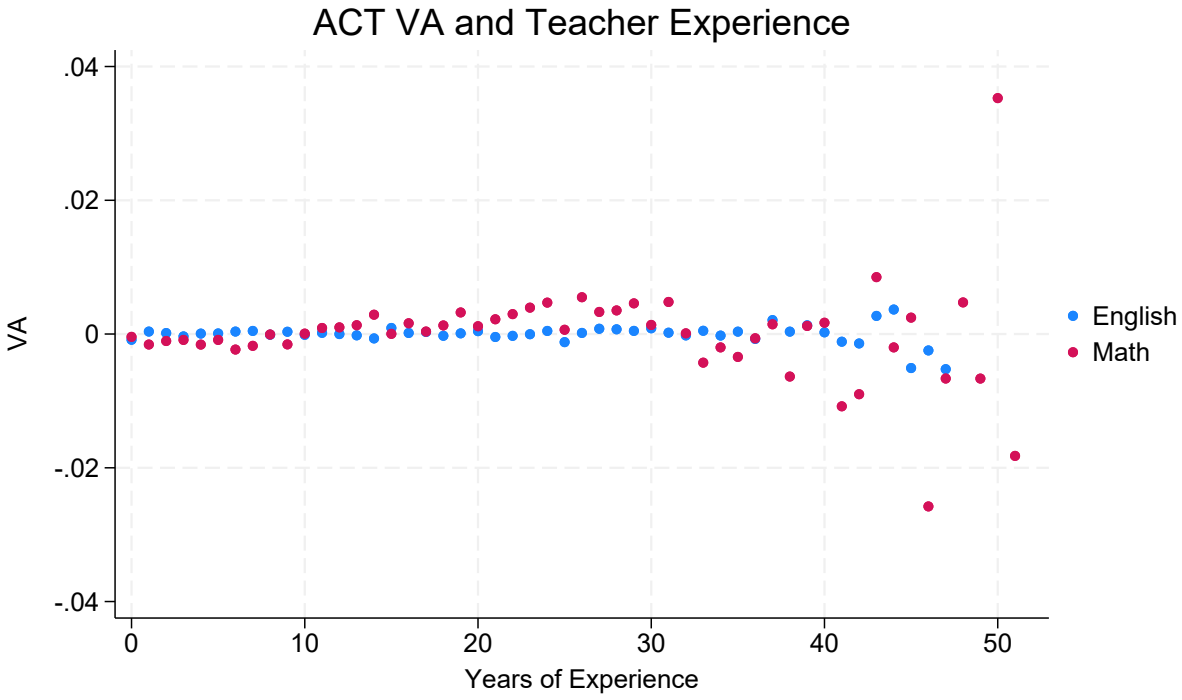
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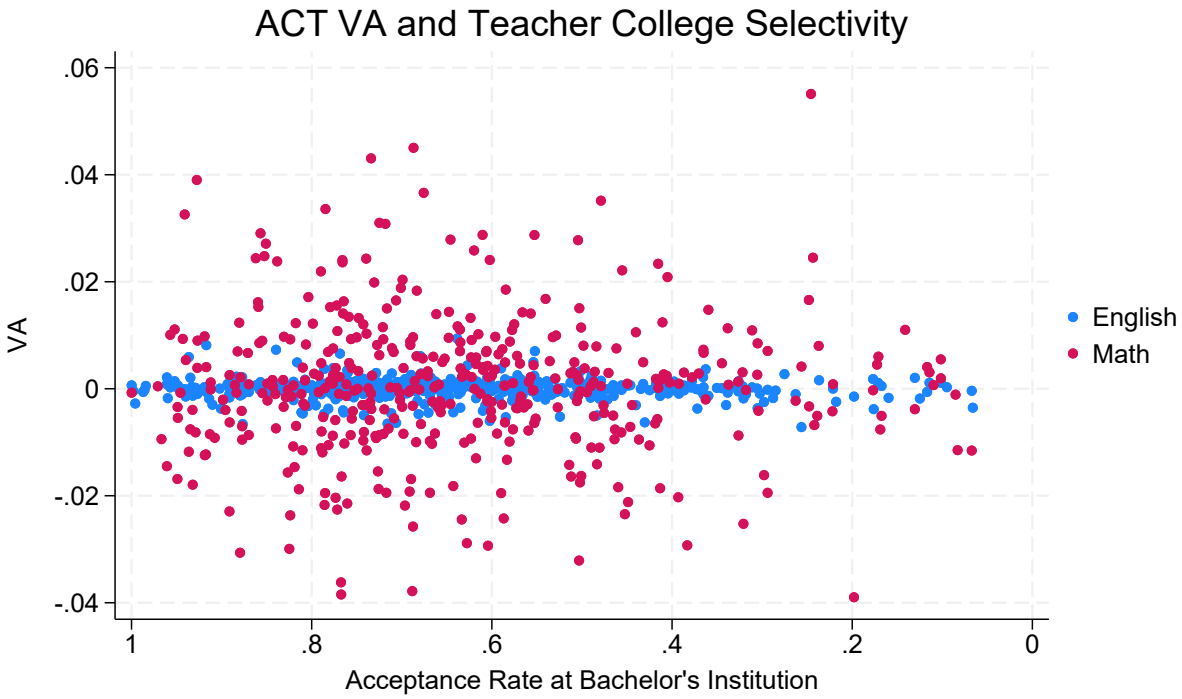
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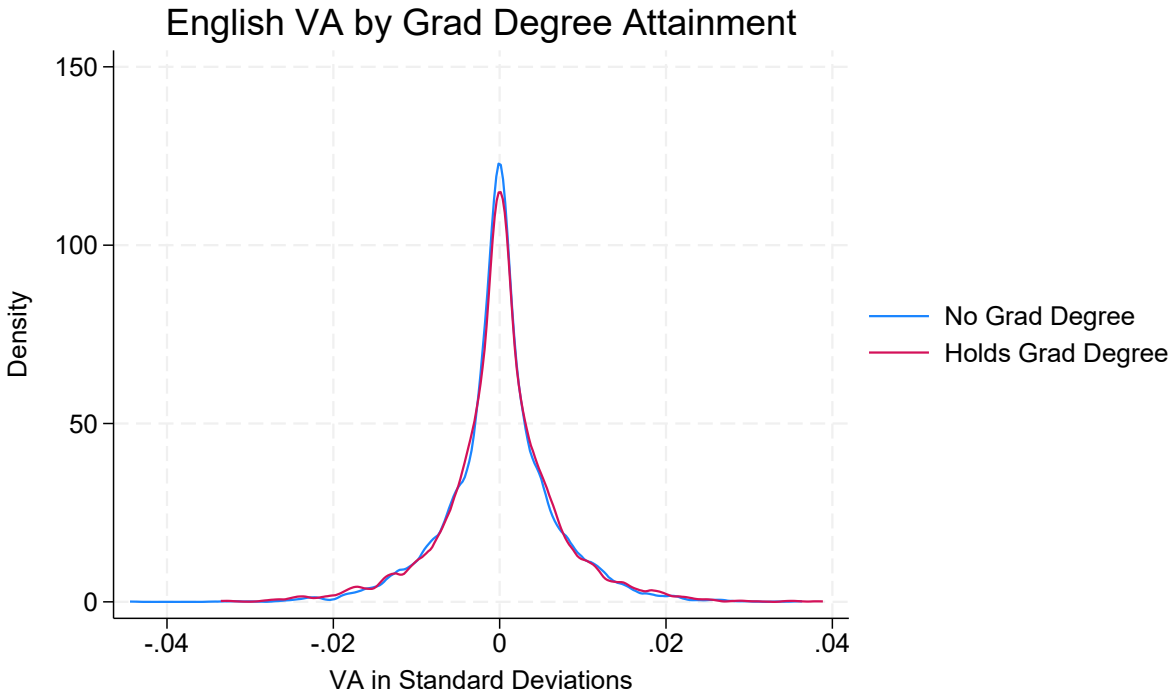
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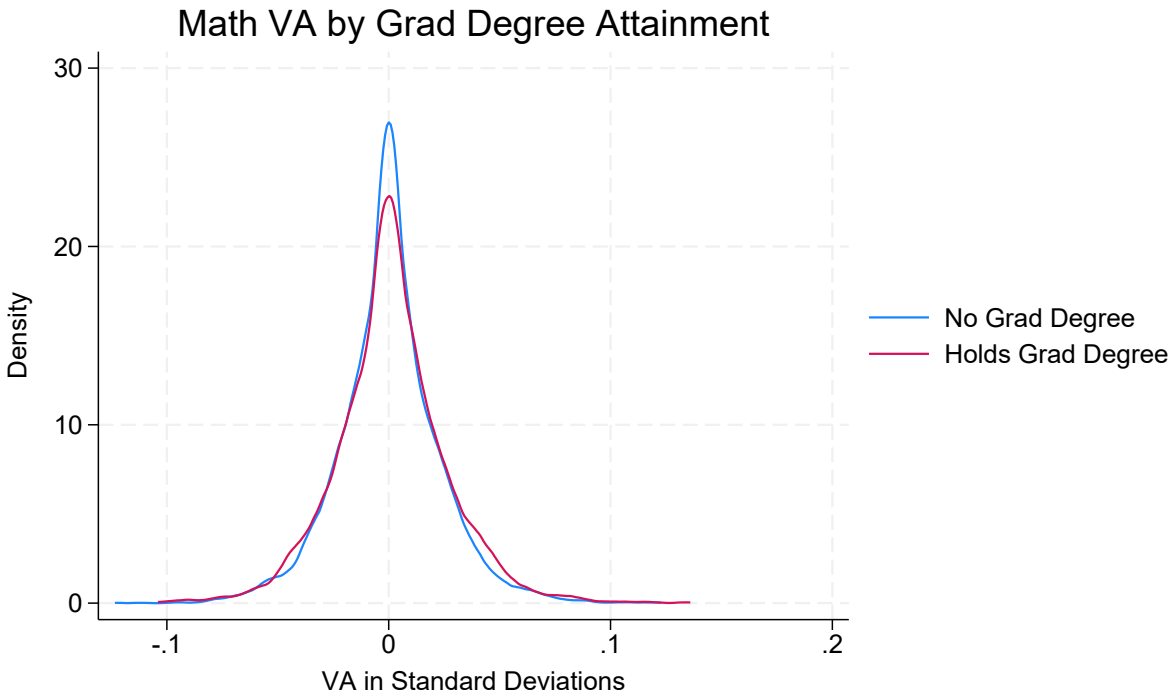
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A ACT Score Value Added & Teacher Characteristics






English VA by Grad Degree Attainment
Density
150
100
50
0
-.04
-.02
0
.02
.04
VA in Standard Deviations
No Grad Degree
Holds Grad Degree


Math VA by Grad Degree Attainment
Density
30
20
10
0
-.1
0
.1
.2
VA in Standard Deviations
No Grad Degree
Holds Grad Degree

B North Carolina Course Scheduling Algorithm

Here, I briefly summarize the procedure used by North Carolina high schools to create course assignment schedules. First, students select the courses they want to take and submit a list of courses to their school. The school uses students' course selections to determine how many sections of each class will be offered, then school assigns teachers to courses.

The crucial randomization step occurs using a program called "PowerSchool", the official student information system used statewide for storing and managing student data.[26] The school enters student course selections and course listings into PowerSchool, which uses an algorithm to create the course schedule and assign students to courses with the objective of minimizing scheduling conflicts. Finally, the remaining unavoidable scheduling conflicts are resolved manually by guidance counselors who are familiar with students. This could introduce a limited amount of non-randomness in the student-teacher assignment procedure. Additional sources of non-randomness could include parent advocacy and course-specific time constraints created by part-time teachers or other factors.

[26] For more information on PowerSchool, see https://www.dpi.nc.gov/educators/home-base/powerschool-sis.

C English Teacher Value Added on ACT vs EOC Tests

Here, I estimate English teacher value added on 10th grade English 2 end-of-course (EOC) test scores. The estimation sample includes 10th grade English 2 test-takers from 2013-2018 who are matched with English teachers. I construct a sample of 637,112 English students using similar procedures to those used in the estimation of ACT score value added.[27] I estimate the following value added model using the Chetty et al. (2014a) estimation procedure, to maintain close comparability with ACT score value added estimates.

$$\text{EOC_English}_{ijst} = \beta_0 + \beta_1 \text{EOG}_{it-2} + \beta_2 \text{EOG}_{it-3} + \beta_3 X_{it} + \beta_4 S_{st} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (12)$$

Here, $\text{EOC_English}_{ijst}$ is the English 2 end-of-course test score of student i assigned to teacher j in school s and year t. EOG_{it-2} includes the student's 8th grade lagged end-of-grade (EOG) math and reading test scores and EOG_{it-3} includes the student's 7th grade EOC math, reading, and science test scores.[28] X_{it} is the same vector of student-level controls included in ACT score value added specifications. T_{jt} is a vector of 10th grade English 2 teacher indicator variables, and θ_j are the parameters of interest. T_{jt} is a vector of 10th grade English 2 teacher indicator variables, and θ_j are the parameters of interest.

The estimated standard deviation of teacher value added on English 2 EOC test scores is 0.0831, similar to prior estimates found by Jackson (2014, 2018) using an earlier sample period and a similar specification with high school fixed effects.[29] Among the 71.14% of

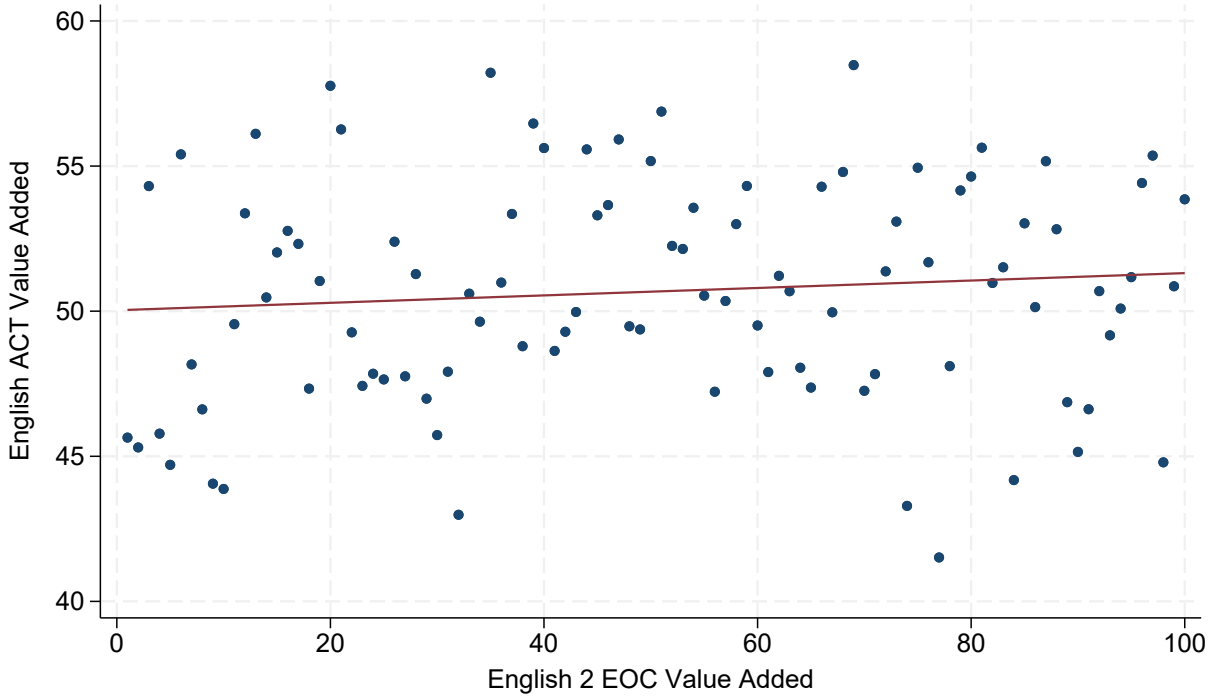
[27] On average, each English teacher is observed in 7 sections with 77 students over 2.54 years. I use students' fall 10th grade English course enrollments if they are enrolled in different fall and spring English courses and spring enrollments otherwise.

[28] Students with missing 8th grade math or reading end-of-grade test scores are excluded from the sample. Missing 8th grade science end-of-grade test scores and missing 7th grade math and reading end-of-grade test scores are imputed using the standardized mean of 0 and missing test score indicators are included as covariates.

[29] Jackson's preferred estimates include school-track fixed effects, leveraging a narrower source of identifying variation by comparing students enrolled in the same set of core academic courses. Additionally, Jackson estimates the impacts of 9th grade English teachers on 9th grade English 1 EOC test scores, while I estimate the impacts of 10th grade English teachers on 10th grade English 2 EOC test scores without a 1-year lagged test score covariate. Thus, Jackson's main estimates report a smaller standard deviation of English teacher value added. The identification of school-track fixed effects in the ACT score value added setting is infeasible due to divergence in student course-taking patterns later in high school. Thus, I estimate teacher value added on English 2 EOC test scores without school-track fixed effects for comparability across ACT and EOC value added estimates.

English teachers in my sample who taught both 11th grade students and 10th grade students during the sample period, I find a positive but relatively low correlation of 0.0135 between ACT score value added and English 2 EOC score value added. Figure A1 plots the percentiles of English 2 EOC score value added distribution against the mean percentiles of the corresponding teachers' ACT score value added estimates.

Figure A1: English 2 EOC Score Value Added vs ACT Score Value Added



To understand the relative predictive power of ACT score value added versus EOC score value added for long-run outcomes, I regress both ACT score value added and EOC score value added measures on an indicator for on-time enrollment in the UNC system during the summer or fall semester immediately following high school graduation, conditioning on student-level covariates and school and cohort fixed effects.[30] I find that ACT score value added and EOC score value added are similarly predictive of college performance. EOC score value added is slightly more predictive despite not being a direct input to the college admissions process, suggesting that dynamic complementarities in the production of English

[30]The student-level covariate vector X_{it} is defined in the value added estimation model shown in equations (1) and (2).

language skill may amplify the effects of English teacher value added in earlier years. Another potential explanation is that English teacher value added on EOC scores improves the quality of students' application essays, therefore influencing college admissions.

Table A1: Impacts of ACT vs EOC Value Added on College Enrollment

	(1)	(2)	(3)
English ACT Score Value Added	0.00272		0.00226
	(0.0114)		(0.0114)
English EOC Value Added		0.0278***	0.0278***
		(0.00657)	(0.00657)
N	189224	189224	189224
R^2	0.225	0.226	0.226

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

D Heckman Selection Correction

Here, I employ a classic Heckman selection correction procedure to estimate the impacts of ACT score value added on college performance, accounting for selection into observed college performance through enrollment in the UNC system. In this model, selection into college enrollment is binary. The relationship between college performance and selection into college enrollment is modeled to be the same across all colleges within the UNC system; that is, the selection term is a constant function of student and high school characteristics regardless of which college a student selects. I model college performance and selection into UNC system enrollment as follows:

$$\begin{aligned} College_Performance_{icst} &= \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ &\quad + \pi_3 S_{st} + \alpha_t + \tau_c + u_{icst} \qquad (13) \\ enrollment_{ist} &= \mathbb{1}[\omega_0 + \omega_{1English}\hat{\omega}_{English-t} + \omega_{1Math}\hat{\theta}_{Math-t} + \omega_2 X_{it} \\ &\quad + \omega_3 S_{st} + \omega_4 distance_{st} + \omega_5 distance_{st}^2 + \alpha_t + v_{ist} > 0] \qquad (14) \end{aligned}$$

Here, $\hat{\theta}$, X_{it}, and α_t are defined as in equations (11). S_{st} is a vector of school-level control variables.[31] τ_j are college fixed effects, included in the college performance equation to account for cross-college differences in student performance measurement. $distance_{st}$ is the distance (in kilometers) from the student's high school to the nearest UNC system institution. The distance instruments $distance_{st}$ and $distance_{st}^2$ are excluded from the college performance equation. Similar exclusion restrictions are commonly used in empirical education research following Card (1995).[32] $College_Performance_{icst}$ is observed only when $enrollment_{ist} = 1$. I make the standard conditional independence assumptions: $\hat{\theta} \perp u \mid X, S, \alpha_t$ and $\hat{\theta} \perp v \mid X, S, \alpha_t$. I make the standard distributional assumption that u and v follow a bivariate normal distribution with mean zero.

Under these assumptions, consistent estimates of $\pi_{1English}$ and π_{1Math} can be obtained using the following procedure. First, I estimate the first stage selection equation (14) using a probit regression on the full sample of data. I use these coefficient estimates to obtain the estimated inverse Mills ratio:

$$\begin{aligned}\hat{\lambda}_i = \lambda(&\hat{\omega}_0 + \hat{\omega}_{1English}\hat{\theta}_{English-t} + \hat{\omega}_{1Math}\hat{\theta}_{Math-t} + \hat{\omega}_2 X_{it} \\ &+ \hat{\omega}_3 S_{st} + \hat{\omega}_5 distance_{st} + \hat{\omega}_6 distance_{st}^2 + \hat{\alpha}_t)\end{aligned} \tag{15}$$

I then estimate the second stage equation using an OLS regression for continuous college performance outcomes or a probit regression for binary college performance outcomes.

$$\begin{aligned}College_Performance_{icst} = &\pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ &+ \pi_3 S_{st} + \alpha_t + \tau_c + \pi_\lambda \hat{\lambda}_i + \epsilon_{icst}\end{aligned} \tag{16}$$

[31] School-level control variables include indicators for locale type (city, suburb, town, rural), average daily membership, average daily membership squared, percentage of grade level proficient students, percentage of fully licensed teachers, percentage of teachers with three years of experience or less, percentage of teachers with advanced degrees, percentage of students on free or reduced-price lunch, short-term suspension rate, number of crimes or acts of violence per 1,000 students, racial composition of student body, and total per-pupil funding. High school fixed effects are omitted from the selection equation in order to identify coefficients on the distance instruments, which vary at the high school level.

[32] This exclusion restriction provides exogenous variation in students' propensities to attend college, so that identification in the Heckman selection correction model is not based solely on nonlinearities in the probit selection equation.

Table A2 presents coefficients on the distance instruments from equation (14). Both kilometers from the student's high school to the nearest UNC system institution and its square are highly predictive of UNC system enrollment, as confirmed by a χ^2 test of joint significance.

Table A2: First Stage: Testing Relevance of Distance Instruments

	(1)
Distance to Nearest Public College (km)	-0.00672***
	(0.00123)
Distance to Nearest Public College (km)^2	0.0000443***
	(0.0000122)
High School FE	No
Observations	262747
Mean	0.364
Pseudo-R^2	0.226
χ^2 from joint test of instrument significance	41.76

Standard errors in parentheses, clustered at the high school level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3 demonstrates that distance to the nearest college in the UNC system is not predictive of 12$^{\text{th}}$ grade GPA, providing evidence in support of the exclusion restriction.

Table A3: Exclusion Restriction: Impacts on 12$^{\text{th}}$ grade GPA
OLS Coefficient Estimates

	(1) 12$^{\text{th}}$ Grade GPA
Distance to Nearest Public College (km)	0.000509
	(0.000881)
Distance to Nearest Public College (km)^2	-0.00000890
	(0.00000936)
Observations	173504
Mean	3.046
R^2	0.375
χ^2 from joint test of instrument significance	1.747

Standard errors in parentheses, clustered at the high school level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4 presents estimates from the second stage college performance equation (13)

without correcting for selection into college enrollment. Table A5 presents estimates from the second stage college performance equation (16) with the selection correction.

Table A4: Second Stage: Impacts on College Performance without Selection Correction

	(1) GPA	(2) Credits	(3) Dropout	(4) 4-Year Completion	(5) 5-Year Completion
English ACT VA	0.0228	0.276*	-0.00907	0.0217*	0.0112
	(0.0183)	(0.164)	(0.00611)	(0.0118)	(0.0131)
Math ACT VA	0.0201***	0.134***	-0.00684***	0.00738	0.00855*
	(0.00702)	(0.0480)	(0.00253)	(0.00490)	(0.00515)
Observations	86897	86897	93976	71139	54917
Mean	2.964	27.87	0.0921	0.6089	0.7050
R^2/Pseudo-R^2	0.209	0.0840	0.0414	0.115	0.117

Standard errors in parentheses

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

Columns (1)-(2): Coefficients from OLS regressions

Columns (3)-(5): Average marginal effects from probit regressions

Coefficients standardized to reflect 1σ increase in value added

Table A5: Second Stage: Impacts on College Performance with Heckman Correction

	(1) GPA	(2) Credits	(3) Dropout	(4) 4-Year Completion	(5) 5-Year Completion
English ACT VA	0.0225	0.274*	-0.0116	0.0229*	0.0122
	(0.0183)	(0.164)	(0.00808)	(0.0121)	(0.0139)
Math ACT VA	0.0202***	0.134***	-0.00906**	0.00863*	0.00969*
	(0.00702)	(0.0480)	(0.00353)	(0.00501)	(0.00554)
Observations	86827	86827	95618	95618	95618
Mean	2.964	27.87	0.0921	0.6088	0.7050

Standard errors in parentheses

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

Columns (1)-(2): Coefficients from OLS regressions

Columns (3)-(5): Average marginal effects from probit regressions

Coefficients standardized to reflect 1σ increase in value added

E Nested Logit Coefficient Estimates

Table A6: First Stage Nested Logit Coefficients

	(1)
4-Year College Enrollment	
Standardized English ACT Value Added	0.00260
	(0.0775)
Standardized Math ACT Value Added	0.0449**
	(0.0225)
Inclusive Value Term	0.00991
	(0.0524)
2-Year College Enrollment	
Standardized English ACT Value Added	0.0437
	(0.100)
Standardized Math ACT Value Added	-0.0908***
	(0.0246)
Inclusive Value Term	-0.154
	(0.107)
Observations	247098

Standard errors in parentheses

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

Coefficients standardized to reflect 1σ increase in value added

Table A7: Second Stage Nested Logit Coefficients, Part 1

	(1)
Appalachian State	
Standardized English ACT Value Added	0.297
	(0.239)
Standardized Math ACT Value Added	-0.101
	(0.0885)
East Carolina	
Standardized English ACT Value Added	0.357
	(0.233)
Standardized Math ACT Value Added	-0.166*
	(0.0918)
Elizabeth City State	
Standardized English ACT Value Added	0.0836
	(0.499)
Standardized Math ACT Value Added	-0.101
	(0.175)
Fayetteville State	
Standardized English ACT Value Added	0.630**
	(0.299)
Standardized Math ACT Value Added	-0.212
	(0.139)
NC A& T	
Standardized English ACT Value Added	0.219
	(0.213)
Standardized Math ACT Value Added	-0.243**
	(0.100)
NC Central	
Standardized English ACT Value Added	0.484*
	(0.251)
Standardized Math ACT Value Added	-0.229*
	(0.119)
UNC Asheville	
Standardized English ACT Value Added	0.168
	(0.295)
Standardized Math ACT Value Added	0.0980
	(0.125)
UNC Chapel Hill	
Standardized English ACT Value Added	0.562**
	(0.245)
Standardized Math ACT Value Added	0.130
	(0.103)

Table A8: Second Stage Nested Logit Coefficients, Part 2

UNC Charlotte	
Standardized English ACT Value Added	0.354
	(0.230)
Standardized Math ACT Value Added	-0.0629
	(0.0908)
UNC Greensboro	
Standardized English ACT Value Added	0.540**
	(0.222)
Standardized Math ACT Value Added	-0.184**
	(0.0903)
UNC Pembroke	
Standardized English ACT Value Added	0.114
	(0.291)
Standardized Math ACT Value Added	-0.177
	(0.122)
UNC Wilmington	
Standardized English ACT Value Added	0.509**
	(0.247)
Standardized Math ACT Value Added	-0.0521
	(0.102)
Western Carolina	
Standardized English ACT Value Added	0.622**
	(0.248)
Standardized Math ACT Value Added	-0.122
	(0.102)
NC State	
Standardized English ACT Value Added	0.507**
	(0.234)
Standardized Math ACT Value Added	0.0693
	(0.0912)
UNC School of the Arts	
Standardized English ACT Value Added	-0.477
	(0.646)
Standardized Math ACT Value Added	-0.192
	(0.222)
4 Year Private/Out of State	
Standardized English ACT Value Added	0.409*
	(0.218)
Standardized Math ACT Value Added	-0.0288
	(0.0833)
Observations	96878

Standard errors in parentheses

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

Coefficients standardized to reflect 1σ increase in value added